ARTIFICIAL NEURAL NETWORKS: A NEW METHOD FOR MINERAL-PROSPECTIVITY MAPPING

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Abstract

The results of a pilot and detailed case study show that neural networks are a powerful technique for integrating regional exploration data from GIS databases into mineral prospectivity maps. Neural networks are trained to indicate the presence or absence of deposits, using feature vectors formed by combining the values from co-registered grid cells in raster-based GIS thematic layers containing geological, geophysical, and geochemical data and binary target values.

In a pilot study, multilayer perceptron (MLP) neural networks, trained with a gradient descent, back-propagation algorithm, are used to estimate the favourability for disseminated intrusion-related, granite-hosted and related alluvial gold deposits in the Tenterfield 1:100,000 sheet area, New South Wales, Australia. The neural network method produces a geologically-plausible mineral prospectivity map similar, but superior, to fuzzy logic and weights-of-evidence maps of the same district. The results indicate that the use of neural networks for the integration of large multisource data sets used in regional mineral exploration, and for prediction of mineral prospectivity, offers several advantages over existing methods. These include the ability of neural networks to; 1) respond to critical combinations of parameters rather than increase the estimated prospectivity in response to each favourable parameter, 2) combine data sets without the loss of information inherent in existing methods, and 3) produce results that are relatively unaffected by redundant data, spurious data and data containing multiple populations. Statistical measures of map quality indicate that the neural network method performs as well as, or better than, existing methods, while using approximately a third less data than the weights of evidence method.

Factors affecting the performance of a neural network approach are investigated in detail in a case study, based on a large exploration database provided by Goldfields Exploration Pty Ltd. Neural networks are used to predict the potential for orogenic lode-gold deposits in the Archaean Kalgoorlie Terrane, Western Australia.

Three new methods are used to compare the quality of prospectivity maps produced using neural network, fuzzy systems and weights-of-evidence methods; 1) Spearman's and Kendall's rank correlation coefficients which, show the degree to which the conditional probability of occurrence of known deposits, increases with increasing prospectivity map class (for a nine-class prospectivity map), 2) $P(D/C_k)$, the posterior conditional probability of a deposit D , given that a cell occurs in an area corresponding to a particular map class C_k , and 3) $P(D/C_k)/P(D)$, the ratio of posterior conditional probability to the prior probability of a deposit. The area under receiver-operating characteristic (ROC) curves

is also used as a measure of map quality.

A new statistical method, the cumulative bivariate J-function, and two methods developed in this study (i.e., interval-based bivariate J-function, and a plot of $(O - E)/E$, where O is the observed and E is the expected number of deposits in a buffer) are effective in identifying positive spatial associations between known deposit points and spatial features represented by line segments (e.g., faults and lithological contacts). These methods are also suitable for analysing spatial associations between deposit points and regions (e.g., magnetic anomalies) and point data (e.g., intersection of faults). However, the cumulative bivariate J-function is not well suited to measuring spatial associations for parameters that do not involve distances (e.g., density of faults or strike orientation of regional faults) or where positive or negative associations occur within discrete ranges of parameter values. A procedure for calculating the bivariate J-curve, in which the J-function is estimated for successive distance intervals rather than for cumulative distances, overcomes this problem. These methods, together with contrast of weights, chi-squared, and the Kolmogorov-Smirnov cumulative distribution function, are also used to estimate parameter values corresponding to the most favourable (prospective) regions for gold deposits.

Since the Kalgoorlie database comprises approximately 60 primary and derived GIS layers, a systematic method for selecting the most useful GIS layers as inputs to the neural networks is required. Ranking and selection criteria are compared on the basis of the generalization ability of the trained networks and statistical measures of the quality of the resultant prospectivity maps. The best criterion is $D \times (D/A)$, where D is the percentage of known deposits in the favourable region of a temporary binary layer and A is the percentage of the total map area occurring within the favourable region. Other methods are to select layers with the highest value of; 1) D/A from each evidence category, 2) D/A which also satisfies the criterion $D \geq \sim 20\%$, and 3) $D \times (D/A)$ provided the criteria $D \geq \sim 20\%$ and $D/A \geq \sim 3$ are satisfied.

The addition of random noise to augment the number of deposit patterns available for training (from approximately 50 to 1000) significantly improves the classification performance of trained networks and the quality of the resultant prospectivity maps. For example, using $\pm 40\%$ uniform random noise, the classification performance for the independent test-set increases from 67.9% and 68.0% to 72.8% and 77.1% for overall and deposit patterns, respectively. Indices for the quality of the resultant prospectivity map, D/A and $D \times (D/A)$ (where D is the percentage of deposits and A is the percentage of the total area for the highest prospectivity map-class), and area under an ROC curve, also

increase from 8.2, 105, and 0.79 to 17.9, 226, and 0.87, respectively. Increasing the size of the training-stop data set results in a further small increase in classification performance and map quality statistics. The method described here is not restricted to MLP networks, but could be applied to increase the number of training patterns for other types of neural networks or in other applications in which training data are rare, difficult or expensive to obtain.

Using fuzzy membership values as neural-network inputs is an effective method of combining subjective geological knowledge with empirical data in a neural network approach to mineral prospectivity mapping. Both subjective fuzzy-membership inputs and objective fuzzy-membership inputs, which are based on the statistical relationships between known gold deposits and the parameter in the GIS thematic layer, are used. Fuzzy-membership inputs represent a useful alternative to the 1-of-n coding commonly used for categorical inputs, particularly if there are a large number of classes.

Hybrid fuzzy-neural networks produce mineral prospectivity maps that clearly reflect the geology and structure in the input GIS maps. However, at the same time, they appear to smooth some of the noise and artifacts, which are apparent in neural-network maps, without the loss of information that is apparent in maps produced using the fuzzy systems. Thus, the hybrid fuzzy-neural systems have several advantages compared with either the neural-network or fuzzy systems, including; 1) ability to incorporate prior knowledge, 2) good generalization, reflected in best test-set classification performance, 3) very high values for map quality statistics, and 4) mineral prospectivity maps with low noise, no artifacts and a high level of geological detail. Fuzzy-membership inputs are applicable to a large range of subjective data (e.g., favourability of tectonic environment, host stratigraphy, or reactivation along major faults) currently used in regional exploration programs, but which would normally not be included as inputs in an empirical neural-network approach.

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Preface

This study represents the first comprehensive study of the application of neural networks to mineral prospectivity mapping. At the time this study was commenced in 1997, there were only two published reports on the use of neural networks for mineral prospectivity mapping. No comparative studies of neural networks and statistical- or fuzzy systems-methods existed until 1999 and, even then, the methods are described only in general terms by the researchers. Little information existed to indicate which factors might be important in determining the performance of a neural network approach to mineral prospectivity mapping.

Consequently, much of the methodology for pre- and post-processing, selection of inputs, and the quantitative assessment of map quality needed to be developed and documented within this study. In addition, many alternative parameters for assessing the quality of the GIS layers selected as neural network inputs, and methods for assessing the quality of the output prospectivity maps, had to be tested in this study. This contrasts with the situation in more established fields, such as the classification of remotely-sensed images or visual information retrieval, where methodologies and metrics for evaluating performance are better established.

All of these factors have contributed to the length of this thesis. To assist the reader to assimilate this material, important aspects and results are presented as a summary section at the end of each chapter.

Chapter 1

Introduction

1.1 Problem Statement

The development of faster, more efficient and objective Geographic Information Systems (GIS)-based methods for the integration and analysis of regional exploration data sets has a potentially important role in supporting the decision making process for geologists in terms of ground acquisition and the selection of exploration targets.

There is a need for such methods as the volume and complexity of regional data available to the exploration geologist is increasing rapidly from a variety of sources. For example, remote sensing, airborne geophysics (Hone *et al.*, 1997) and large commercially-available geochemical databases compiled from open-file exploration reports (Beams, 1995) all contribute to the increasing volume of digital map data in exploration programs. New developments such as the use of airborne electromagnetic methods as a regolith and bedrock geological-mapping tool (Green & Munday, 1998), airborne gravity gradiometers (Hannaford & Opat, 1998) and differential vector magnetometers (Schmidt, 1998) are likely to continue this trend. As the amount of data increases, so too will the need for an effective means of integration and analysis (Cucuzza & Goode, 1998).

GIS represent an ideal environment for the integration and analysis of map data (Wyborn *et al.*, 1995b; Burrough & McDonnell, 1998). Although GIS are emerging as an important technology in mineral exploration, the maximum benefit to be derived from the considerable time and cost of entering map data into the GIS are not realized if the system is only used to store and print paper maps. Despite the role of digital map data in exploration and the increasing difficulty of finding new world-class ore deposits, there has been relatively little research on methods to combine large regional data sets within a GIS in a way that can assist geologists. The process of combining digital map data from multiple sources

Figure 1.1. Illustration of how this study fits into the task of regional mineral exploration.

in order to produce a single mineral prospectivity map, depicting areas ranked according to their potential to host mineral deposits of a particular type, is the focus of this study (Fig 1.1).

Existing methods for producing prospectivity maps have some important limitations. Empirical statistically-based methods, for example, weights of evidence (WofE) based on Bayesian probability (Bonham-Carter *et al.*, 1988), require a statistically significant number of mineral occurrences to estimate the relative importance of geological evidence associated with the deposits, and are, therefore, not applicable in poorly-explored areas containing few known deposits.

Conceptual methods, such as index overlay or fuzzy logic (An *et al.*, 1991; Eddy *et al.*, 1995), and the specific and interactive modules of the mineral systems approach developed by Wyborn *et al.* (1994c, 1995b), overcome this problem, but rely on a deposit expert to make subjective assessments. All these conceptual methods depend on the application of a deposit model to decisions about which geological parameters might be significant. The problem here is that new deposit types are still being discovered; for example, Olympic Dam (Woodall, 1994), and models for well-investigated deposit styles are constantly being revised in the light of new discoveries, such as, Century (Legge, 1995).

A further disadvantage of existing methods is that they are either exclusively conceptual (deposit-model-driven) or empirical (data-driven). On the other hand, Woodall (1994) has emphasized that discoveries are made when the right blend of conceptual and empirical

evidence is applied. Part of the potential of a neural network system lies in the possibility of creating hybrid systems that enable the geologist's knowledge of deposit models and processes to be incorporated into the search for patterns and important relationships in very large data sets.

1.2 Generation and Statement of Hypothesis

Artificial neural networks¹ offer a new approach to the problem of mineral-prospectivity mapping. Neural networks represent a type of adaptive computing system that can learn from the data. Properties of neural networks that make them particularly suitable for pattern recognition and classification include their ability to: 1) extract underlying patterns from a data set which may be imperceptible to humans and to standard statistical techniques, 2) require no statistical model for the data, 3) operate without the need for pre-existing knowledge (e.g. a deposit model), 4) operate at acceptable accuracy when the data are noisy or contains outliers, 5) perform well when the input parameters are inter-dependent and exhibit significant nonlinearity, 6) be flexible and retrained when new data become available, and 7) be used on large mixed data sets.

These features suggest that neural networks could be well suited to integration of mineral exploration data. By analogy to the way in which bands in remotely-sensed imagery are combined into composite images to create signatures for alteration minerals, digital geological, geophysical and geochemical maps can be superimposed in a GIS to produce an image from which the signatures of ore deposits can be extracted. The thrust of this study is that neural networks can be trained to recognize these signatures, and hence predict the location of new deposits of similar type. To test this concept, a neural network is used to integrate regional exploration data from a small GIS database into a single prospectivity map, and the performance of the neural-network approach is compared with Bayesian statistical and fuzzy-logic methods.

¹The term artificial neural network is used to distinguish artificial neural networks implemented as computer software or hardware from the biological networks upon which they were originally based. Since only the former type is discussed in this paper, they are referred to as neural networks.

1.3 Aim of the Research

1.3.1 Primary Aims

The main aims of this study are to;

1. investigate the application of a combined neural network GIS approach to the problem of integrating and analyzing geoscientific data sets to produce mineral prospectivity maps,
2. to evaluate the neural-network approach and quantitatively compare it with existing empirical and conceptual methods for mineral prospectivity analysis, and
3. test the general applicability and limitations of the neural-network approach using a GIS database typical of those used routinely by the mining industry in exploration.

One of the difficulties in this study is that little previous work has been done on the topic. At the time this study commenced, there was only one paper in the literature that described the use of neural networks to produce a mineral prospectivity map (Singer & Kouda, 1996). Consequently, there is a huge range of aspects of the problem that could be investigated. What type of neural network architecture is best suited to the analysis of mineral prospectivity? What type of pre-processing should be performed? What training strategies can be used to cope with the enormous imbalance in the ratio of positive to negative training examples (i.e. deposits to barren cells)? How should the relative importance of input features be assessed? The question as to whether a neural-network approach can work with a range of deposit types and GIS data sets in which the quality, extent of coverage, types of thematic layers and scale of data capture and compilation vary, is also important and can only be answered with case studies. How does the performance of a neural-network approach compare to existing methods is a question that is also addressed in this work.

The problem with all of this is a combinatorial one. Each network architecture could be trained with a variety of subsets of input features, network parameters (e.g. learning algorithms, topologies) and training strategies, (e.g. encoding of categorical input features using *1-of-n* or fuzzy membership values) and tested on different GIS databases. For each of the two databases analysed in this study, the results of a neural-network approach could be compared with examples of existing empirical and conceptual methods (the weights-of-evidence method and fuzzy logic are selected). This potentially amounts to a large number of mineral prospectivity analyses.

To limit this scope, the weights-of-evidence methods is only applied to the database used in the pilot study. Recent work by Harris & Pan (1999), Singer & Kouda (1999a), and Kemp *et al.* (2001) suggests that probabilistic, general regression and radial basis function neural networks are suited to mineral exploration applications. However, the MLP network is the most commonly used type of neural network. It has powerful generalization abilities and is applicable to a wide range of applications. Consequently, an MLP network architecture is chosen for this study. MLP networks are used for experiments on the effect of input feature selection, training strategy, and the effect of incorporating expert knowledge on the performance of a neural-network approach to mineral-prospectivity mapping.

1.3.2 Secondary Aims

An important aspect of this work is to determine the most effective way of applying neural networks to the problem of mineral-prospectivity mapping.

One of the common criticisms of neural networks is that it is not possible to predict from theory what the most suitable network architecture, topology and parameters for a given problem should be. Also, before a neural network can be used to classify patterns, the raw data must be converted to a form suitable for processing by a neural network and attributes, known as features, which are relevant to solving a problem must be selected from the data. Pre-processing must also be adapted for each individual problem. Consequently, a secondary aim is to develop and evaluate a variety of different pre-processing strategies in order to improve neural network performance.

Since a vast number of different neural network architectures and learning algorithms exist today, another secondary aim is to test the suitability of selected types of neural networks for the task of estimating mineral prospectivity.

A general goal in this work is to make use of all the available sources of information in order to improve the mineral prospectivity analysis. In remote sensing applications, expert knowledge and ancillary information are important for generating reliable classifications (Milne, 1999). Novel techniques like stress mapping (Groves *et al.*, 1997), shape analysis (Gardoll *et al.*, 2000), and layers that depict essential components in a mineral system (Wyborn *et al.*, 1994c) could be used to generate additional map layers to supplement the traditional geology, geochemistry and geophysics used in mineral exploration. As an example of this latter type of layer, features like hydrothermal alteration zones, metamorphic grade, favourable host-rock geochemistry, or zones with a high fracture-related permeability could be used to produce input layers suitable for processing by a neural net-

work. Subjective geological knowledge of the type used in the fuzzy-logic method could be used as additional input to a neural network.

1.3.3 Limitations

Several ways in which the scope of this study has been limited are listed below.

1. Prospectivity mapping is only performed in two dimensions in the plane of geological maps. Although GIS can be extended to deal with three dimensions (Wyborn *et al.*, 1996a), such systems are currently in the early research stages and are not commercially available. A three-dimensional approach on a regional scale for prospectivity analysis would also be difficult due to the very interpretive nature of cross sections at this scale and the limited availability of suitable data.
2. Although MLP neural networks form the basis for this study, a wide variety of neural network architectures have been developed since the mid-eighties. A review of six commonly-used architectures, which appear to have characteristics suitable for prospectivity analysis problems is presented in Appendix A. These networks cover a range of paradigms. Four networks (MLP, probabilistic, radial basis function, and general regression neural networks) require supervised training, in which training data comprise examples of both the inputs and the required outputs. This contrasts with the Kohonen neural networks which require unsupervised training. Here it is not necessary to know which class the patterns used in training belong to: that is, whether the patterns correspond to deposit locations or not. Only MLP networks and a hybrid fuzzy-neural network system similar to that developed by Kasabov & Kozma (1999) are tested in Chapter 7.
3. This study does not attempt to apply neural networks to the analysis of geological patterns within a single two-dimensional plan or image. One of the great strengths of neural networks is their ability to recognize and classify patterns in two dimensional images. An example is the use of neural networks to recognize hand-written digits in post-codes (Le Cun *et al.*, 1989). The recognition of roughly circular-shaped features in topographic or magnetic anomaly maps corresponding to kimberlite pipes is a geological example in which pattern recognition could be applied in a single map layer. Pattern analysis in geological maps to define analogues of the patterns of folded strata and rock-competency contrasts associated with deposits has been applied to Archaean lode-gold deposits in the Kalgoorlie area, Western Australia (Gardoll *et al.*, 2000). Although neural networks could be applied to these two

geological tasks, pattern recognition and image understanding represent very difficult problems in artificial intelligence and are the subject of intensive research in the fields of robotics and machine vision (Cawsey, 1998). Each one of these two examples would constitute a major investigation.

1.4 Research Approach

The research in this thesis consists of two main parts; a pilot study and a series of experiments based on a case study. The pilot study, based on intrusion-related gold deposits in the Tenterfield area, New South Wales (N.S.W.), was conducted to test the viability of using a neural network to produce a prospectivity map (Brown *et al.*, 1997, 1999, 2000a).

The second part of this work consists of a case study based on Archaean lode-gold deposits in the Kalgoorlie area, W.A. Australia. The work is designed to test the general applicability and limitations of the neural network method on a large geoscience data set used in current exploration (Chapter 5).

The Kalgoorlie study area is the basis for a series of experiments aimed at improving the performance of the neural network method used in the pilot study. This investigation is based on the five main steps involved in solving a problem with a neural network as described by Zaknich (1999);

1. data collection,
2. pre-preprocessing,
3. selection and combination of attributes from data (feature extraction),
4. selection of an neural network type and topology, and
5. neural network training and testing.

As the databases in this study have been compiled at the University of New South Wales (Barnes, 1993; Jusmady & Taylor, 1997) and Goldfields Exploration (now Placer Dome), an examination of steps 1 and 2 do not form part of this study.

It is generally recognized that the success of any neural network application depends, not only on the information supplied as input, but also, on how effectively the problem is presented to the network. Although neural networks are robust with respect to noise and can deal with irrelevant and confusing data, the training time is reduced and classification accuracy is improved if the task of the neural network is kept as simple as possible (Masters, 1993b; Zaknich, 1999). This can be achieved by performing as much work as possible

in the initial pre-processing and feature selection stages. The effect of feature selection on network performance and on the quality of the resultant mineral prospectivity maps is investigated in Chapter 6. The possibility of improving the predictive quality of mineral prospectivity maps by incorporating subjective expert knowledge into the otherwise empirical neural-network approach is investigated in Chapter 5. The expert knowledge can be built into GIS layers that are derived from the primary data. The effect of using different types of training data and training strategies on network performance and map quality is also investigated in Chapter 7.

Maps produced in this study, using the neural network method, are checked in two ways.

1. The neural-network maps are compared to those produced with the empirical weights of evidence and fuzzy-logic methods. A comparison with the weights-of-evidence method establishes whether the neural network result accounts for the major spatial relationships between map features and known deposits. Comparison with the fuzzy-logic map shows whether the neural network accounts for current understanding of the factors important for controlling the location of mineralization.
2. A range of statistical and probability measures of prospectivity map quality are used to assess the effectiveness of different implementations of the neural network method.

1.5 Organization of Thesis

Chapter 2 discusses previous work in mineral-prospectivity mapping, the application of neural networks in mineral exploration, and other artificial intelligence and statistical techniques that could potentially be used for prospectivity analysis.

Chapter 3 outlines mineral prospectivity methods, GIS databases, software and hardware used in the thesis.

Chapter 4 describes a pilot study, based on intrusion related and placer gold deposits in the Tenterfield 1:100000 map sheet area, which tests the feasibility of using an MLP neural network to produce a mineral-prospectivity map.

Chapter 5 describes the Kalgoorlie study area, and the processing required to produce primary and derived GIS layers. A number of techniques for including geological knowledge and subjective judgement into GIS layers are demonstrated. These techniques include the use of novel derived GIS layers, which depict parameters that represent important controls on the location of mineralization.

Chapter 6 applies a variety of statistical techniques to test the candidate GIS layers in order to select best predictors of known deposits as the inputs for neural networks.

Chapter 7 consists of a series of experiments based on the Kalgoorlie case study area. The experiments systematically test factors affecting the performance of neural networks and the quality of mineral prospectivity maps. Methods for improving the results and for overcoming limitations to the neural networks are also investigated.

Chapter 8 summarizes and discusses the key results of the work and includes suggestions for future work.

Appendix A explains the organization of the CD-ROM's, which contain all GIS databases used in the study, and describes metadata standards used to document the data.

Appendix B documents the Tenterfield GIS database used for the pilot study.

Appendix C documents the Kalgoorlie GIS database used for the case study.

Appendix D describes the neural network processing based on C++ programs used in the pilot study.

Appendix E lists and briefly describes MATLAB functions and scripts used for the Kalgoorlie case study.

Appendix F contains graphs and tables used in the evaluation of candidate GIS input layers for the Kalgoorlie study area.

Appendix G contains tables documenting the detailed results of MLP neural network and fuzzy systems experiments based on the Kalgoorlie case study.

Appendix H contains tables documenting the detailed results of neural network and fuzzy systems experiments based on the Kalgoorlie case study.

Appendix I gives an explanation of the ARCVIEW layer names in the Kalgoorlie GIS database.

CD-ROM 1 contains the ARCVIEW database, C++ programs used in the pilot study, and MATLAB programs used in the case study.

CD-ROM 2 contains input GIS layers and mineral prospectivity maps in GEOSOFT format and an interface for viewing the maps.

1.6 Publications Based on this Study

This study is supported by the following publications, of which the author was the major contributor.

Articles

BROWN, W. M., GEDEON, T. D. & GROVES, D. I. 2003. Use of noise to augment training data: a neural network method of mineral potential mapping in regions of limited known deposit examples. *Natural Resources Research*, **12**, p. 141–151.

BROWN, W. AND GROVES, D. I. & GEDEON, T. D. 2003. Use of fuzzy membership input layers to combine subjective geological knowledge and empirical data in a neural network method for mineral potential mapping. *Natural Resources Research*, **12**, p. 183–200.

BROWN, W. M., GEDEON, T. D., BADDELEY, A. J. & GROVES, D. I. 2002. Bivariate J-function and other graphical statistical methods help select the best predictor variables as inputs for a neural network method of mineral prospectivity mapping. *In*: Bayer, U. and Burger, H. and Skala, W. eds *IAMG 2002 8th Annual Conference of the International Association for Mathematical Geology*, vol. 1, pp. 263–268. International Association of Mathematical Geology.

BROWN, W. M., GEDEON, T. D., GROVES, D. I. & BARNES, R. G. 2000. Artificial neural networks: a new method for mineral prospectivity mapping. *Australian Journal of Earth Sciences*, **47** 757–770.

BROWN, W. M., GEDEON, T. D. & BARNES, R. G. 1999. The use of a multilayer feedforward neural network for mineral prospectivity mapping *In*: Gedeon, T., Wong, P., Halgamuge, S., Kasabov, N., Nauck, D., and Fukushima, K. eds *ICONIP'99, Proceedings of the 6th International Conference of Neural Information Processing*, vol. 1, pp. 160–165. IEEE, Piscataway.

Submitted

BROWN, W. M., GEDEON, T. D. & GROVES, D. I. 2002. Use of noise to augment training data: a neural network method of mineral potential mapping in regions of limited known deposit examples. *Natural Resources Research*, in press.

BROWN, W. M., GROVES, D. I. & GEDEON, T. D. 2002. Use of fuzzy membership input layers to combine subjective geological knowledge and empirical data in a neural network method for mineral potential mapping. *Natural Resources Research*, in press.

Abstracts

BROWN, W. M., GEDEON, T. D. & GROVES, D. I. 2002. Use of noise to augment training data to compensate for lack of deposit examples in training a neural network for mineral potential mapping *In*: Kouda, R., Koike, K., Singer, D. & Coughlan, J. eds *Abstracts and Programs for Seventh International Symposium on Mineral Exploration: Application of Neural Networks to the Earth Sciences*, 20–21 August, NASA Moffett Field, Mountain View, California, pp. 9.

BROWN, W. M., GROVES, D. I. & GEDEON, T. D. 2002. Use of fuzzy membership input layers to combine subjective geological knowledge and empirical data in a neural network method for mineral potential mapping *In*: Kouda, R., Koike, K., Singer, D. & Coughlan, J. eds *Abstracts and*

Programs for Seventh International Symposium on Mineral Exploration: Application of Neural Networks to the Earth Sciences, 20–21 August, NASA Moffett Field, Mountain View, California, pp. 10–11.

BROWN, W. M., GEDEON, T. D., GROVES, D. I. & BARNES, R. G. 2000. Mineral prospectivity mapping: a comparison of MLP neural network, fuzzy logic and weights of evidence methods *In: 15th Australian Geological Convention, Sydney, Abstracts*, vol. 59, pp.63. Geological Society of Australia.

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Chapter 2

Review of the Literature

2.1 Introduction

In Chapter 1, the need for efficient methods of integration and analysis of multisource data sets is presented in the context of the large amounts of digital data currently generated in regional exploration programmes and the limitations of two of the most popular current methods; i.e. weights of evidence and fuzzy logic. It is the purpose of this chapter to examine previously-used methods and to summarize some of their strengths and weaknesses in order provide a background against which any potential neural network method can be compared.

It is also suggested in Chapter 1 that neural networks have many characteristics that appear to be particularly suited to geoscience applications and that neural networks in combination with a GIS represent a potentially useful new approach to mineral-prospectivity mapping. Since the GIS is an integral part of any mineral prospectivity method, key aspects of GIS that relate to this study are also briefly reviewed. This is followed by an examination of some neural network concepts relevant to the multilayer feedforward neural network, which is the main class of neural networks used in this study. Application of neural networks to geoscientific applications, particularly in spatial analysis and mineral exploration is also discussed.

A great variety of different types of neural networks exist. Although this chapter contains a review of the theory and applications relating to MLP neural networks, other architectures that are potentially useful for mineral-prospectivity mapping are described in Appendix A.

2.2 Mineral-Prospectivity Mapping Methods

For the purpose of this review, mineral prospectivity or favourability mapping is defined as the process of making regional scale maps (1:50000 - 1:250,000) showing the relative potential to host a mineral deposit of a particular type. Singer & Mosier (1988) suggested that the range of methods for regional assessment of mineral resources should be considered in terms of who is going to use the results and the required form of the output. This study is concerned with the way geologists involved in the early stages of regional exploration can combine and analyze geoscience data sets to make decisions about ground acquisition and target selection. Consequently, the focus of this review is on methods that

1. can be used to combine many different types of spatial geoscientific data sets,
2. produce output in map form,
3. estimate favourability according to geological rather than economic criteria,
4. apply to a single type or group of metallic mineral deposits, and
5. apply to regional-scale mineral exploration rather than land assessment.

Such criteria exclude mineral resource assessment undertaken for economic forecasting purposes. Some of these methods are described by Singer & Mosier (1988), which they refer to as crustal abundance methods, cumulative-tonnage-frequency methods. These methods make an overall assessment of a large region and do not take account of local variations in geology and do not attempt to predict the probable location of individual deposits. For example, Allais (1957) used statistics on the deposit occurrences and values in France and Western United States to predict the expected number and value of deposits for a one million square kilometre area in the Algerian Sahara. The study was based on the following assumptions; 1) geologic conditions are uniform (in particular, that control and study areas are similar), 2) frequency of deposits follows a Poisson distribution, 3) value of deposits follows a log-normal distribution, and 4) nearly all deposits in the control areas have been discovered. The calculation of total endowment by Allais (1957) in terms of the value of contained metal required estimates of the number of deposits per square kilometre, and the grade and tonnage of deposits. By contrast, the goal in this study is much more limited; that is, to estimate the relative favourability of areas represented by grid cells to host mineralization of a specific type.

⁰Methods used in this study are reviewed in Chapter 2. The other main mineral prospectivity mapping methods are reviewed in Appendix A

A list of the methods which fulfill the criteria listed above, and which are considered in this review, are shown in Table 2.3. Bonham-Carter (1994) distinguished two broad categories of mineral favourability mapping methods; data-driven (or empirical) and knowledge-driven (or conceptual) methods. These categories are indicated in Table 2.3 on page 56.

The historical development of mineral-prospectivity mapping methods is shown in Table 2.3, which lists methods according to the chronological order in which they were first applied to mineral-prospectivity mapping.

2.2.1 Overview

The initial work on integrating spatial geoscience data sets generally took an empirical or data-driven approach and was based on statistical methods (Table 2.3). A range of techniques are described in the literature, from simple statistical techniques, such as correlation coefficients and Boolean logic (Bates, 1959), to multivariate analysis techniques such as; multiple linear regression (Sinclair & Woodsworth, 1970; Agterberg *et al.*, 1972), cluster analysis (Briggs & Press, 1977), multiple discriminant analysis (Prelat, 1977), a form of principal component analysis (Botbol *et al.*, 1978), logistic regression (Chung & Agterberg, 1980), Bayesian statistics combined with frequency distributions and an area of influence procedure (Singer & Kouda, 1988), weights-of-evidence (WofE) (Bonham-Carter *et al.*, 1988) and canonical correlation (Pan & Harris, 1992).

Some earlier work dealt with conceptual approaches. For example, although the work of Bates (1959) was statistical, the technique used to integrate layers was Boolean logic. Harris (1973) combined subjective estimates of the number of deposits, grade and tonnages with statistics to estimate the total metal endowment. Koch *et al.* (1981) and Reddy & Koch (1988) used a method involving a favourability score which is equal to a linear combination of geological variables in which the weighting factors were estimated by a subjective method. Both methods are equivalent to subjective overlay methods described by Bonham-Carter (1994). A different type of conceptual approach has been developed by Wyborn *et al.* (1994c, 1995b). Rather than focusing on the integration of existing data sets, the mineral systems approach involves identifying parameters considered essential for ore formation (e.g. source rock, reactive minerals, structures for fluid infiltration) and translating these parameters into mapping criteria or attributes that may be extracted from a regional-scale GIS database. It should be noted though that this approach to the creation of input layers could be incorporated into any of the methods shown in Table 2.3.

Knowledge-driven or conceptual methods feature in later work and employ a range of artificial intelligence approaches¹ such as expert systems² (Duda *et al.*, 1978; Katz, 1991; Reddy *et al.*, 1992), Dempster-Shafer evidential belief theory (Moon, 1990), fuzzy systems (An *et al.*, 1991), decision-tree induction systems (Reddy *et al.*, 1992; Bui *et al.*, 1998), and a hybrid statistical-fuzzy-logic approach (Knox-Robinson & Groves, 1997a). Neural networks represent a data-driven approach within the field of artificial intelligence.

The following sections review the theory and literature describing mineral prospectivity methods which are directly used in this thesis. Other methods that have previously been used to predict the potential for mineral deposits are described in Appendix A. An excellent review of a variety of methods for analysing and combining geoscience data sets is given by Pan & Harris (2000).

2.2.2 Weights of Evidence

Weights of evidence is a statistical method that uses a log-odds formulation of Bayesian probability to update prior probability estimates on the basis of evidence. The method was developed for medical diagnosis (Lusted, 1968; Aspinall, 1983; Spiegelhalter & Knill-Jones, 1984) and later adapted to spatial data and mineral exploration by Bonham-Carter *et al.* (1988), Agterberg (1989c) and Agterberg *et al.* (1990). The following summary of the weights-of-evidence method is based on descriptions by Bonham-Carter *et al.* (1988, 1989) and Bonham-Carter (1994).

The weights-of-evidence method is based on the concept of prior and posterior probabilities. If each deposit is assumed to occupy a single cell (where data are in raster format), then the prior probability of any cell chosen at random containing a deposit is equal to the ratio of the number of deposit cell to the total number of cells:

$$P(D) = \frac{n(D)}{n(T)} \quad (2.1)$$

where D represents the event that a cell contains a deposit and T is the total number of cells in the map.

This prior probability can be updated using additional information, in the form of binary

¹The term artificial intelligence has tended to be replaced with the terms intelligent computing or soft-computing.

²Expert systems are now more commonly referred to as knowledge-based systems.

maps depicting the presence or absence of some parameter favourable for mineralization¹. An example of a favourable map pattern in the case of exploration for skarn deposits could be “*presence of limestone*” or “*magnetic anomaly*”. If $P(D|E)$ represents the conditional probability of a deposit occurring in a grid cell given the presence of an evidence pattern E that is favourable for mineralization in a binary evidence map, then Bayes’ rule states that:

$$P(D|E) = \frac{P(E|D)}{P(E)} \cdot P(D) \quad (2.2)$$

In equation 2.2, the prior probability $P(D)$ is updated with the factor $P(E|D)/P(E)$ to give the posterior conditional probability, $P(D|E)$.

In order to extend this approach to multiple maps, an assumption of conditional independence between parameters with respect to deposits must be made; that is, the effects of the interactions between parameters used as evidence to modify the prior probability must be ignored. The approach is same as the one used in Bayesian updating of probabilities in expert systems described in equations A.22-A.26 on page 455. The discussion in the next section is based on the description by Stackhouse & Boyd (1985). Bayes’ rule for N items of evidence (i.e. binary maps containing patterns favourable for mineralization) is:

$$P(D|E_1 \cap E_2 \cap \dots \cap E_n) = \frac{p(E_1 \cap E_2 \cap \dots \cap E_n|D)}{P(E_1 \cap E_2 \cap \dots \cap E_n)} \times P(D) \quad (2.3)$$

If events $E_1, E_2, \dots, E_n$ are assumed to be conditionally independent then:

$$P(E_1 \cap E_2 \cap \dots \cap E_n|D) = P(E_1|D) \times P(E_2|D) \times \dots \times P(E_n|D) \quad (2.4)$$

Substituting equation 2.4 into the denominator on the right-hand side of equation 2.3

¹Although weights of evidence has usually been applied as a binary method, it is not restricted to binary data. A 3-class geological map was used as an input in the first application of the weights-of-evidence method by Bonham-Carter *et al.* (1988) and a geological map with over 20 classes was used in a study of the mineral potential of the Slave Province (Bonham-Carter *et al.*, 1998a,b). Multiclass maps can be used as inputs without reclassification in the weights-of-evidence module of the software package for ARCVIEW called ARCSMDMKemp *et al.* (2001). Bonham-Carter (pers. comm.) has pointed out that the main reason for reclassification is to enable robust weight estimates in data sets with a small number of known deposits.

gives:

$$P(H|E_1 \cap E_2 \cap \dots \cap E_n) = \frac{P(E_1|D) \times P(E_2|D) \times \dots \times P(E_n|D)}{P(E_1 \cap E_2 \cap \dots \cap E_n)} \cdot P(D) \quad (2.5)$$

Converting to odds involves taking the ratio of the probability that the event occurs to the probability that the event does not occur (i.e. odds $O = P/\bar{P}$). Converting equation 2.5 to odds gives;

$$\begin{aligned} \frac{P(D|E_1 \cap E_2 \cap \dots \cap E_n)}{P(\bar{D}|E_1 \cap E_2 \cap \dots \cap E_n)} &= \frac{P(E_1|D) \times P(E_2|D) \times \dots \times P(E_n|D)}{P(E_1|\bar{D}) \times P(E_2|\bar{D}) \times \dots \times P(E_n|\bar{D})} \cdot \frac{P(D)}{P(\bar{D})} \\ O(D|E_1, E_2, \dots, E_n) &= O(D) \cdot \frac{P(E_1|D)}{P(E_1|\bar{D})} \times \frac{P(E_2|D)}{P(E_2|\bar{D})} \times \dots \times \frac{P(E_n|D)}{P(E_n|\bar{D})} \end{aligned} \quad (2.6)$$

Taking the natural logarithm of both sides of equation 2.6 allows several factors $P(E_n|D)/P(E)$, corresponding to multiple evidence maps to be expressed as the sum of weights as follows;

$$\ln[O(D|E_1 \cap E_2 \cap \dots \cap E_n)] = \ln[O(D)] + \sum_{i=1}^N W_i^\pm \quad (2.7)$$

$$\text{where } W_i^\pm = \begin{cases} W_i^+ = \ln \left[\frac{P(E_i|D)}{P(E_i|\bar{D})} \right] & \text{if pattern } E \text{ present} \\ W_i^- = \ln \left[\frac{P(\bar{E}_i|D)}{P(\bar{E}_i|\bar{D})} \right] & \text{if pattern } E \text{ absent} \\ 0 & \text{if data are missing} \end{cases} \quad (2.8)$$

and E_i represents evidence patterns that are useful as predictors of mineralization. Equation 2.8 is used to calculate prospectivity expressed as a posterior probability in the weights-of-evidence method. The intuitive appeal of the weights-of-evidence method lies in the fact that the contribution of each factor considered favourable for mineralization can be calculated in terms of a pair of weights for each input binary evidence map separately and then combined using equation 2.8 above. The output prospectivity map is presented in terms of probability values calculated from the posterior log-odds.

A binary predictor map is produced by reclassifying multiclass maps. Selected categories of categorical data (e.g. rock types) or, in the case of ratio data (e.g. magnetic intensity), a selected range of values or a group of class intervals, are re-labelled as being favourable for

mineralization. All other categories or values are considered unfavourable. These areas are assigned values of one and zero, respectively. The choice of categories or cut-off value used to re-classify the multiclass map is made so that the spatial association between deposit points and pattern is maximized. The proximity relationships between deposits and linear map features such as faults and lithological contacts can be quantified by using the spatial overlay functionality of a GIS to create a series of buffer zones around the relevant lines.

Bonham-Carter (1994) described a method for selecting the class threshold which maximizes the spatial association between the predictor patterns and deposit points using a quantity called contrast. Contrast is defined as:

$$C_W = W^+ - W^- \quad (2.9)$$

Weights are calculated for cumulative distances and plotted against cumulative distance. A peak in the contrast-cumulative distance graph can be used to choose an optimal cut-off distance for which the spatial association between the deposit points and the buffer pattern is strongest. Optimal cut-off values for classed ratio data like magnetic intensity and radiometric response are also selected using this procedure. Bonham-Carter (1994) used the standard deviation of contrast, $S(C)$, and the studentized contrast, $C/S(C)$, to check the reliability of the contrast for any particular threshold value of class. Bonham-Carter (1994) states that a significant contrast should have a studentized contrast value greater than about 1.5 to 2.0. Further methods for the quantification of spatial relationships between deposits and geological features are discussed by Knox-Robinson (1994).

A pair of weights is calculated for each binary predictor map using the conditional probability ratios estimated from area proportions (where data are stored in vector format) or numbers of cells (raster format). The positive weight is used in equation 2.8 when the favourable pattern is present and expresses how the prior probability is upgraded by the presence of the pattern. The negative weight is used when the pattern is absent and downgrades the prior probability. The procedure for calculating posterior probabilities differs slightly according to whether input maps in the GIS database are stored in a vector or raster format. For input maps stored in vector format, a unique conditions map is prepared showing the set of polygons representing all the overlap combinations of the binary input maps. The appropriate positive or negative weights are then added to the prior log-odds depending on whether the favourable pattern in each map is present or absent in the particular overlap combination. In raster mode, the overlap conditions are iteratively determined and appropriate weights added for each cell in the grid representing the study area.

The weights-of-evidence method has been applied to mineral prospectivity studies of turbidite-hosted vein gold deposits in the Meguma Terrane, Nova Scotia (Bonham-Carter *et al.*, 1988, 1989). A comparison of the weights-of-evidence and logistic regression methods was made by Agterberg *et al.* (1993), who applied the methods to the prediction of hydrothermal vents on the East Pacific Rise. They concluded that mutually inter-related evidence maps usually lead to an overestimate of the posterior probabilities because the conditional independence assumption is violated. They demonstrated that the logistic regression method is less sensitive to this problem. Watson & Rencz (1989) used the weights-of-evidence method to combine geological, geophysical, and geochemical data and predict the prospectivity for gold deposits in the Bathurst area, New Brunswick, Canada. More recent studies include the estimation of mineral prospectivity for epithermal gold deposits in Western United States (Raines, 1999), porphyry copper deposits in the Philippines (Carranza & Hale, 2002) and Queensland, Australia (Scott & Dimitrakopoulos, 2001), base-metal deposits in Rajasthan, India (Venkataraman *et al.*, 2000), orogenic gold deposits in Ontario, Canada (Harris *et al.*, 2001), Carlin gold deposits in Nevada (Mihalasky, 1999), and continental-scale resource assessment (Raines & Mihalasky, 2002). An example of an application of weights of evidence outside the area of economic geology is that of Daneshfar & Benn (2002) who investigated the spatial relationship between seismicity and faults.

Advantages of the weights-of-evidence method include (Bonham-Carter *et al.*, 1989);

1. weights are easier to interpret than coefficients in multiple regression equations,
2. missing data are easily handled, the weight for the missing data is set to zero so that it neither upgrades nor downgrades the prior probability,
3. all of the cells in a map are included in the analysis, not just those cells in the control areas as in other statistical methods,
4. it is simple to update the analysis if a new evidence map becomes available, and
5. the method allows an estimate of uncertainty to be made.

A difficulty with the weights-of-evidence method stems from the assumption of conditional independence with respect to deposits for evidence patterns. The requirement of conditional independence referred to above is rarely satisfied completely in geological data sets, particularly for those involving geochemical data (Bonham-Carter, 1994). To check the extent of the problem, chi-squared tests for pair-wise conditional independence are performed for each possible pair of input maps for cells where a deposit is present. Where a

significant correlation between binary map parameters exists, either one of the dependent maps must be omitted or dependent maps can be combined using Boolean operators (AND or OR), multiple regression or principal component analysis (Bonham-Carter *et al.*, 1988; Agterberg, 1992b; Bonham-Carter, 1994).

Bonham-Carter *et al.* (1989) and Bonham-Carter (1994) have also described an overall goodness-of-fit test that can be applied to check whether the assumption of conditional independence of the evidence patterns with respect to deposit points is satisfied. They suggest that the total number of deposits predicted by the posterior probability map should be no greater than 10-15% larger than the observed number of deposits. For raster maps, the predicted number of deposits is given by equation 2.10:

$$N(D)_{calc} = \sum_{i=1}^N P_i N(A)_i \quad (2.10)$$

where $N(D)$ = the predicted number of deposits, P_i is the posterior probability of a deposit for the i^{th} unit cell (or polygon for vector maps) on the map, and $N(A)$ is the area of the polygon in terms of unit cells. A distinction should be made between the unit cell (which is the area for which the posterior probability has been calculated) and the raster cell size as they are not necessarily the same (Bonham-Carter, pers. comm.).

However, in a recent study with a data set for VMS deposits in the Chisel Lake area, Manitoba, Canada, Singer & Kouda (1999a) demonstrated that although a chi-squared independence test indicated no significant correlation among variables, a test for the expected number of deposits demonstrated that the data clearly violate the independence assumption. Singer & Kouda (1999a) performed simulations which showed that using variables with correlations of 1.0 or -1.0 can double the expected number of deposits and that small to moderate correlations with only 6 to 8 variables resulted in adverse effects. It should be noted that Agterberg & Cheng (2002) have published a statistical test for conditional independence that is better than the omnibus test (where no information on statistical significance is possible) and the pairwise chi-squared test (Bonham-Carter, 1994) which breaks down if the number of deposits are small).

Another problem with the weights-of-evidence is that a considerable amount of the information available in the raw data, that might otherwise have contributed to the prospectivity estimate, is discarded prior to the integration step. This occurs when input maps

that contain continuous variables or multiple classes are converted to binary maps² Values below the threshold used to re-classify multiclass maps to binary maps play no role in determining prospectivity, and values above the threshold (included in the binary evidence map) are treated as though they are equal because they are assigned the same weight.

2.2.3 Fuzzy Systems

Fuzzy systems, like neural networks, are a computing paradigm that represents an attempt to build computer systems with a human-like ability to reason and make decisions based on data that are uncertain, imprecise or subjective (Kasabov, 1996). Whereas neural networks can learn from data, fuzzy systems require explicit statements of uncertain knowledge as inputs. Therefore, fuzzy systems represent a conceptual or knowledge-driven approach to mineral-prospectivity mapping (Bonham-Carter, 1994). Fuzzy set theory and fuzzy logic originated from the work of Zadeh (1965) and is widely used today in many disciplines of engineering, particularly in control applications.

In classical set theory, elements either belong to a set or they do not. In two-valued Boolean logic, propositions like “*soil gold concentration is anomalous*” is either true or false with no other choice in between. Fuzzy systems model uncertainty by allowing an element to belong to a set partially and fuzzy propositions include all the greyness between the two extremes. Crisp sets can be viewed as a special case of fuzzy set theory where only two membership values, 0 and 1, are defined. The degree to which a variable belongs to the fuzzy set is defined by a fuzzy membership function:

$$\mu_A(u) : U \longrightarrow [0, 1] \quad (2.11)$$

where μ_A is a fuzzy membership function which maps values, u , to real numbers in the interval $[0, 1]$ and U is called the universe of discourse and represents the set of all possible values for the fuzzy variable. For example, for the fuzzy proposition “*soil gold concentration is anomalous*”, a fuzzy membership value of zero means that the raw parameter value is definitely not a member of the fuzzy set “*anomalous*”, while a membership value of one means that the raw parameter value definitely is a member of the fuzzy set “*anomalous*”. A fuzzy set A is represented as a sequence of fuzzy membership degree-value pairs; $A = \{\mu_A(u)/\mu\}$, where the symbol “/” separates the membership degrees from the value

²Although a binary reclassification is usually applied, the WofE method is not restricted to binary data. See footnote on page 1.

of the fuzzy variables.

In practice, fuzzy membership values are usually assigned by an expert according to subjective judgement. An example of how a geologist might assign membership values to classes of gold soil concentration is given in Table 2.1 below.

Table 2.1. Example of the assignment of fuzzy membership values to soil gold concentration values. The membership values express the degree of membership of each of the assay values to the fuzzy set *anomalous gold concentration*. The set of paired, variable, values-membership function values represents a fuzzy membership function.

Gold concentration u (ppb)	Membership degree μ_A in fuzzy set A, “ <i>anomalous</i> ”
< 2	0.0
2–5	0.5
> 5	1.0

Membership assignments take both the favourability for mineralization and the reliability of the data into account.

Fuzzy operators can be used to combine the fuzzy membership values from different fuzzy sets to produce a single new fuzzy-membership value. In mineral prospectivity studies, the GIS layers containing raw data are converted to layers containing fuzzy membership values. At each grid cell, the fuzzy membership value from each layer is combined. The resultant output fuzzy membership values represent the degree of membership of the fuzzy set “*favourable for mineralization*”. The five main operators used in mineral prospectivity studies are listed below (Bonham-Carter, 1994);

$$\text{fuzzy AND} \quad \mu_{comb} = \min(\mu_1, \mu_2, \mu_3, \dots, \mu_n) \quad (2.12)$$

$$\text{fuzzy OR} \quad \mu_{comb} = \max(\mu_1, \mu_2, \mu_3, \dots, \mu_n) \quad (2.13)$$

$$\text{fuzzy algebraic product} \quad \mu_{comb} = \mu_1 \times \mu_2 \times \mu_3 \times \dots \times \mu_n = \prod_{i=1}^N \mu_i \quad (2.14)$$

$$\text{fuzzy algebraic sum} \quad \mu_{comb} = 1 - (\mu_1 \times \mu_2 \times \mu_3 \times \dots \times \mu_n) \\ \mu_{comb} = 1 - \prod_{i=1}^N (1 - \mu_i) \quad (2.15)$$

$$\text{fuzzy gamma operator} \quad \mu_{comb} = [1 - \prod_{i=1}^N (1 - \mu_i)]^\gamma \times (\prod_{i=1}^N \mu_i)^{1-\gamma} \quad (2.16)$$

where $\gamma \in [0, 1]$. Detailed descriptions of these fuzzy operators are given by Zimmermann (1984), Klir & Folger (1988) and Bonham-Carter (1994).

Fuzzy systems have been applied to mineral prospectivity mapping in a number of studies. Fuzzy systems have been applied to prospectivity studies on base-metal and iron deposits by An *et al.* (1991), silver-zinc deposits by Tabesh (1992), vein gold deposits by Donaldson (1996), MVT deposits by Eddy *et al.* (1995) and D'Ercole *et al.* (2000), orogenic lode-gold deposits by Knox-Robinson & Wyborn (1997) and Knox-Robinson (2000), and epithermal gold deposits by Carranza & Hale (1999). GIS layers containing raw data are converted to layers containing fuzzy membership values. At each grid cell, the fuzzy membership value from each layer is combined. The main fuzzy operators used to combine GIS input layers in mineral prospectivity studies are described by Bonham-Carter (1994). Output fuzzy membership values represent the degree of membership of the fuzzy set *favourable for mineralization*.

To determine which combination of fuzzy operators to use in order to combine the data layers, Eddy *et al.* (1995) reduced deposit model descriptions for MVT, sedimentary copper and sediment-hosted sulphide deposits to a series of simplified statements in which the essential parameters were linked with Boolean AND and OR operators. These logical statements were then applied to the data sets using equivalent fuzzy operators (from equations 2.12 to 2.16).

In all of the studies referred to above (except for Knox-Robinson, 2000, who used a vectorial technique and Tabesh, 1992, who used fuzzy *AND* and *OR*), the gamma function (equation 2.16) was used in the final step to combine fuzzy membership values in the derived layers to produce a prospectivity map. Gamma values in the range [0.95-0.98] were used in these studies. The fuzzy-logic method overcomes the problem of applying a fixed cut-off values, which are used in the weights-of-evidence method to produce binary evidence maps, by assigning fuzzy membership values on a continuous scale from zero to one. However, a loss of information still occurs in the fuzzy-logic method during the conversion of raw data values to fuzzy membership values when single fuzzy-membership values are applied to a whole class or range of values, as in the studies by An *et al.* (1991) and Eddy *et al.* (1995). This is the same procedure as was applied in Table 2.1 above. Rather than assigning a single membership degree to a complete class of values, it is more common in engineering applications to use a continuous function to convert raw values to membership values over the complete range [0,1] (Jang & Sun, 1995). This approach was used by Cheng & Agterberg (1998), who combined weights of evidence with fuzzy sets to create a hybrid method, which allows the use of both subjective and objective definitions of a fuzzy membership function. Figure 2.1 shows two commonly-used membership functions.

There are two further problems with the fuzzy-logic method. First, the fuzzy membership

Figure 2.1. Each figure shows three different fuzzy sets, background, weakly anomalous and strongly anomalous for the variable soil gold concentration. The fuzzy sets are defined using two commonly-used membership functions: A. triangular and B. sigmoidal.

values are often applied according to the degree to which parameter values conform to a deposit model, which itself may be flawed. Second, the assignment of fuzzy membership values is often entirely subjective (e.g. An *et al.*, 1991; Eddy *et al.*, 1995; Donaldson, 1996; D'Ercole *et al.*, 2000). Although spatial analysis can provide a basis for estimating the fuzzy membership values as, for example, the use of statistically-determined fuzzy membership values by Knox-Robinson & Wyborn (1997), subjective judgement is still used to determine the structure of the fuzzy inference net and to select the fuzzy operators used to combine the GIS layers. However, more recently, studies have been published by Luo & Dimitrakopoulos (2003) and Porwal *et al.* (2003a) in which fuzzy membership functions are data driven. In the study by Porwal *et al.* (2003a), fuzzy membership functions are defined using piece-wise linear functions based on quantified spatial associations between map features and known deposits. The same approach is used in this study in Chapter 5 (5.5.14).

2.2.4 Mineral Systems Approach

The mineral systems approach proposed by Wyborn *et al.* (1994c, 1995b,a) is a conceptual method. Although it does not constitute a distinct mineral prospectivity method, it should be emphasized that this approach can also be embedded in the practice of prospectivity mapping, whatever implementation is being followed. The method is important because it provides a framework to view the relationship between the components of the deposit forming process and the kind of geological evidence that can be captured in a regional GIS. In addition to providing a generic approach to the selection of input GIS layers, Wyborn

et al. (1995a) developed an extension to the ARC/INFO package that implements both conceptual and empirical mineral prospectivity mapping methods.

The mineral systems approach is based on the concept that an ore deposit results from an exceptional coincidence in space and time of ordinary mechanical and chemical processes and that these processes are mappable on a much larger scale (i.e. tens to hundreds of kilometres) than the ore deposit itself (Wyborn *et al.*, 1994c). The utility of this concept is that the mineral system represents a far larger target for exploration than the actual ore deposit and the scale of the evidence of this mineral system is comparable to a regional scale GIS. Wyborn *et al.* (1994c) defined mineral systems as all geological factors that control the generation and preservation of mineral deposits and list the following six major components;

1. energy source to mobilize fluids and drive chemical reactions,
2. sources of transporting ligands,
3. sources of metals,
4. transport pathway,
5. trap zone (and ore deposit location) with a chemical and/or physical cause for mineral precipitation at the trap site, and
6. outflow zone.

An approach of this sort had been advocated as early as 1983 by Taylor & Steven (1983). They proposed a structured subjective approach which involves the integration of all parameters that indicate the favourability for ore-forming processes, including known mineralization, geochemical and geophysical anomalies, rather than making statistical estimates. However, they did not describe how such an approach should be implemented.

In a later paper, Wyborn *et al.* (1995b) describe a mineral systems approach to evaluating mineral prospectivity that consists of three steps;

1. Define the essential ingredients that make up the components in Figure 2.2. For example, identify the specific form of the energy source (component 1 in Fig. 2.2) as a magmatic rather than a regional metamorphic event.
2. Construct a geoscientific GIS that incorporates these mappable geological criteria as searchable attributes in the GIS database. The GIS has to be constructed so that a metallogenic analysis is possible. In particular, such a GIS must contain consistent and validated attribute data and topologically correct layers. For example, granite attributes should include granite type (S- or I-type), degree of fractionation and oxidation state. Reactive minerals and rock types are also important; for example,

Al-silicates (kaolinite, K-feldspar, and sericite), sulphides, carbonate, carbonaceous rocks, Fe-rich rocks (e.g. hematite BIF).

3. Develop conceptual methods to analyse the GIS for mineral potential that can be applied to 'greenfields' areas.

The relationship between mineral systems components, essential ingredients (i.e. the specific form these components take in a particular system) and mappable criteria is shown in Figure 2.2. Wyborn *et al.* (1995b) contrast the mineral system approach, which considers the regional-scale features that contribute to the location of ore deposits, with deposit models, which are mainly concerned with characteristics of the deposits and focus on local-scale criteria.

Wyborn *et al.* (1995b) developed a menu-driven ARC/INFO extension that implements three different types of prospectivity analysis using a mineral systems approach, referred to as specific, interactive and generic modules.

The specific module allows the user to select a deposit type and specific criteria to find areas that match the criteria for that deposit type; for example, for Proterozoic granite-related gold deposits, the system extracts all areas with graphite present, an age greater than 1700 Ma, and which are within a distance of 5 km of fractionated I-type granites.

The grid-based interactive module allows the user to choose their own model. The user can select layers and input criteria for each layer. Criteria can be combined using Boolean AND or OR and XOR operators. Each GIS layer is converted to a binary map with areas satisfying the criteria set to "one" and other areas set to "zero". Binary layers are combined using Boolean *AND*, *OR*, or *XOR* so that the binary pixel value of the final map indicates whether there is a match between the data and the user specified criteria.

The generic module is also grid-based but, in contrast to the conceptual specific and interactive modules, it is an empirical method. This module allows the user to find all areas which have similar characteristics to a deposit or anomaly selected by the user. The system creates a buffer area around the selected point location. The user selects which attributes to use in the matching process. Layers are combined using the Boolean AND operator and the output is a binary map.

In contrast to the empirical multivariate techniques, discussed above, the conceptual mineral systems approach can be applied to areas where there are few known deposits or where no deposits are known. Multivariate methods require a minimum number of known

Figure 2.2. Components and criteria in the mineral systems approach developed by Wyborn *et al.* (1995b)

deposits in order to perform a statistically valid analysis.

The difficulty with the mineral systems approach is that the criteria represent features that are not normally included in a regional GIS database. Consequently, new attribute fields, along with the corresponding data, must be collected and incorporated into the GIS database before undertaking this type of analysis. Another limitation of the method is the simple additive technique used to combine the layers and the fact that all layers have the same weight.

2.3 Geographic Information Systems

2.3.1 Overview

Geographic Information Systems (GIS) are systems that can capture, store, retrieve, transform, analyse and display both spatial (i.e. geographically referenced) and non-spatial data (Burrough & McDonnell, 1998). GIS are important in this study because they are used to create the input and display the output of the mineral prospectivity methods. Although the majority of the mineral prospectivity studies referred to above were based on specially built image-processing systems (e.g. PROSPECTOR, CHARAN, SIMSAG, and FINDER), the availability of commercial GIS since the late 1980's means that at least some of the work of preparing input for current mineral prospectivity studies is performed in a GIS.

Development of GIS began with the cell-based SYMAP, GRID and IMGRID computer mapping and analysis systems developed at the Harvard School of Landscape Design, which were used for predicting urban growth (Burrough, 1986; Burrough & McDonnell, 1998). This system produced grey-scale output by overprinting characters on a line printer. Early graduate students of the school went on to produce some of the commercial GIS in use today (e.g. Dangermond, ESRI, Sperry; ERDAS, and Tomlin; MAPS).

One of the main problems in the early development of GIS was the limitations imposed by computer graphics: for example, the PROSPECTOR system (described above) could only display a maximum of 128×128 pixels at a time when one LANDSAT image consisted of approximately 3000×4000 pixels (Fabbri & Kasvand, 1988).

Factors that contributed to the development of GIS were the rapid improvement in the performance and a reduction in the cost of computers, particularly following the intro-

duction of the first personal computers (e.g. Apple in 1977 and IBM in 1981 Faust *et al.*, 1991) and the development of user-friendly graphical user interfaces (GUI) popularized by the Apple Macintosh computer. Success of the Earth Resources Technology Satellite (in 1972) and LANDSAT 4 and 5 (in 1982-84), and the availability of digital imagery also encouraged the development of GIS (Faust *et al.*, 1991).

The storage of non-spatial attribute data is one of the features that distinguish GIS from image processing and CAD systems. The development of relational database systems, based on the model proposed by Codd (1970) and first developed by IBM in the early 1980's (Blasgen, 1981), was important. They were incorporated into GIS because they support a large range of types of database queries which do not all have to be anticipated in advance as part of the design of the database. Relational databases are structured like tables consisting of rows (which hold data records) and columns of fields (which hold attributes).

Underlying the relational database model is the process of normalization, which is concerned with defining the simplest structure for a given set of data. It deals with the dependency between attributes and prevents the loss of information when records are inserted or deleted.

Advantages of the relational data model are that it is the most flexible model and it can support a wide range of query types, and allows for the efficient update of data. Queries involving more than one table require tables to be linked via common attribute. This process is known as a relational join. Each record in one table is connected to a record in another table that shares the same value for a common item. However, data retrieval, in the relational model can be slow, since only common attributes between tables can be indexed.

A further disadvantage of the relational database model is that it is not an efficient method for storing spatial data because spatial data do not naturally conform to one of Codd's normal forms (Date, 1999). One of Codd's requirements for a relational database is that the rows can be changed without changing the meaning of the data, but obviously the order of the data does matter if rows contain xy -coordinate pairs for individual vertices along line segments. Also, in a GIS, it would be more efficient if data could be accessed as groups, each one comprising all the pairs of coordinates for a given line or all the line identifiers for the lines forming the boundary of a polygon. However, such a scheme would violate Codd's first normal form that all fields are atomic and cannot be decomposed (Zhou *et al.*, 1997).

A dual database model overcomes these difficulties by maintaining non-spatial attribute data as tables in a Relational Database Management System (RDBMS), but storing spatial data using conventional file techniques to ensure speed of access. This is the approach adopted in the ARC/INFO GIS (Aronson & Moorehouse, 1983). Commercially available RDBMS (e.g. INFO, ORACLE, INGRES, INFORMIX) are used for the storage of non-spatial attributes, whereas specialized file systems are used to represent the geometry and topology of spatial objects (Burrough & McDonnell, 1998).

The most commonly used type of dual database is the arc-node-RDBMS model, which uses a full vector arc-node topology. ARC/INFO GIS used in this study is an example of this type of system, which can also operate in a raster mode (Burrough & McDonnell, 1998).

Data Structures

At the highest level, data in a GIS are structured according to the cartographic model used in the Map Analysis Package developed by Tomlin (1983, 1990). The database is viewed as a collection of map layers which are all registered according to a common geographic coordinate system with each depicting a particular type of data or theme. Within map layers, two main data structures are used to represent spatial objects, i.e. raster and vector structures. In the raster model, thematic layers are divided into a grid of square cells. Each cell is represented by either; a coordinate pair and a set of attributes, or a single attribute whose cell position is recorded implicitly by its position within the two-dimensional matrix of cells. In the vector model, the fundamental primitive is a point represented as a pair of coordinates. The points along a line (or arc), called vertices, define the shape of the arc. The end-points of an arc are called nodes. Polygons are represented as a series of *xy*-coordinates that enclose an area. Topological information, such as a list of the polygons to the left and right sides of each arc, is also stored by the system (Rhind & Connolly, 1995).

Most GIS support the use of both vector and raster structures and enable data to be converted between the two formats. The merits of both systems have been discussed by Zhou (1994) and Burrough & McDonnell (1998). The choice of which model to use is largely dictated by the type of data to be used. Discrete entities are best represented using the vector model whereas continuous fields (e.g. magnetic intensity survey data) are best represented by the raster model. Zhou (1994) notes that the raster model is required for the efficient manipulation and enhancement of digital images. Remotely-sensed imagery

can only be efficiently processed in the raster format (Zhou, 1994). Burrough & McDonnell (1998) state that, if each cell potentially represents a different value, then the simple raster structure is the most suitable one.

Another advantage of the raster model, in which each attribute is represented as a separate theme, is that mathematical operations performed on attributes of cells can be applied to whole maps of gridded data using the same algebraic notation. The process of producing a new attribute is represented as follows:

$$A_{new} = f(A_1, A_2, A_3, \dots, A_n) \quad (2.17)$$

where A_i represents the value of an attribute in the i^{th} layer. This method can be extended to an entire map layer using a raster format as follows:

$$M_{new} = f(M_1, M_2, M_3, \dots, M_n) \quad (2.18)$$

where M_i represents the i^{th} map layer. The method represented by equation 2.18 is referred to as map algebra (Tomlin, 1983, 1990).

Data Modelling and Analysis Tools

Data modelling and analysis tools provide a GIS with a functionality that goes beyond the digital and storage and production of maps. Detailed discussions of GIS analysis and modelling functions are given by Burrough (1986), Tomlin (1990), and Burrough & McDonnell (1998). The application of GIS functions to mineral prospectivity analysis has been described in detail by Bonham-Carter (1994).

Examples of the type of GIS functions used in mineral prospectivity analysis include;

1. interpolation of point locations of geochemical analyses to polygons representing drainage basins,
2. creation of a series of buffers around fault lines,
3. overlaying a layer containing deposit point locations over fault buffers to determine the numbers of deposits at different distance intervals from faults, and
4. re-classification of a range of buffer intervals to form a binary pattern representing a favourable distance from faults.

Wyborn *et al.* (1995a) and Hazell & Wyborn (1995) have highlighted the issues and problems associated with creating GIS for metallogenic analysis or mineral-prospectivity mapping. According to these authors, such a GIS must;

1. contain attributes relevant to metallogenic analysis,
2. contain topologically correct coverages; for example, ones which do not contain any over- or undershoots, open polygons and gaps, and sliver polygons,
3. be compiled at a suitable scale. Wyborn *et al.* (1995a) suggested that the geological base map should be compiled at the scale of the original field photographs; for example, 1:25000, and
4. contain consistent and validated non-spatial data. Wyborn *et al.* (1995a) suggested the use of authority tables for stratigraphic names and rock codes. Roach (1994) has advocated the use of specially designed attribute structures for geological applications.

2.4 Neural Networks

2.4.1 Overview

Neural networks are a type of adaptive computing system that can learn from data and generalize from stored knowledge to produce appropriate outputs in response to new data.³ Although neural networks were inspired by studies of biological neurons they are more closely related to mathematical models like non-parametric pattern classifiers, non-linear filters and cluster algorithms, than models of neural or cognitive phenomena. Neural networks consist of simple processing elements, called neurons, interconnected by links associated with numeric coefficients or weights indicating the strength of each connection (Fig. 2.3).

Most computers today are based on the von Neumann model, and consist of one, or a few, complex CPUs and a central location for data. They perform actions that are determined by a program that remains fixed during run-time. In contrast, the large number of simple processors in a neural network can potentially be active at the same time, providing a model for massively parallel computation. Neural networks are adaptive in the sense that

³Computation with neural networks may be referred to elsewhere as parallel-distributed processing, neural computation, and neurocomputing.

Figure 2.3. Architecture of a 3-layer multilayer perceptron (MLP) neural network. The network transforms a set of inputs ($x_1 \dots x_3$) to a set of outputs ($y_1 \dots y_3$). Three inputs and a single output are shown as an example only. Networks can have multiple outputs or two hidden-layers. Processing is performed by units called neurons (shown as circles), which are connected by links. Associated with each link is a numerical coefficient or weight. Learning is achieved by iteratively adjusting the weights so that the network produces the correct output for a given set of inputs for each example in the training data set.

knowledge is acquired through a process of learning from examples. Once trained, the stored knowledge is distributed throughout the network in the form of the weight values that have been modified as a result of learning. The globally complex behaviour of the network is determined by the pattern of connections linking the units and the values of the weights associated with those links. This type of knowledge representation is referred to as sub-symbolic and distinguishes neural networks from expert systems in which knowledge is stored as symbolic structures such as rules or decision trees.

When to Use Neural Networks

The question of which are appropriate types of problem to solve with neural networks has been addressed by a number of researchers. Kasabov (1996), writing from a knowledge engineering point of view, states that: 1) statistical methods are appropriate when data are available and the type of underlying relationship is known, 2) symbolic artificial intelligence (used in expert or rule-based systems) is suitable where well-defined rigid rules exist, 3) fuzzy systems are applicable when approximate, possibly contradictory, heuristic rules exist, and 4) neural networks are applicable where there is problem knowledge, including

Figure 2.4. Diagram showing that the suitability of artificial intelligence (AI), soft computing (neural networks, fuzzy systems and genetic algorithms) and statistical techniques for solving a problem depends on the amount of data and theoretical knowledge available (after Kasabov, 1996; ©MIT Press).

mainly data rather than rules, and where the nature of the underlying function relating the inputs to the outputs is unknown. Huang & Williamson (1994) and Zaknich (1999) suggest that neural networks are suitable for problems with the following characteristics;

1. non-linearities,
2. high dimensionality; for example, large number of input parameters,
3. noisy data due to imperfect measurements,
4. inadequate conventional approaches due to problem complexity,
5. problem dependence on multiple interacting parameters, and
6. no known mathematical algorithm to determine the solution.

Figure 2.4 summarizes the relationship between the suitability of different methods where knowledge of the problem involves different degrees of theoretical knowledge, or rules, versus data. Neural networks, fuzzy systems and genetic algorithms (a paradigm based on an evolutionary analogy) are collectively known as soft computing techniques.

Although the first, simple, neural network was developed in 1958 (Rosenblatt, 1958), there has been an upsurge of interest and development of neural networks since 1986, due to a combination of theoretical advances and improvements in the performance and the cost of computer hardware. Neural networks are now used in a very wide range of commercial and industrial applications. Descriptions of such systems are given by Dillon *et al.* (1997). Generic functions that neural networks can perform include (Patterson, 1996; Zaknich, 1999);

1. classification (e.g. identification of crop types from remotely sensed images),
2. function approximation (e.g. process control in manufacturing industry, typically where a result is dependent on multiple parameters that depend on one another and which are non-linear in their behaviour),
3. prediction (e.g. stock prices and customer credit worthiness for banks),
4. optimization (e.g. optimal location of pumping wells for the clean-up of contaminated aquifers), and
5. noise reduction (e.g. non-linear signal filtering to recover clean tone bursts from noisy Morse code and telemetry signals).

2.4.2 Applications of Neural Networks in the Geosciences

The reason for applying neural networks in geoscience problems is that they are known to be particularly well-suited to the task of pattern recognition (Bishop, 1995; Schalkoff, 1997). Geologists are also expert at recognizing pattern, especially where patterns are on one or two paper maps. However, due to the increasing volume of digital data now available in regional exploration, the problem can be viewed as one of extracting numeric patterns from multiple layers of digital map data and there may be 20 or more layers. In addition to their pattern recognition capabilities, neural networks have other attributes which are suited to processing geoscientific data. These include the ability to deal with;

1. uncertain and noisy data,
2. outliers in the data,
3. very complex distributions, including large deviations from normality and multi-modal distributions,
4. multiple interdependent input parameters,
5. highly non-linear relationships between input and output parameters,
6. large heterogeneous data sets, and

7. no prior knowledge or assumptions about the statistical distributions of the input data.

The potential of combining neural network and GIS technologies was recognized by Jeffrey & Rossner (1986) and Ritter *et al.* (1988) soon after the revival of interest in neural networks that followed the development of learning algorithms for multilayer feedforward networks by Rumelhart *et al.* (1986b). Much of the subsequent geoscience research has focused on automated pattern recognition and the classification of remotely-sensed imagery (Decateur, 1989; Ritter & Hepner, 1990). Applications include the classification of radar terrain images (Decateur, 1989), discrimination of snow-covered surfaces and cloud types in arctic areas (Key *et al.*, 1989), and classification of sea-ice (Orlando *et al.*, 1990) and land-cover types (Ritter & Hepner, 1990).

Many of these studies demonstrated that neural networks could be used to combine large numbers of data sets to perform classification. For example, Benediktsson *et al.* (1993) used a Multilayer Perceptron (MLP) neural network to classify High Resolution Imaging Spectrometer (HIRIS) data to classify LANDSAT MSS and topographic data containing sixty variables. Seventeen input channels, consisting of Landsat Thematic Mapper (TM) and ancillary textural data, were used by Bruzzone *et al.* (1997) to classify a region with complex land-use. Recent studies of geographic and remote sensing applications of neural networks are presented in Lees (1996).

Non-spatial applications in which neural networks have been used as classifiers include seismic event discrimination (Dowla *et al.*, 1990), first-arrival picking in seismic data (Wagner *et al.*, 1990), and classification of lithofacies from wireline log data (Baldwin *et al.*, 1990; Rogers *et al.*, 1992; Cardon & van Hoogstraten, 1995).

Neural networks have also been used for function approximation (i.e. the estimation of a continuous-valued output variables) in applications such as seismic inversion (Roethe & Tarantola, 1991, 1995), prediction of porosity and permeability of petroleum reservoirs from wireline log data (Osborne, 1992; Wong *et al.*, 1995b), and ore-grade estimation (Clarici *et al.*, 1993; Denby & Burnett, 1993). Guo & Hansen (1992) used an MLP network to predict the lithology and location of lineaments from aeromagnetic data over the Pueblo Quadrangle, Colorado, USA. A similar approach has been adopted by Larsen (2000), who used spectral content, simple statistics and grey-level run-length distributions over a small moving window of cells in regional aeromagnetic data to classify lithology into similar areas in southern Greenland. Poulton *et al.* (1992) used a variety of neural network types to predict horizontal offset, depth, and conductivity of a sub-surface targets from

high resolution ground EM data. Detailed examples of the use of neural networks in the environmental sciences and geosciences are given by Dowla & Rogers (1995).

In contrast, there are very few studies that describe the application of neural networks to mineral exploration. All of those documented in the literature are briefly reviewed in the next paragraphs⁴. Studies involving the classification of non-spatial data include; 1) the use of MLP and Kohonen neural networks trained using fifty geological, mineral and structural parameters to classify gold deposits into grade-tonnage classes (Brodeur *et al.*, 1992), 2) the classification of gossans into Fe and Cu deposit categories using the assay values of eight elements as inputs to an MLP neural network (Yudong, 1994), and 3) the use of a probabilistic neural network to classify mineral deposits into types defined by ore-deposit models. The network was trained using ore and alteration mineralogy and rock types (Singer & Kouda, 1997b,a).

Several studies describe the use of neural networks for geological mapping. Schau *et al.* (1994) used a neural network to construct a reconnaissance bedrock-geology map of a 225 km² area on the Melville Peninsula, Canada. The network was trained using satellite and airborne geophysical data and rock types determined from ground traverses. About 1% of the total pixels were used to train the network.

In a similar study, An *et al.* (1994) used an MLP network, trained with input data from 17 bands of Landsat TM and airborne magnetic and radiometric survey data, to classify an area containing felsic and mafic rocks into areas with hydrothermal alteration and unaltered areas.

In a study comparing Dempster-Shafer evidential belief theory with neural network classifiers, Gong (1996) used Landsat TM, gravity, and airborne magnetic and gamma-ray survey data to produce a map showing the distribution of four rock types on the Melville Peninsula, Canada. Similar accuracies were achieved for the neural network and evidential reasoning methods (92.1% and 89.3% methods, respectively). Gong (1996) concluded that the neural-network map was more similar to manually produced geological maps and was less sensitive to noise than the evidential reasoning method.

Clare & Cohen (2001) used a Kohonen neural network to identify patterns and anomalies in geochemical analyses for 33 elements in stream sediment samples from north-eastern NSW, Australia. The clusters are related to sub-catchment geology and topography, while

⁴Gahegan (1997) suggested using neural networks for pattern recognition and classification in mineral exploration, particularly for the interpretation of complex data sets such as airborne EM: however, no work was undertaken.

the outliers generally represent sub-catchment basins containing major mineral occurrences and deposits. They produced maps which were coloured according to the degree of similarity between the individual catchment (grid cell values) and the trained neural network cluster vectors.

Although Bonham-Carter (1994) referred to neural networks as a possible empirical method for mineral-prospectivity mapping in his book in 1994, at the time this study commenced, the use of neural networks for mineral-prospectivity mapping had been described in only one study by Singer & Kouda (1996). Singer & Kouda (1996) used an MLP network to produce a map depicting the distance to the nearest Kuroko-type deposit. Training data consisted of the relative abundance of four alteration minerals in drill holes. The prediction accuracy over the entire data set (including the training data set) was 79%. The use of a proprietary neural-network system, called PROSPECT EXPLORER, for the classification of anomalies in multisource mineral exploration data has been described also by Clare *et al.* (1997). The pilot study for this thesis, in which an MLP neural network method for producing mineral prospectivity maps is compared with fuzzy logic and weights of evidence, was reported by Brown *et al.* (1997). Two more recent studies in which probabilistic neural networks are used are described in the relevant section below.

Skabar *et al.* (2000) has applied a data-mining approach using an inductive symbolic learning technique combined with genetic algorithms and fuzzy membership functions to mineral-prospectivity mapping using exploration data for orogenic lode gold deposits in central Victoria and compared the results with those of an MLP network. Data mining involves the use of a variety of techniques that are applied in combination in order to search for relationships and complex patterns in large databases (Hair *et al.*, 1998).

2.4.3 Application of Neural Networks to Spatial Analysis

Spatial Data Without Use of Location

Neural networks are used in a large variety of applications involving spatial data. Some of the ways in which neural networks have been used to process spatial data are shown in Table 2.2. The upper part of the table summarizes applications where data are spatial but the location or spatial relationships are implicit and do not form part of the networks inputs or outputs.

In many spatial data processing applications, the neural network inputs and outputs refer to a single location (i.e. a pixel in an image or cell in a GIS layer), but the output is not

a function of the location of the data. The feature vectors merely belong to a location stored implicitly in a raster grid and thus can be processed independently of one another (refer to Table 2.2). Examples of this use of neural networks include the classification of land-cover types in remotely-sensed images (Key *et al.*, 1989) and (Benediktsson *et al.*, 1990a,b) and production of geological maps (Schau *et al.*, 1994; An *et al.*, 1994; Gong, 1996).

In the study by Singer & Kouda (1996), proportions of four alteration minerals from drill core were used to predict the distance to VMS deposits in unexplored grid cells. Inputs to the network are processed without the location of the data being explicitly presented to the network; however, the network output is a function of location. This is because the development of alteration minerals is a function of proximity to the volcanic vent responsible for the formation of the VMS deposit. This represents an example of inverse modelling (1b in Table 2.2).

Dowla & Rogers (1995) used a combination of neural networks and genetic algorithms to optimize possible well locations designed to clean up contaminated ground water. The problem was to select combinations of 23 potential extraction wells and five injection wells that could contain a contaminant plume. The 28 well locations were chosen by experts. The aim was to select a small subset of these locations which would be sufficient to achieve the remediation.

The solution consisted of three steps. First, ground water flow and solute transport models were used to predict; 1) whether the pumping pattern could contain the plume within its current boundaries (i.e. a binary decision), 2) the total mass of contaminant extracted, and 3) the cost. The mathematical model was only used to calculate these parameters for 325 well-site combinations because each calculation took 2–3 hours.

In the second step, these data were used as target outputs to train separate neural networks to predict the three parameters. Inputs consisted of binary values to indicate whether the corresponding well location is used for pumping or not. Once trained, the networks were able to speed up the prediction of the three parameters by an order of roughly one million.

In the third step, a genetic algorithm was used to produce 20000 generations of suitable well combinations. The measure of fitness for each member of the population was the sum of the three criteria (plume containment—yes or no, mass of contaminant extracted and cost). The neural networks were used to estimate the three criteria for each member of the population after each new generation was created. Four million subsets of the 268 million possible subsets of well patterns were evaluated in this way.

This is an example of forward modelling, in which the inputs to the network refer to multiple locations. For example:

$$\text{Mass of contaminant extracted, containment, cost} = f[(x_1, y_1), \dots, (x_n, y_n), well_1, \dots, well_n] \quad (2.19)$$

where (x_i, y_i) is the location of the i^{th} well, n is the number of wells and w_i is a binary variable indicating if the i^{th} well is operating or not. Although the output is a function of spatial location, the location information is not supplied to the network.

Spatial Data and Location Data Explicitly Processed

Spatial location is supplied directly to the network in cases where the inputs consist of;

1. x, y coordinates,
2. neighbourhood or window containing contextual information, or
3. a pattern of pixels in 2-D.

Examples illustrating each of these three cases are discussed below.

Use of XY-Coordinates as Network Inputs

The classic example where xy -coordinate data are used as inputs to a network is the two-spiral problem, which was devised by Lang & Witbrock (1988) as a benchmark to evaluate the generalization capacity of neural networks with different architectures and training algorithms. To solve this problem, the network acts as a pattern classifier. Inputs to the network are the xy -coordinates of a point in a rectangle and the output is either 0.9 or 0.1 representing spiral A or spiral B, respectively.

Wong *et al.* (1998) used a modification of a radial basis function (RBF) network called an interpolation network to interpolate porosity measured in wells in a fluvial sandstone petroleum reservoir. Inputs used to train the network were the xy -coordinates of the well, a rough estimate of porosity obtained from a hand-drawn isoporosity map and a categorical variable to represent the type of depositional facies. The result of the analysis was a more reliable porosity map that reflected all the available geological knowledge (Table 2.2).

Another example of the use of spatial coordinates as inputs to a neural network is the work of Wong *et al.* (1998). Wong *et al.* (1998) used a combination of neural networks

and geostatistics to map the top structure of an oil reservoir. A neural network was used to interpolate a predictable (trend) component of the spatial variation and kriging was used to model the noise (residual component). Inputs to the neural network consisted of the depth to the top of the petroleum reservoir determined from seismic data and the location of the data in terms of xy -coordinates. Target outputs used during training were the depths determined from wells.

Window of Neighbouring Cells

In the classification of remote sensing images, values from a neighbourhood or window of pixels surrounding the current pixel is moved across the image to provide textural or context information. For example, Ritter & Hepner (1990) used an MLP network to classify land cover types. Input parameters were obtained from a 3×3 pixel moving window over images representing four bands of LANDSAT TM.

Cells in the neighbourhood of the current processing cell were also used in a study by Müller *et al.* (1998) in which a neural network was used to classify a back-scatter image mosaic from side scan sonar of the sea-floor. The resultant map divided the sea-floor into areas of foraminiferal ooze, mixed sediments, and metamorphic basement and volcanic rocks. Textural features, consisting of 18 grey-level (pixel brightness) statistics derived from a 32×32 pixel window, were used as inputs to an MLP neural network. The correct classification of the training examples was known from sampling of the sea-floor. Müller *et al.* (1998) suggested that the method of feature extraction could be applied to patterns of geological and geophysical features related to targets in mineral exploration.

Two-dimensional Patterns

Two-dimensional patterns of pixels can also be used as inputs to neural networks. For example, Le Cun *et al.* (1989, 1990a,b) developed a series of hierarchical networks for the recognition of hand-written digits in postcodes. Grey-scale levels in a 28×28 image were used as inputs. Two types of hidden layers were used; 1) layers for feature detection, and 2) layers for averaging and sub-sampling. Digit shapes were recognized by detecting and combining local features in the input image.

Feature detection is performed in layers consisting of sets of neurons arranged in squares called feature maps (Fig. 2.5). Each unit in the feature map receives its input from a 5×5 window or kernel that is scanned over the image, moving one pixel at a time. Because

Figure 2.5. Hierarchical neural network used to recognize hand-written digits. Diagram adapted from Le Cun *et al.* (1990a).

the weights connecting the feature map units to each window location on the image are the same, the units in a feature map are constrained to perform the same operation on different parts of the image. This is useful because features of a digit could be distorted or displaced or some features could occur in different places in different characters. Multiple feature maps are used to extract different feature types from the image (layers H_1 and H_3). Sub-sampling and averaging is performed by layers H_2 and H_4 in Figure 2.5. A 4×4 window is moved across the corresponding feature maps in layer H_1 (so that the positions do not overlap), and the output of the four units is directed to just one unit in layer H_2 . The loss of resolution has the effect of increasing the level of abstraction and reduces the effect of distortion or translation of the input image on the representation of features in subsequent layers. Similar operations are performed in layers H_3 and H_4 .

The output layer contains 10 units which represent digits 0 to 9. If the input pattern corresponds to a 5, then the 5th output unit is set to +1 while the others are set to -1. Implemented in hardware, the system was able to process 10-12 digits per second with a 92% success rate. (7% were rejected as indecipherable and 1% were incorrectly classified.)

Two-dimensional patterns of pixels were processed in a similar way by Zaknich (1997) in a study of the physical properties of aluminium hydroxide particles produced during

Figure 2.6. Example of the use of patterns of pixels used to train a network to recognize particle boundaries. Diagram adapted from Zaknich (1999)

the Bayer aluminium process. The task involved discriminating the boundaries between particles. Pixels in grey-scale SEM images were classified as belonging to either particle surfaces, particle edges or boundaries between particles (Fig. 2.6). A 5×5 moving window centred on the pixel to be classified provided 25 inputs to the neural network in the form of grey-scale pixel values. The output was presented as three different grey-scale values according to the class of the input pixel, thereby creating a new classified image.

A similar approach was used by Penn *et al.* (1993). He used a set of four edge patterns to train a neural network to detect geological boundaries in a single band LANDSAT TM image. Input to the neural network was obtained from a 9×9 moving window over a normalized grey-scale image and a value representing the contrast between the foreground and the background. The network was trained to output a one for patterns representing edges and a zero for all other patterns.

Zaknich (1995) used a different approach to recognize, count and measure the size of sodium oxalate crystals which form during the Bayer process used to refine aluminium. Shapes were classified using features such as perimeter, area, radius, geometric and central moments and best-fitting ellipses.

Table 2.2. Analysis of spatial data by neural networks. All applications listed in the table involve spatially registered data. In the examples listed in the top part of the table, the location or pattern of the data in two-dimensional plane of the image or GIS thematic layer is not processed. In the bottom part of the table, spatial properties of the data, e.g. xy -coordinates or information about the neighbourhood around a cell, are used as inputs to the network.

No. of locations referred to in input	Output = fn of location?	Example	References
Location not processed			
single location	no	classification of remotely-sensed images	Key <i>et al.</i> (1989, 1990) Benediktsson <i>et al.</i> (1990a,b) Gong (1996)
	yes	prediction of distance to nearest VMS deposit	Singer & Kouda (1996)
multiple locations	yes	optimization of pumping well locations for groundwater remediation	Dowla & Rogers (1995)
Location or 2-D pattern processed			
xy -coords	yes	interpolation of porosity measured in wells in an oil reservoir	Wong <i>et al.</i> (1997b)
	yes	neural network-residual kriging to interpolate the depth to top of oil reservoir	Wong <i>et al.</i> (1998)
	yes	2-spiral pattern recognition problem	Lang & Witbrock (1988)
textural features determined from moving window in image	yes	land-cover classification of remotely-sensed images	Bruzzzone <i>et al.</i> (1997)
	yes	classification of sonar images of sea floor	Müller <i>et al.</i> (1998)
	yes	classification of cracks and scratches in industrially treated surfaces	Schramm & Spinnler (1993)
input of all pixels from moving window(s) in image	yes	land-cover classification of remotely-sensed images	Ritter & Hepner (1990) Bischof <i>et al.</i> (1992)
	yes	recognition of hand-written digits in postcodes	Le Cun <i>et al.</i> (1989, 1990a, 1990b)
	yes	detection of edges of $\text{Al}(\text{OH})_3$ particles in Bayer Al refining process	Zaknich (1999)
	yes	detection of faults and rock unit boundaries in remotely-sensed images	Penn <i>et al.</i> (1993)

2.4.4 Selection of Neural Network Architecture

Although a large number of different types of neural networks exist, reflecting the different type of the units, connections, and learning and recall algorithms possible, a Multilayer Perceptron (MLP) neural network is used to test a neural-network approach to mineral prospectivity mapping in the pilot study presented in Chapter 4.

There are several reasons for this choice. An MLP neural network;

1. performs very well for a large variety of problem types,
2. has powerful learning and generalization capabilities (i.e. applicable to regression and classification problems) (Hornik, 1991; Masters, 1993b),
3. (with one hidden layer) is capable of approximating any continuous multivariate function to any desired accuracy, provided a sigmoidal (squashed S-shaped) activation function, appropriate network parameters, and a sufficient number of hidden units are used (Cybenko, 1989; Funahashi, 1989; Hornik *et al.*, 1989), and
4. is likely to give better generalization performance in cases where only a few training samples are available. Clearly, this last characteristic is particularly important in mineral prospectivity applications where the training set size is severely limited due to the paucity of deposit patterns Masters (1993b).

A number of other neural network architectures that are potentially useful for the estimation of mineral prospectivity are examined in Appendix A. These are the probabilistic (PNN), general regression (GRNN), radial basis function (RBF) and self-organizing feature map (SOFM) or Kohonen neural networks and a hybrid neuro-fuzzy system.

Before describing the multilayer neural network (MLP) in detail, some neural network terminology is introduced and the differences between the main types of networks are briefly explained. Inputs to a neural network are selected according to their usefulness in predicting the output. In the case of a pattern recognition task, the output is the class to which the input pattern belongs. Inputs are presented to the network in the form of row vectors (i.e. $\mathbf{x}^n = (x_1, x_2, x_3, \dots, x_n)$, where n is the dimensionality). These are generally called input feature vectors, although the term feature generally refers to input parameters which have been pre-processed or combined in some way. If $n = 3$, the input feature space is three-dimensional and inputs can be represented as points in space. Higher dimensional feature vectors are said to be located in hyperspace (Bishop, 1995).

MLP neural networks classify patterns by dividing multidimensional feature space representing input vectors into class regions using decision boundaries called hyperplanes. For

two input variables, feature space is represented by a two-dimensional plane and hyper-planes are represented by lines. These lines are called decision boundaries (Fig. A.16). In contrast, PNN, GRNN, RBFNN's are all kernel, or receptive field classifiers because they partition feature space using radial basis functions that can be represented in 2-D as local circular areas of influence.

MLP, GRNN, and RBFNN neural networks learn with a strategy known as supervised training. This involves presenting the network with both the inputs and the corresponding correct output during training. In contrast, in unsupervised training used with the self-organising map (SOM or Kohonen network), only the input vectors are presented to the network, and the network creates its own classification of the patterns. The SOM network performs classification based on the labelled training examples (for which the classes are known) that are nearest to the unknown input vector.

The fuzzy-neural system represents a hybrid architecture that combines the ability of fuzzy systems to deal with imprecise or error-prone inputs with the pattern recognition capability of neural networks. This enables conceptual and empirical approaches to be combined by incorporating subjective geological knowledge into an otherwise data-driven neural network method.

2.4.5 Multilayer Perceptron (MLP) Neural Networks

Architecture of MLP Networks

An MLP neural network is a type of multilayer feedforward network containing perceptron-like processing units. An MLP network consists of input and output layers and one or two hidden layers (refer to Fig. 2.3 above). Unlike the hidden and output layer units, the input units do not perform any processing and only serve to connect the network to a source of input signals and pass these signals on to other units. It is the presence of the hidden layer, containing units with a non-linear activation function, that enables multilayer networks to solve non-linearly separable problems. Whereas the number of input and output units is dependent on the problem being solved and the training data that are available, the number of hidden-layer units must be determined by trial and error for each particular problem. The term feedforward refers to the fact that there are no feedback connections back to units of previous layers or connections between units within the same layer.

Each unit in the hidden and output layers of an MLP neural network performs the same series of simple operations involving multiplication and addition, as well as applying a

non-linear transformation to the input signals it receives (Fig. 2.7).

In detail these three steps are performed as described below.

1. The net input to a neuron or processing unit is determined by multiplying each input signal by the coefficient or weight, representing the strength of the connection (which may be positive or negative).
2. The weighted inputs are summed:

$$net_j = \sum_i w_{ij} o_i \quad (2.20)$$

where net_j is the net input to unit j , w_{ij} is the weight of the connection from unit i to unit j , and o_i is the activation or output unit i (refer to Fig. 2.7).

3. The output or activation of a neuron is the result of transforming the net input by a non-linear activation function:

$$o = f(net) \quad (2.21)$$

The activation function used in the MLP network in Chapter 4 is the sigmoidal(squashed S-shaped) logistic function:

$$f(net) = \frac{1}{1 + e^{-net}} \quad (2.22)$$

where net is the weighted, summed input to the processing unit, calculated from equation 2.20.

The output value o , for an individual processing unit is referred to as the activation and becomes the signal on all the connections fanning out from the unit. If the unit is in a hidden layer, then this output becomes the input for units at the other end of the links in the next layer.

Learning in MLP Neural Networks

Learning in MLP neural networks is achieved by modifying the connection weights while a set of training examples is repeatedly processed. This training method is referred to as supervised because each example specifies all the input parameters together with the desired outputs. The set of inputs to the network constitutes a real-valued vector, $(x_1, x_2, x_3, \dots, x_n)$. Each vector component represents a feature that is considered to be useful in predicting the output⁵. As the MLP neural network used in Chapter 4 contains

⁵If multiclass nominal variables are being used then they should be recast as continuous numerical variables.

Figure 2.7. Computations performed in a single processing unit of a neural network. The input on each link is determined by multiplying the input signal by the weight associated with the link. Individual inputs are summed and then transformed by a non-linear sigmoidal activation function.

only a single output unit, the training data consist of a list of paired input vectors and a single scalar value representing the target or desired output.

During training, both the input feature vector and the target output value pairs are presented to the network (2.8). Initially, the weights are set to small random numbers (e.g. in the range $[-0.2, +0.2]$) and so, to begin with, the actual output is quite different to the target output.

The difference between the desired output and the output produced by the network represents the error. During training, this error signal is fed back into the network and forms the input to a learning algorithm. Learning proceeds by applying a learning algorithm to iteratively adjust the weight values in order to minimize this error the next time the pattern is presented to the network. The set of input and output pairs is called a training data set. Processing each pattern represents one cycle or epoch of training. Depending on the value of the random initial weights and other network parameters, such as the learning rate, hundreds or possibly several hundred thousand epochs of training may be required in order to reduce the network error to an acceptably small value. After training is completed, the weight values remain fixed. The network should then be able to generalize; that is, produce appropriate responses for inputs that have not been used during training.

Figure 2.8. Block diagram representing the training process in a multilayer perceptron neural network (after Zaknich, 1999). The difference between the actual output produced by the network (y) and the desired output (d), supplied in the training data, represents the network error. The error-backpropagation algorithm iteratively modifies the connection weights in order to minimize the network error function.

Error-Backpropagation Algorithm

The learning algorithm used to minimize the network error during training in the MLP network in Chapter 4 is known as the error-backpropagation algorithm. The following discussion is based on descriptions of the algorithm by Rumelhart *et al.* (1986b), Rumelhart *et al.* (1986a), Beale & Jackson (1990), Winston (1992), Hassoun (1995) and Zaknich (1999).

The algorithm was independently developed by Werbos (1974), and later by Parker (1985a) and Rumelhart *et al.* (1986b). The algorithm adjusts weights using a technique called gradient descent optimization. The concept behind the gradient descent algorithm is to make small changes to the weights proportional to the negative derivative of the error with respect to each weight for the current pattern of network inputs, as follows:

$$\Delta w_{ij} \propto -\frac{\partial E_p}{\partial w_{ij}} \quad (2.23)$$

where w_{ij} is the weight on the link connecting unit i to unit j and E_p is the network error for a single input pattern, p ⁶ The discussion that follows refers to the case where weights

⁶In this nomenclature, indices, i, j, k refer to units in successive layers from the input towards the output (refer to Fig. 2.3).

Figure 2.9. Effect of a single weight on the network error function (after Zaknich, 1999). At A where the slope is negative, the network error is reduced by a positive weight change. At B where the slope is positive, a negative weight change is required. A disadvantage of gradient-descent is that the network can converge to a local (D), rather than a global minimum (E).

are updated incrementally after processing each pattern.

The application of the weight update rule in equation 2.23 can be explained in terms of a hypothetical two-dimensional representation of an error function⁷, which describes the effect of a single weight on the network error at a single output unit (Fig. 2.9). In Figure 2.9, if the weight is too large, the gradient of the error function is positive and equation 2.23 indicates that the error can be reduced by subtracting a small amount from the weight. Conversely, if the gradient is negative, the error is reduced by increasing the weight by a small amount. Thus, weight changes are applied as follows:

$$w_{ij}^{new} = w_{ij}^{current} + \Delta w_{ij} \quad (2.24)$$

where W_{ij} is the updated weight value for the weight connecting unit i to unit j and $w_{ij}^{current}$ is the current weight value.

One of the problems inherent in a gradient descent algorithm like error back-propagation is

⁷Since a real network contains many weights, the error function actually forms a complex surface in multidimensional weight space. If there were just two weights, the error function would form a surface, like a landscape with plateaus and deep valleys in multidimensional weight space.

Figure 2.10. Nomenclature for units and variables in the generalized delta rule. The variables o_i and δ_j refer to units at opposite ends of the link associate with weight $w_{i \rightarrow j}$ that is to be updated. o_i is the output from unit i that becomes one of the inputs to unit j . δ_j is the delta term for unit j .

that the network may converge to a local, rather than a global, minimum (Fig. 2.9). This depends partly on where training starts in weight space as a result of initializing weights to small random values. To avoid local minima, the training procedure is repeated using a different random set of initial weights each time.

A commonly-used error function is the sum of squares error. For a single input pattern, p , and a network with N output units, the error function is given by:

$$E_p = \frac{1}{2} \sum_{k=1}^N (d_k - o_k)^2 \quad (2.25)$$

where E_p = error for pattern p , d = desired output, o = actual output and the subscript index k denotes the k^{th} output unit. Rumelhart *et al.* (1986b) used this error function to evaluate the partial derivative in equation 2.23 and derive the propagation learning rule⁸:

$$\Delta w_{ij} = -k \frac{\partial E_p}{\partial w_{ij}} = \eta \delta_j o_i \quad (2.26)$$

where k is a proportionality constant, E_p is the error for pattern p , Δw_{ij} is the change in weight on the link from unit i to unit j , η is a proportionality constant called the learning rate, δ_j is the delta term for unit j on the output end of the link and o_i is the output from unit i on the input end of the link (Fig. 2.3). The delta term, δ_j depends on unit j and is proportional to; 1) the slope of the sigmoidal transformation function (at the point defined by the net input to unit j ; Fig. 2.10), and 2) the network error due to unit j .

⁸The weight update rule used in the back-propagation algorithm is also known as the generalized delta rule

The weight update rule that results from substituting equation 2.26 into equation 2.24 is:

$$w_{ij}^{new} = w_{ij}^{current} + \eta \delta_j o_i \quad (2.27)$$

For an output unit, the delta term can readily be determined since the delta term is proportional to the error-weight partial derivative (Equation 2.23) and the error for an output unit is given by equation eqn-netwk-error-fn. The delta term for an output unit is given by:

$$\delta_k = f'(net_k)(d_k - o_k) \quad (2.28)$$

where the subscript k refers to unit k in the output layer, d_k is the desired output, o_k is the actual output, net_k is the total input to unit k , and f' is the derivative of the activation function shown in equation 2.22.

The contribution a hidden unit makes to the network error is not clear. Although a learning rule for a single perceptron unit was known since about 1960 in the form of the least mean square rule (Widrow & Hoff, 1960), no method for updating the weights of a hidden layer unit in multilayer perceptron neural networks was known until Rumelhart *et al.* (1986b) described the error backpropagation algorithm in 1986. They reasoned that, since the error of a hidden unit (e.g. unit j in Fig. 2.3) is expressed through the output units (units k in Fig. 2.3), the δ term for a hidden unit is proportional to the weighted sum of the δ terms for all the output units to which it is connected. The formula proposed by Rumelhart *et al.* (1986b) for the calculation of the delta term for units in a hidden layer is given by equation 2.29:

$$\delta_k = f'(net_k) \sum_k \delta_k w_{jk} \quad (2.29)$$

Equation 2.29 shows that the delta term for a hidden unit j is defined recursively in terms of the delta values for the units in the output layer (denoted by the subscript, k). Consequently, the calculation of the delta terms for the output units must be propagated backwards in order to calculate delta terms for the hidden layer units. Hence the name error back-propagation algorithm. In order to evaluate delta terms for hidden and output layer units, the value of the derivative of the activation function, f' , must be determined. The derivative for the logistic activation function (equation 2.30) used in the pilot study has the following simple form:

$$f' = f(1 - f) \quad (2.30)$$

Substituting equation 2.30 in place of f' , and then substituting equation 2.21 for f , allows equations 2.28 and 2.29 to be rewritten;

$$\delta_k = o_k(1 - o_k)(d_k - o_k) \quad (2.31)$$

$$\delta_j = o_j(1 - o_j) \sum_k \delta_k w_{jk} \quad (2.32)$$

$$(2.33)$$

Equations 2.31, 2.32 and 2.27 are used to modify the weights after each presentation of a training pattern.

The error back-propagation consists of the following steps;

1. Calculate outputs o_i, o_j, o_k . In the forward pass, the input vector is presented to the network and the activations of the units are calculated using equations 2.20, 2.21 and 2.22.
2. Calculate δ_k for output unit(s). At the output layer, the activations of the output units are then compared to the target outputs to give the error for each output unit. Delta terms are calculated for the output units according to equation 2.31.
3. Calculate δ_j for hidden units. In the backward pass through the network, delta terms for each hidden unit are determined recursively in terms of the output units directly connected to it using equation 2.32.
4. Calculate weight changes. The weight updates are calculated by multiplying the delta terms for the unit on the output side of the link by the activation of the unit on the input side of the link, according to the delta rule given by equation 2.26.
5. Update weights using $w^{new} = w^{old} + \Delta w$.

In this way, the errors of the output units are propagated backwards.

2.4.6 Summary of Previous Work

A summary of the main prospectivity mapping methods described in this Chapter and in Appendix A, together with the assumptions and data requirements, is given in Table 2.3 below.

The effectiveness of the multivariate statistical methods, such as multiple linear regression, multiple discriminant analysis, logistic regression and canonical correlation, are limited to varying degrees if the following underlying assumptions and requirements are not met;

1. relationship between the independent and dependent variables is linear (or in the case of logistic regression, a log-linear relationship is assumed; the Boolean and index-overlay methods also involve linear combinations of explanatory variables),
2. there is multivariate normality of independent variables,
3. homoscedasticity (constant variance over the range of the range of the independent variable is achieved, and
4. there is no significant multivariate collinearity between variables, or in the case of the weights-of-evidence method, conditional independence of binary input patterns with respect to deposit points (expert systems that use Bayesian updating of probabilities also require conditional independence of explanatory variables).

The assumption of linearity is the most serious limitation. If the underlying physical relationships are not linear, they cannot be adequately modelled using linear methods. Many physical relationships related to ore-forming processes are well documented and known to be highly non-linear. For example, three of the parameters used to describe the tendency of a substance to react with another, i.e. equilibrium constants, free energy and oxidation potential, are all non-linearly dependent on temperature (Krauskopf, 1979).

If the exact nature of a non-linear relationship is known, then it is sometimes possible to transform the variables to compensate for the non-linearity. However, Masters (1993b) notes that the type of non-linear relationship is generally not known and there are many types of non-linear relationships which can not be linearized by transformations.

Other limitations of the empirical methods previously discussed above include;

1. sensitivity to the inclusion of irrelevant variables in the model (e.g. cluster analysis),
2. the need for specially constructed GIS databases (e.g. mineral systems approach),

3. the need to re-classify input data (i.e. conversion of continuous variable to multiclass variables) resulting in a loss of information (e.g. weights-of-evidence)⁹, and
4. large training sets (multiple linear regression, multiple discriminant analysis, logistic regression, canonical correlation and decision-tree induction systems).

Subjective methods include index-overlay, expert systems, fuzzy-logic, and the mineral-systems approach (see lower part of Table 2.3). These methods may be limited by their use of deposit models. Specifically, their performance may be adversely affected if;

1. undiscovered deposits are of the same type as that described by the deposit model in use, but have features that are significantly different to previously discovered deposits, (e.g. the Century Zn-Pb deposits; Legge, 1995),
2. undiscovered deposits may be of a different type to that described by the model, and
3. deposits of previously unknown types may exist (e.g, Olympic Dam Cu-Au-U-REE deposit at the time of discovery; Woodall, 1994).

These comments also apply to empirical methods. However, because conceptual methods involve an explicit definition of the ranges of variable values that are favourable, conceptual methods are likely to be more strongly affected by these problems than empirical methods. In addition, the result of any subjective method may be difficult to reproduce since experts are likely to make different assessments about the relative importance of the evidence.

⁹Although weights of evidence has usually been applied as a binary method, it is not restricted to binary data. For example, a geological map with over 20 classes was used in a study of the mineral potential of the Slave Province (Bonham-Carter *et al.*, 1998a,b).

Table 2.3. Summary of the main mineral-prospectivity mapping methods described in the literature. Blank fields indicate *not applicable*

Method	Data Type		Map Type	Assumptions and Data Requirements						Sensitive to			References
	Inputs	Output		Linearity	Normality	Const. co-variance	Co-linearity minor	Binary reclassification	Train set size	Outliers	Irrelevant inputs	Redundant inputs	
Empirical													
Linear Regression	metric ^a	metric	fav.	yes	yes	yes	yes	no	med-lge	yes	yes	yes	Kelly & Sherriff (1969)
Logistic Regression	metric	metric	prob.	yes ^d	yes ^e	yes ^e	yes ^e	no	med-lge	no	no	no	Agterberg (1974)
Discriminant Analysis	metric	cat. ^b	fav.	yes	yes	yes	yes	no	med-lge	yes	yes	yes	Prelat (1977)
Cluster Analysis	metric	cat.	bin.	no	no	no	yes	no	large	yes	yes	no	Briggs & Press (1977)
Characteristic Analysis ^c	bin.	metric	class.	yes	?	?	?	no	small	yes	yes	yes	Botbol <i>et al.</i> (1978)
Weights of Evidence	multiclass	metric	prob.	yes ^d	?	?	yes ^f	no	med-lge	no	no	yes	Bonham-Carter <i>et al.</i> (1988)
Decision Tree, C4.5 ^g	metric	cat.	class	?	?	?	?	no	med-lge	yes	yes	no	Reddy & Bonham-Carter (1991b)
Canonical Correlation	metric,cat	metric	fav.	yes	no	yes	yes	no	med-lge	yes	yes	yes	Pan & Harris (1992)
MLP Neural Network	metric	metric	fav.	no	no	no	no	no	med-lge	no	no	no	Singer & Kouda (1996)
Fuzzy/genetic Learner	metric	metric	fav.	no	no	no	no	no	med-lge	no	no	no	Skabar <i>et al.</i> (2000)
Hybrid Fuzzy-Neuro	metric,cat	metric	fav.						none		yes	yes	Brown <i>et al.</i> (2002b)
Conceptual													
Boolean Logic	bin	bin.	bin.					yes	none	no	yes	no	Bates (1959)
Expert Systems	metric,cat	metric	prob.				yes ^h	yes ⁱ	none	no	yes	yes	Duda <i>et al.</i> (1978)
Index-overlay	multiclass	metric	fav.	yes			yes	yes	none	no	yes	yes	Koch <i>et al.</i> (1981)
Dempster-Shafer	metric	metric	fav.					no	none	no	yes	yes	Moon (1990)
Fuzzy Systems	metric	metric	fav.					no	none	no	yes	yes	An <i>et al.</i> (1991)
Mineral Systems	metric	binary	bin.					yes	none	no	yes	no	Wyborn <i>et al.</i> (1994c)

^aMetric = continuous variable.^bAbbreviations: bin = binary, cat = categorical, fav. = measure of favourability, NN's = neural networks, prob. = probability value.^cAlthough referred to as characteristic analysis by the authors, the method is similar to factor and principal component analysis (Agterberg, 1989a).^dA log-linear relationship between dependence and independent variables is assumed.^eNormality and conditional independence are required but the method is robust where these requirements are not fulfilled.^fConditional independence of deposit patterns with respect to deposits is assumed.^gData refer to Bui *et al.* (1997, 1998) who used the package C5.0 (Quinlan, 1993). C5.0 generates rules automatically from the data.^hThe PROSPECTOR expert system uses Bayesian updating as the main inference method and therefore assumes evidence is conditionally independent.ⁱThe PROSPECTOR expert system requires binary & categorical input for attribute data and integer input to indicate reliability of evidence.

2.5 Summary

The main points discussed in Chapter 2 are listed below.

1. The purpose of mineral prospectivity maps is to estimate the relative favourability of areas represented by grid cells to host mineralization of a specific type.
2. Bonham-Carter (1994) distinguished two broad categories of mineral favourability mapping methods; that is, data-driven or empirical (e.g. weights of evidence) and knowledge-driven or conceptual methods (e.g. fuzzy systems). Neural networks represent a data-driven approach.
3. Weights of evidence (WofE) (Bonham-Carter *et al.*, 1988) is the most widely-used statistical method for mineral prospectivity mapping. Evidence maps containing continuous variables are re-classified into binary or multiclass maps. In each evidence map, these classes representing ranges of variable values are converted to a pair of weights which express the degree to which the presence or absence of that class of values upgrades or downgrades the prior probability of a deposit, respectively. A prospectivity map displaying posterior probability values is created by combining all the weights corresponding to each cell location.
4. A difficulty with the WofE method is the assumption of conditional independence between parameters with respect to deposits. This requirement is rarely satisfied completely in geological data sets.
5. Where the assumption of conditional independence is seriously violated, either; 1) one of the dependent maps must be omitted or 2) dependent maps must be combined or 3) the logistic regression method can be applied (recommended when using ARCSDM). In the latter case, nominal multiclass maps are automatically treated as $1, \dots, n$ variables.
6. Fuzzy systems are the most widely used, conceptual mineral-prospectivity mapping method. A fuzzy membership function is used to transform raw parameter values u , to real numbers in the interval $[0, 1]$. In most mineral-prospectivity mapping applications, fuzzy membership values represent the degree to which the parameter belongs to the fuzzy set *favourable for deposits*.
7. In most studies documented in the literature, the gamma function (with gamma values in the range $[0.95-0.98]$) is used in the final integration step to combine fuzzy membership values to produce a prospectivity map.

8. In most applications of the fuzzy-logic method to mineral prospectivity mapping, raw data values are converted to fuzzy membership values by assigning a single fuzzy-membership value to a whole class or range of raw values. This leads to a loss of information. In engineering applications, continuous fuzzy-membership functions are used to map raw values to membership values.
9. There are two further potential problems with the fuzzy-logic method; 1) fuzzy membership values are often applied according to the degree to which parameter values conform to a deposit model, which itself may be flawed, and 2) the assignment of fuzzy membership values, although often performed subjectively, could be performed objectively using the empirically-determined spatial associations between input features and known deposit points using methods described by Luo & Dimitrakopoulos (2003) and Porwal *et al.* (2003b).
10. The mineral systems approach, proposed by Wyborn *et al.* (1994c), relates the essential ingredients of the deposit forming process to the type of geological evidence that is likely to have been captured in a regional-scale GIS.
11. A mineral system represents a far larger target for exploration than the actual ore deposit, and the scale of the parameters that define a mineral system is comparable to a regional-scale GIS.
12. Neural networks are suited to problems involving geoscience data because of their ability to deal with; 1) uncertain and noisy data, 2) outliers in the data, 3) very complex distributions, including large deviations from normality and multimodal distributions, 4) multiple interdependent input parameters, 5) highly non-linear relationships between input and output parameters, and 6) large heterogeneous data sets. In addition, they require no prior knowledge nor assumptions about the statistical distributions of the input data.
13. The multilayer perceptron (MLP) is the most generally applicable and by far the most widely used, type of neural network (Jang & Sun, 1995)
14. MLP neural networks are chosen for this study because they; 1) perform very well for a large variety of problem types, 2) have powerful learning and generalization capabilities, and 3) are likely to give better generalization performance in cases where only a few training samples are available.
15. A problem with the gradient-descent algorithm used to train MLP neural networks is that the network may converge to a local, rather than a global, minimum. This depends partly on where training starts in weight space as a result of initializing

weights to small random values. To avoid local minima, the training procedure is repeated using a different random set of initial weights each time.

Chapter 3

Methods and GIS Databases

3.1 Introduction

This chapter describes the processing methods, databases and software environment used in this study. As stated in Chapter 1, the aims of the study are;

1. to develop a neural-network approach to integration of mineral exploration data and predict the favourability for mineralization,
2. quantitatively compare the results of a neural-network approach with those of other methods, and
3. test the applicability of a neural network method on variety of exploration data sets.

Aims one and two involve the preparation of mineral prospectivity maps and so the first part of this chapter outlines the procedures used in this study. Then, since many of the GIS map layers used as inputs represent modified rather than raw data, the types of derived layers and the methods used to produce them are summarized. This is followed by a description of the processing steps required to implement a neural-network approach to mineral prospectivity mapping.

The weights-of-evidence and fuzzy-logic methods are chosen to check the validity of the neural network results and to provide a basis for comparing the quality of mineral favourability maps produced in Chapter 4. These two methods are representatives of empirical and conceptual approaches, respectively, and are currently quite commonly used in industry. A brief description of the processing required to implement the weights-of-evidence and fuzzy-logic methods, together with a discussion of why they were chosen, forms a

third section of this chapter. Although a fuzzy-logic inference net in which evidence maps are combined using fuzzy AND, OR and gamma functions is far from the most advanced fuzzy method available ¹², this simple fuzzy-logic method is used in this study because it is the main conceptual method for mineral prospectivity mapping in current use and therefore provides a good basis for comparison with neural networks. A variety of techniques are employed to assess the generalization and classification performance of trained neural networks and the most suitable methods for this study are reviewed.

There are very few reports in the literature that quantitatively compare the quality of mineral prospectivity maps produced by different methods³. Consequently, several approaches to this problem using both statistical and probability measures are developed and discussed.

In order to test the general applicability of a neural network method and to discover what factors may influence its performance, a case study is presented. The case study is based on a GIS database, which is in current use in an exploration program for an Archaean orogenic gold deposits. for a particular type of mineral deposit. The last part of the chapter gives a summary of the software and hardware used in this study.

3.2 Preparation of Mineral Prospectivity Maps

3.2.1 Preparation of Derived Thematic Layers

Map layers obtained by processing primary GIS thematic layers are called derived layers (e.g. a layer depicting distance to the nearest major fault can be derived from a primary structural layer). Derived layers are important because they represent a means of incorporating expert knowledge and encoding spatial relationships into the neural network input. It is clear that these categories can overlap if deposit knowledge indicates that certain spatial relationships are important requirements for ore formation.

Derived layers were prepared using the in-built functions of either the ARC/INFO or the ARCVIEW GIS systems. The choice of which system to use depended on the system in which the data were originally compiled and on the complexity of the derived layer required. ARC/INFO contains a larger range of in-built functions than ARCVIEW and is

¹Kóczy, (pers. comm.)

²Rule-based and hybrid fuzzy systems are described in Section A.2.5 in Appendix A

³An exception is the study by Harris & Pan (1999).

more convenient to use because extensions can be written in the VISUAL BASIC programming language rather than the proprietary object-oriented language, AVENUE, used in ARCVIEW.

All operators, functions, statements and commands used to produce derived grid layers represent a type of map algebra operation (Tomlin, 1983, 1990) and result in the creation of a new map layer. The operation is applied to all locations in one or more input grids and has the following form:

$$newmap = f(map_1, map_2, \dots, map_n) \quad (3.1)$$

The types of derived layers and the generic and specific GIS functions used to create them are summarized in Table 3.1.

Only a few simple derived layers were used in the pilot study in Chapter 4. Experiments dealing with ways in which feature selection⁴ and the incorporation of prior knowledge into the neural network can improve performance are described in Chapter 5.

Conversion of Input Layers to Raster Format

One pre-processing step performed within the GIS that is common to all neural network, weights-of-evidence and fuzzy-logic methods is the conversion of GIS thematic layers, such as image and ARCVIEW polygon coverages, to raster format (Fig. 3.1). Depending on the choice of cell size, some layers initially in raster format may need to be re-gridded in order to change the cell size to a common value.

All other processing in this study is based on raster GIS layers. A raster rather than a vector format was chosen because raster layers can more easily be converted to numerical patterns of the type used to train neural networks. In addition, only raster layers can be conveniently processed outside of the GIS using external programs and software packages. The use of raster layers allowed neural-network processing to be performed using C++ programs and the C-like scripting language in MATLAB rather than the proprietary *Avenue* scripting language used in ARCVIEW⁵

An additional reason for using the raster format is that, although the vector format is

⁴feature selection is the process of transforming raw data so that it represents the essential information required for the neural network to perform the classification task (Bishop, 1995).

⁵Prior to the introduction of Microsoft Visual Basic in 1999, the only script language available in ARC/INFO was a proprietary interpreted language with limited capabilities called AML.

Table 3.1. Examples of derived layers used to encode spatial relationships and prior knowledge into layers used as inputs. The main ARC/INFO functions used to create each layer are also shown, where applicable.

Cell value in derived layer	ARC/INFO command ^a
Spatial Relationships	
distance to nearest fault	eucldistance
distance to nearest fold axis	eucldistance
distance to nearest lithological boundary	eucldistance
distance to fault/major lineament intersection	eucldistance
distance to nearest deposit	eucldistance
distance to nearest geochemical anomaly	eucldistance
dip and strike of nearest fault	eucldistance
distance to fault interval with strike 45°	Visual Basic ^b , eucldistance
slope of top of lithological unit ^c	slope
derivatives of potential fields; e.g. gravity, magnetic ^c	slope, slope2
density of faults in cell neighbourhood ^c	Visual Basic
tonnes of contained metal in cell neighbourhood ^c	Visual Basic
complexity in cell neighbourhood (faults, lithology) ^c	focalvariety(<i>grid</i> , <i>neighbourhood</i>)
Expert Knowledge	
functions of parameters e.g. $U + Th$, $(U + Th)/mag$	+, −, ×, / operators
hydrothermal alteration; Landsat TM bands 5/7	/ operator
presence of reactive host rocks; e.g. Fe/(Fe + Mg) wt%	reclassification ^d
presence of alteration minerals	reclassification
degree of fractionation & oxidation of granitoids	reclassification
age of rock units	reclassification
thickness of lithological unit	− operator
layer excluding faults formed after mineralization	ARCEDIT functions
layer depicting low mean principal stress	external programs
max. rock rheological contrast in cell neighbourhood ^c	focalmax(<i>grid</i> , <i>neighbourhood</i>)

^aARC/INFO commands, operators, functions and scripts

^bAvenue code required to convert a structural layer showing the presence or absence of faults to one in which each cell represents the dip or strike of the fault along a specified interval, was developed by S. Gardoll.

^cThese are focal functions that determine the value of the current cell from the values of cells around it within a small neighbourhood. The other functions and operators shown are local and only involve a single location.

^dReclassification is performed by applying the following conditional statement in an ARC/INFO GRID *DO CELL* processing loop to each cell in the grid: *if(condition<statement list> else if(condition)<statement list> endif*

Figure 3.1. The first pre-processing step is the conversion of all GIS thematic layers (images and polygon coverages in vector format) to raster format. Layers initially in raster format may need to be converted to a consistent cell size.

preferable for layers containing discrete entities like polygons and lines, representing lithological units and faults respectively, the raster format is better suited for representing geochemical and geophysical data sets and satellite imagery. By far the majority of the input layers used in this study correspond to this latter group. Finally, a much greater variety of spatial analysis and image processing functions are available in most GIS for raster data (Burrough & McDonnell, 1998).

3.2.2 Neural Network Method

The approach taken in this study was first to determine if and how a neural network could be used to predict prospectivity maps and then (based on the success of this first part) to investigate the factors which determine the quality of maps produced using neural networks.

In Chapter 2, it is shown that neural networks are a powerful type of model-free classifier and universal function approximator and that neural networks have many characteristics that are well suited to geoscience applications.

The investigation in Chapters 5-7 into how neural networks can best be applied to the problem of mineral prospectivity is based on the steps which are common to solving any problem with neural networks. These steps, described by Zaknich (1999) are:

1. data collection,
2. raw data processing,
3. selection of a neural network type and topology,
4. feature extraction from pre-processed data, and
5. training and testing.

Although the use of GIS databases which have been compiled elsewhere eliminates the first two steps from consideration in this study, each of the other points forms the basis of a separate investigation in later chapters.

The problem of how best to apply neural networks to the problem of predicting mineral prospectivity is investigated by testing the factors that determine the performance of a neural-network approach. The factors and the chapters in which they are examined are;

1. type of neural network architecture (Chapter 7),
2. type and coding of features used as inputs (Chapter 5),
3. training strategy (training data set design, learning algorithm, model selection and classification threshold (Chapter 7), and
4. use of prior knowledge (Chapters 5 & 7).

Although many different types of neural networks exist, some of the main neural network architectures used in practical applications are examined in detail in Chapter 2 and in Appendix A. Of these, the Multilayer Perceptron (MLP) is the most generally applicable and by far the most widely-used type of neural network (Jang & Sun, 1995). Consequently, it was selected for the pilot study described in Chapter 4. The neural network method described here is the general processing scheme that is applicable to neural network experiments to both the pilot and the case study (Chapters 4 & 5-7). Details of the processing steps, which apply only to a specific experiment, are given in the relevant sections.

Processing Steps

Data collection, raw data processing, and some of the work of the feature extraction¹ had already been performed in the production of the GIS thematic maps used as the starting point of this study.

The following processing steps are performed in the neural network method;

¹Feature extraction is the one of the main subjects of Chapter 6.

1. convert images, polygon coverages (vector format) and grids to ASCII raster format with the same cell size,
2. produce derived GIS thematic layers (feature extraction),
3. combine GIS thematic layers to produce input feature vectors,
4. perform pre-processing; scale input data to [0,1],
5. create training data sets,
6. train neural network (and collect test-set performance statistics),
7. process entire study area using trained network,
8. scale and classify outputs,
9. produce prospectivity map, and
10. analyze prospectivity map quality.

The first two steps involving the preparation of derived layers and conversion of input layers to raster format are explained in Sections 3.2.1 and 3.2.1, respectively. The other steps are briefly explained in the section that follows.

1. **Combine GIS thematic layers to produce input feature vectors.** The key to applying a neural network to the solution of any problem is to formulate the problem as a series of numerical patterns of inputs and corresponding outputs that can be used to train the network¹.

The way in which data stored in GIS thematic layers in raster format are converted to a series of patterns of inputs and outputs, that can be used to train an MLP neural network, is shown in Figure 3.2. Input GIS layers that depict features that are useful for predicting the location of mineralization are shown superimposed. Each layer represents a different data type (Fig. 3.2). The bottom layer represents an important additional layer. This depicts the locations of known deposits and occurrences of a particular type and is coded in binary form. The presence of mineral deposits or occurrences is indicated by a *one*, and barren locations by a *zero*. Viewing the stack of GIS layers from above, if a particular location corresponds to a deposit, then the string of numbers forms a feature vector, which can be viewed as a type of ore signature, just as the reflectance bands from a LANDSAT TM image can be used to give a signature for alteration minerals. The concept central to this thesis is that neural networks can be trained to recognize the signatures of known deposits and, once trained, predict the prospectivity of other areas. Thus, in Figure 3.2, the first four layers encoded as the input feature vector represent the input to the neural network (in both training and production modes) and the deposit layer values

²This is the situation if supervised training is used. For the unsupervised training scheme used for the Kohonen's Self-Organizing Feature Map, only the input patterns are presented to the network.

represent the target output used to train the neural network. A paired input feature vector and scalar, target output value constitutes a single training pattern.

Figure 3.2. Relationship between GIS layers and feature vectors used as inputs to the neural network. For each cell location on the map grid, the components of the input feature vector for that location are set to the values stored in the thematic layers. Target vectors, which are used for training, contain a single component set to 1 if a deposit is present, otherwise the value is set to 0.

2. **Pre-processing.** Although pre-processing and feature selection can have a significant effect on the generalization performance of a trained neural network, only basic pre-processing is described here. This topic is investigated in Chapter 6. Linear re-scaling of input variables to the range [0,1] was always performed as a first pre-processing step for all neural network experiments according to equation 3.2:

$$x = r(m - m_{min}) + x_{min} \quad (3.2)$$

where

$$r = \frac{x_{max} - x_{min}}{m_{max} - m_{min}} \quad (3.3)$$

and

m_{max} is the maximum limit of the measured variable

m_{min} is the minimum limit of the measured variable

x_{max} is the maximum limit of the scaled variable, i.e. 1

x_{min} is the minimum limit of the scaled variable, i.e. 0

If the logistic activation function is used in the output units of an MLP neural network (as in Chapter 4), then the practical limits of the outputs are 0.1 and 0.9. Training is facilitated if both the target output values used in training and the input values are scaled to the practical limits of the network output (Masters, 1993b). Bishop (1995) notes that it is particularly important to normalize the input variables of the radial basis function network, so that they span similar ranges, otherwise variables with significantly smaller ranges than the others will be ignored by the network. The scaling operation was performed once for the entire set of training data.

Scaling of inputs is also necessary because input variables can have significantly different ranges of values; for example, total magnetic intensity and the orientation of the nearest fault have values that differ by two orders of magnitude. If raw values were used as inputs, variables that typically have large values would have an unduly large effect on the network output compared to variables with small values. Scaling allows inputs to be recognized by the network to be of equal importance.

The creation of feature-vector-target-output pairs (step 1) and linear scaling (step 2) were performed using a single C++ program, *merge_sls*. Details of the program are given in Appendix E and the code is included on the attached CD-ROM (vol. 1).

3. **Create training data sets** For network architectures in which a supervised training method is used (i.e. MLP, PNN, GRNN, and RBFNN), training data consist of input feature vectors paired with the corresponding correct output (referred to as target or desired outputs). Since only a single output was used in all feed-forward networks in this study, the target output is always a single value.

Training data were divided into roughly equal training, training-stop² and test data sets. A number of authors have stressed the importance of using a completely independent data set for MLP networks in order to gain a true indication of the generalization (classification) performance of the trained network and warned of optimistic bias obtained from the test data set results (Masters, 1993b; Zaknich, 1999; Singer & Kouda, 1999a). For the MLP network, the training data set is used to modify the connection weights, the training-stop data set is used to determine when to stop training and the test data set is used to assess the generalization performance of the network after it has been trained. In the case of probabilistic, general regression and radial basis function neural networks, each pattern in the training data set is stored

²The name *training-stop* data set is sometimes referred to as the *stop* set in tables in later chapters

in the network in the form of weights connecting one of the hidden layer units. The training data set is used to modify network parameters and the test data set is used to check the performance of the trained network.

Training data patterns were selected randomly from cell locations over the entire study area. For experiments with the MLP neural network, approximately equal numbers of patterns representing deposit and non-deposit cells were randomly selected. The training data were then divided randomly between the training, training-stop and test data sets.

Training data were selected (step 5) using a single C++ program, *rand_select*. Details of the program are given in Appendix E and the code is listed on the attached CD-ROM (vol. 1).

4. **Train and test neural network.** The training scheme and adjustable parameters differ for each network type and are therefore described in the sections which document the individual experiments below.

The neural network used in the pilot study described in Chapter 4 was the *bp* (back-propagation) program developed by McClelland & Rumelhart (1988). All other experimentation was performed using the MATLAB software package in conjunction with the neural network and fuzzy tool boxes (i.e. add-on packages, Chapman, 1999).

5. **Processing with the trained network.** Once training is completed, the network parameters and weights are fixed. The network is then used to process feature vectors corresponding to the entire data set. Output values produced are stored as a grid. These values represent the activation of the single network output unit and are floating point values, which lie approximately in the range [0.05, 0.95].
6. **Scale and classify outputs.** The output values from the previous step were re-scaled (using equation 3.2) to the range [0, 8] and then classified into integer intervals to produce a nine class prospectivity map. The scaling and classification are performed using a C++ program, *map_class*, which is documented in Appendix E. A listing of the program code is given on the attached CD-ROM (vol. 1).

Map quality statistics were generated using the program, *map_qstats*, which takes the scaled, classified integer grid as input. This program calculates the chi-squared statistic, Spearman's and Kendall's rank correlation coefficients. A second program, *deposit_locns* is used to count the number of grid cells and deposits for each geological

unit. These quantities are required to calculate the probability-based measures of map quality, described below in Section 3.4.2.

7. **Prepare prospectivity map.** Final map preparation, involving the assignment of colours to map classes, overlaying deposit points on the prospectivity maps and creating legends, scale bars, and grid coordinates, was performed with the GEOSOFT data processing package, OASIS MONTAJ.

In order to import the integer grid file from the previous step into GEOSOFT, the file was converted to GXF format (GEOSOFT, 1999) by inserting the appropriate header information at the start of the file before the data. GXF is a standard ASCII file format for exchanging gridded data among different software systems (ASEG, 1997). GXF Revision 3 implements the exchange of map projection information, which is specified using the Petrotechnical Open Software Corporation (POSC)/European Petroleum Survey Group (EPSG) projection data model and a standard set of geodesy parameters and values (EPSG, 1999). GXF files can be directly imported into the GEOSOFT package and displayed as a map.

The processing steps described above are shown schematically in Figure 3.3.

3.2.3 Assumptions

Several assumptions are common to all data-driven methods for estimating mineral prospectivity. These assumptions are listed below.

1. Undiscovered deposits have similar characteristics to known deposits. In particular, it is assumed that the regional-scale expressions of mineral systems associated with undiscovered deposits are similar to those of known deposits. Small ore deposits are far more abundant than large deposits and, therefore, training data sets are necessarily composed mainly of smaller deposits³. However, giant ore deposits are the targets of most exploration programs, particularly those of larger mining companies. Although there is much discussion about whether giant ore deposits have significantly different characteristics from smaller deposits (Cooke & Pongratz, 2002), Phillips *et al.* (1996), among others, conclude that giant ore deposits are the result of a conjunction of a larger number of favourable factors than smaller deposits.

³A threshold of 1000 kg total contained gold is used in the Kalgoorlie case study in Chapter 7.

Figure 3.3. Schematic diagram of the data processing steps in the neural network method.

2. GIS layers contain evidence for undiscovered deposits; that is, both the type of parameters and scale at which the parameters are captured in the GIS database are appropriate and sufficient to predict the location of the given deposit type.
3. The quality and degree of detail in the GIS layers is similar throughout the map area.
4. The data used for training are representative of the population of both discovered and undiscovered deposits, and cover the range of variation of all the parameters.
5. Grid cells selected to represent barren patterns, in the training set, do not contain any deposits of the type being sought. This is impossible to demonstrate without drilling. However, the rarity of deposits ensures that this assumption is generally true. The problem here is that the training patterns are commonly contradictory, in the sense that barren cells may possess nearly identical attribute values to mineralized cells, and yet the target value is significantly different.

Clearly, it is very difficult to satisfy all these assumptions in practice. However, for the purposes of this study, to test and compare a neural network method of prospectivity mapping with other methods, all data-driven systems and networks tested are subject to the same limitations because they use the same database. Despite these limitations, the use of a test data set that is independent of the training data can provide a useful comparative guide to the expected performance of the systems on completely new data.

3.3 Evaluating Neural Network Performance

Four of the main methods for evaluating the performance of neural networks are described in this section. These are the chi-squared (goodness-of-fit) test, mean square error, confusion matrix, and Receiver Operator Characteristic (ROC) curve. The last three of these methods measure the classification performance of the trained network, while the chi-squared statistic is used to assess the quality of the prospectivity map produced using the trained network.

3.3.1 Chi-Squared Test

Bonham-Carter (1994))has recommended that the chi-squared statistic should be used in an exploratory way without reference to confidence levels in the case of spatial data.

The chi-squared statistic is used in this study to assess the quality of prospectivity maps produced using different methods (Chapter 4).

The chi-squared statistic is calculated with the equation:

$$\chi^2 = \sum_{i=1}^N \frac{(O_i - E_i)^2}{E_i} \quad (3.4)$$

where

- i is the class label
- E_i is the expected frequency of occurrence of class i ; i.e. the number of patterns in class i ,
- O_i is the observed frequency of occurrence of class i ,
- N is the number of classes, and
- $N - 1$ is the number of degrees of freedom

In studies where confidence levels are used, if the chi-squared value exceeds the tabulated value for a given level of confidence, then the null hypothesis (that the observed and expected frequency distributions are the same) is rejected.

In this study, the method is used to compare how well different classes in a nine-class prospectivity map predict the known deposits. Since the overall number of deposits occurring in the map area is known, the expected frequency of occurrence (i.e. prior probability) of deposits per grid cell can be calculated. Once this is known, the *expected* number of deposits can be calculated for each map class based on its area and compared with the actual number of known deposits occurring in that region.

3.3.2 Mean Square Error

The mean square error measures the error at the network output units in terms of the difference between the target output and the actual output calculated by the network. The mean square error is calculated according to equation 3.5;

$$E^n = \frac{1}{K} \sum_{k=1}^K (y_k^n - t_k^n)^2 \quad (3.5)$$

$$E = \frac{1}{N} \sum_{n=1}^N E^n \quad (3.6)$$

where

E^p	= error for a single pattern (average over multiple network output units)
E	= mean square error (average over all patterns in training set)
n	= pattern label,
k	= output unit label
t	= target output,
y_k	= actual network output as a function of the input vector, $\mathbf{x}$,
N	= number of patterns in the training data set, and
K	= number of output units.

The mean square error (MSE) can be used to measure the performance of networks used for both classification and function approximation. The MSE is often used to assess performance during training. McClelland & Rumelhart (1988) used a similar measure of error, namely the sum-of-squares error, to specify the training and test data set error for the bp program used in the pilot study in Chapter 4. The total sum-of-squares error (TSS) has the form:

$$E = \frac{1}{2} \sum_{n=1}^N \sum_{k=1}^K (y_k^n - t_k^n)^2 \quad (3.7)$$

where the variables are the same as those for equation 3.5 shown above. Problems with the MSE and TSS error measures pointed out by Masters (1993b) include;

1. larger errors are emphasized, despite the fact that any error that leads to a misclassification could be important in a classification problem,
2. the measures do not provide any information about the type of errors, and
3. the measures do not indicate the expected frequency of misclassification.

For these reasons, the MSE and TSS error measures are only used during training and are not used to quote the classification performance of trained neural networks.

3.3.3 Confusion Matrix

A confusion matrix is a cross-tabulation of the true classification (rows) and the classification assigned by a system (columns) showing the number or percentages of correct and incorrect classifications for each class (Bonham-Carter, 1994). An example with just two classes is shown in Table 3.2 below.

The nomenclature, which is used commonly used in two-class classification problems is

Table 3.2. A confusion matrix showing the four possible outcomes for a classification decision involving two classes.

		Classified as	
		Class 1	Class 2
Class	Class 1	C_{11}	C_{12}
	Class 2	C_{21}	C_{22}

Table 3.3. Receiver-operating-characteristic table showing nomenclature for a 2-class classification (after Zaknich, 1999).

		Classified as	
		Positive	Negative
Class	Positive	TP	FN
	Negative	FP	TN

shown in Table 3.3. The meanings of the abbreviations are shown below. If class 1 represents deposits and class 2 represents barren cells, then the elements have the following meanings;

- C_{11} = number of deposit cells that were classified as deposits (True positive, TP)
- C_{21} = number of deposit cells that were classified as barren cells (False positive, FP)
- C_{12} = number of barren cells that were classified as deposit cells (False negative, FN)
- C_{22} = number of barren cells that were classified as barren cells (True negative, TN)

Entries in the diagonal positions are correct classifications, whereas all off-diagonal entries represent misclassifications. In a perfect classification, all non-diagonal entries would be zero. A confusion matrix is useful because it shows the type of misclassifications. For example, it is probably better to misclassify possibly barren cells as containing mineralization than it is to classify cells containing known deposits as barren. A confusion matrix would show if this occurs.

A number of single-value measures of classification performance, based on the quantities shown in Table 3.3, are commonly used. Most remote-sensing image classification studies; (e.g. Lees, 1996), use the overall correct classification rate defined by equation 3.8:

$$\text{Overall correct (\%)} = \frac{\sum_{i=1}^N (\text{number correct for class } i)}{\text{total number of patterns}} \times \frac{100\%}{1} \quad (3.8)$$

The overall percentage correct measure is used in the pilot study in Chapter 4. In a study comparing PNNs and the weights-of-evidence methods for mineral favourability analysis, Singer & Kouda (1999a) quoted the classification performance in terms of the classification error rate, which is defined as:

$$\text{Classification error rate (\%)} = \frac{\text{FN} + \text{FP}}{\text{total cells}} \quad (3.9)$$

3.3.4 Receiver Operating Characteristic Curves

The receiver-operating-characteristic (ROC) curve shows how classification performance varies with the threshold value used to divide feature vectors into two classes on the basis of activation at the output unit of the neural network (Zaknich, 1999). When a network is used to distinguish between cells belonging to deposit and non-deposit classes, a decision threshold must be applied to the activation values produced at the output unit. For the MLP neural network studied in Chapter 4, the output activation was approximately in the range $[0.05, 0.95]$. Patterns associated with an output activation greater or equal to the arbitrarily chosen threshold of 0.5 were classified as deposits.

The quantities referred to in the following discussion of ROC curves are those shown in Table 3.3. The probability of making the four types of classification in Table 3.3 depends on the decision threshold and is illustrated in Figure 3.4a below (Masters, 1993b; Zaknich, 1999). The left-hand and right-hand curves show the probability distributions for the output unit activation for barren and deposit cells, respectively. Areas corresponding to the true positive (TP), false positive (FP), true negative (TN), and false negative (FN) probabilities are also shown in Figure 3.4a.

These quantities are related in the following way. If the threshold (indicated by the vertical line at T_h in Fig. 3.4a) for the classification of a pattern as a deposit is very high, then very few barren cells will be mistaken for deposits (FP probability is low) but many cells that are actually deposits may be incorrectly classified as barren (FN probability is high). Conversely, if the threshold is very low (T_l in Fig. 3.4a), a large number of barren patterns will be classified as deposits (FP probability is high) and most deposits will be correctly identified as deposits (TP probability is high).

The following quantities are required in order to represent ROC curves. The true positive rate is defined as;

$$\text{True positive ratio} = \frac{TP}{TP + FN} \quad (3.10)$$

$TP + FN$ equals the total number of deposit patterns.

The false positive ratio is defined as:

$$\text{False positive ratio} = \frac{FP}{FP + TN} \quad (3.11)$$

Figure 3.4. Receiver-operating-characteristic (ROC) curves (modified from Masters, 1993b; Zankich, 1999). Abbreviations: FN = false negative, FP = false positive, NN = neural network, TN=true negative, TP = true positive).

where $FP + TN$ equal the total number of barren patterns. These two parameters are plotted in Figures 3.4b and c, respectively. Thus, there are contradictory requirements; a low threshold is needed for a high true positive ratio (i.e. to make sure the deposits are not missed) and a high threshold is needed for a low false positive ratio (i.e. to make sure the barren cells are not mistaken for deposits).

The ROC curve is generated by plotting the true positive and false positive ratios together for a range of threshold values (Fig. 3.4 d). Curves very close to the top left corner indicate a very good discrimination of classes. On the other hand, a straight line with a slope equal to one corresponds to a situation where no discrimination occurs. To get a straight line, true positive and false positive ratios would have to be equal for all threshold values. The two curves in Figure 3.4a would have to completely overlap corresponding to a network that produces random output activation values in response to deposit and barren patterns (Masters, 1993b).

The area under the ROC curve is used as a measure of classification performance and varies from a minimum of 0.5 to a maximum of 1.0. Masters (1993b) has noted that the shape of the curves are also important because networks with very different performance can produce curves with equal areas.

3.3.5 Harris and Pan's Measures of Performance

Harris & Pan (1999) use a variation of these ideas to represent the performance of different methods for mineral favourability mapping. They plot the percentage correct classification for mineralized and barren cells versus the probability value used as a threshold to make the classification. (Fig. 3.5). A good prospectivity model is one for which the two curves are as close to 100% correct classification for a large range of threshold values.

Harris & Pan (1999) used a second measure of classification performance, which they refer to as exploration performance. The exploration task is viewed as one of selecting the optimum threshold for allocating cells to the mineralized class and it is assumed that all cells classified by the system as mineralized are retained as ground for further exploration. Harris & Pan (1999) measure performance in terms of the percentage of total cells that must be retained to ensure that different percentages of mineralized cells are retained when various cutoff probabilities for mineralization are applied to neural network output probabilities. Their approach results in a plot that is nearly identical to the ROC curve due to the very small proportion of the total number of cells represented by deposits. Since the terms TP and FN in the ROC equation 3.11 refer to deposits, they are exceedingly

Figure 3.5. Classification of input feature vectors as *mineralized* and *barren* using a) probabilistic neural network (PNN) and b) logistic regression methods (Harris & Pan, 1999). Classification performance is measured in terms of the percentages of mineralized cells that are correctly classified because their probabilities of mineralization exceed a threshold (x -axis) and barren cells that are correctly rejected (solid and dashed lines, respectively). Note that at high threshold values, a large fraction of both mineralized and barren cells are correctly classified by the PNN, whereas the fraction of mineralized cells correctly classified by logistic regression is relatively low.

small relative to the terms TN and FP , which refer to barren cells. If the deposit terms are omitted, the ROC equation 3.11 is identical to equation 3.13.

The percentage of mineralized cells that are ‘retained’ is defined as;

$$y = \frac{\text{no. of mineralized cells classified as mineralized}}{\text{total no. of mineralized cells}} \cdot \frac{100\%}{1} = \frac{TP}{TP + FN} \cdot \frac{100\%}{1} \quad (3.12)$$

and the total number of cells retained is defined as:

$$x = \frac{\text{total no. of cells classified as mineralized}}{\text{total no. of cells}} \cdot \frac{100\%}{1} = \frac{TP + FP}{TP + FN + FP + TN} \cdot \frac{100\%}{1} \quad (3.13)$$

The interpretation of the curves in Figure 3.6 is similar to that in Figure 3.4d. To illustrate the use of this plot, suppose that two methods represented by curves 1 and 2 are to be compared and the goal is to retain at 90% of the mineralized cells in a region. Because curve 1 lies to the top left of curve 2, this means that method 1 allows the 90% of the

Figure 3.6. Measure of *exploration* performance used by Harris & Pan (1999) for a) probabilistic neural network (PNN) and b) logistic regression methods. In Harris and Pan's model for exploration decision-making, cells for which the probability of mineralization exceeds a threshold are retained for exploration and those that fall below the threshold are rejected. A good classifier for exploration decision-making is one that accurately classifies both mineralized and barren cells so that only a small fraction of the total cells must be retained in order to retain a high proportion of the mineralized cells.

mineralized cells to be retained using a smaller total number of cells (and therefore at lower cost) than method 2.

3.4 Weights-of-Evidence Method

A literature survey of previously-used mineral prospectivity methods in Chapter 2 reveals that logistic regression and the weights-of-evidence method offer some advantages compared to other multivariate techniques that are based a linear model of the data. In particular, the logistic and weights-of evidence methods are better able to model non-linear relationships and are less sensitive to the degree to which the assumptions of normality and heteroscedasticity are satisfied than other methods. Although the weights-of-evidence method is subject to problems related to the conditional dependence of input data sets, it is simple to implement, easy to interpret, and, because of this, it is more commonly used than logistic regression.

Maps were prepared according to the weights-of-evidence method using the GEODIPS GIS prospectivity analysis package developed by Jusmady & Taylor (1997).

Processing

The weights-of-evidence method used in this study has been described in detail by Bonham-Carter (1994) and is only summarized here. The following steps were performed;

1. Test association of deposit points with patterns in evidence maps,
2. Create binary maps,
3. Create a unique conditions map and table,
4. Test for conditional independence,
5. Combine and eliminate dependent maps, and
6. Create prospectivity map.

These steps are shown in Figures 3.7 and are briefly explained below.

1. **Test association of deposit points with patterns in evidence maps.** The degree to which deposit points are associated with features in the input GIS thematic layers is tested in order to select a threshold value or class to convert multiclass maps to binary maps. Geodips produces a table containing; classes, number of deposit points in each class, weights (W^+ and W^-), weight contrast ($C_w = W^+ - W^-$), standard deviation of the weights and the weight contrast values and the studentized value of the contrast.

The studentized value of the contrast is the ratio of the contrast divided by the standard deviation of the contrast. The studentized value of contrast indicates the reliability of the contrast value. A $Student(C_w)$ value of 1.00 indicates a very high degree of uncertainty while higher values indicate more reliable values of contrast.

For continuous variables, weights and contrast are determined cumulatively (from the minimum to maximum value) and in reverse cumulative order at successive thresholds. The table is used to select the appropriate threshold value to use in order to convert a multiclass map into a binary one. In most cases, the choice of an appropriate threshold from the class-weight tables is subjective. Generally, the class with the maximum C_w or the last class in a sequence of high C_w values before an abrupt decrease in the value of C_w was selected as the threshold. Where these criteria could not be applied, or where the choice was not clear, a threshold with a combination of a high C_w and a $Student(C_w)$ above 1.5 was chosen. Steps 1 to 2 are repeated until an optimal reclassification scheme is determined that maximizes the predictive effect of the binary evidence map.

2. **Create binary maps.** After suitable classes are selected in input maps containing

Figure 3.7. Processing steps used to create weights-of-evidence mineral prospectivity maps in pilot study

discrete entities, or a suitable threshold is selected for maps depicting a continuous field, binary evidence maps are created by reclassifying the multiclass map.

3. **Create a unique conditions map and table.** In the GEODIPS system, used to implement the weights-of-evidence method in the pilot study in Chapter 4, a unique conditions map and table are produced. All binary evidence maps are processed to create a map in which the cell values are codes representing a particular combination of binary evidence patterns that resulted from overlaying the binary maps. For example, for the case where there are just two binary input maps, each containing a binary pattern, which can either be present or absent, there are just four possible combinations of patterns (referred to as unique conditions). For each unique condition, the presence or absence of the favourable pattern in the binary map is stored as a code, the positive and negative weights are summed according to whether the pattern is present or absent, and the resulting value is stored in a table, together with the total number of deposit points associated with that combination of patterns. The table is used in the next step.

The MATLAB code, written to perform the calculations for the weights-of-evidence method in the rest of the study, does not employ a unique conditions map or table. Instead, each binary evidence map is replaced by one containing a positive weight, where the binary pattern is present, and a negative weight where the pattern is absent. Then, at each grid location, weights in the different map layers are added to the log of the prior probability of a deposit to determine the posterior probability of a deposit.

4. **Test for conditional independence.** A table is produced that shows values of the chi-squared statistic (χ^2) for all combinations of map pairs. Map pairs resulting in a χ^2 value above the limit of 5.4, at the 95% confidence level for one degree of freedom, are conditionally dependent (Bonham-Carter, 1994).⁴
5. **Combine and eliminate dependent maps.** For example, in the Tenterfield pilot study, maps corresponding to the K and total count gamma-ray channels were discarded. Maps for the U and Th channels were combined by multiplying them together. This method produced the strongest association between the resultant map pattern and the known deposit points by emphasizing leucogranites of the Stanthorpe granite group, which produce a high radiometric response and are the

⁴A new 'omnibus' test developed by Agterberg & Cheng (2002) and tested by Thiart *et al.* (2003b,a) can also be used for pairwise testing and is superior to chi-squared and Kolmogorov-Smirnov tests in cases with a small number of deposit points.

main hosts of disseminated and placer deposits (Barnes *et al.*, 1995). Steps 1–4 must be repeated for new maps that have been created as a result of combining conditionally dependent ones.

6. **Create prospectivity map.** The posterior probability of a deposit is calculated for each grid cell using Equation 2.8 (Chapter 2), and the data stored in the unique conditions table. Equation 2.8 gives the log of the posterior odds, which is then converted to a probability value. The steps to create the final map are the same as those described for the neural network method (step 7 on page 70).

3.4.1 Fuzzy Systems Method

Conceptual methods referred to in Chapter 2 include statistical-subjective methods (Harris & Carrigan, 1981) and Dempster-Shafer evidential belief theory, expert systems, decision-trees inference systems, fuzzy-logic and hybrid statistical-fuzzy-logic methods, and adaptive neuro-fuzzy inference systems. The fuzzy-logic method was chosen as an example of a conceptual system because it has been widely used (Eddy *et al.*, 1995; Donaldson, 1996; Burgess, 1997). and is relatively easy to implement compared to the other methods. The pre- and post-processing steps are the same as those for the weights-of-evidence method explained in Chapter 3 above. The procedure used has been described in detail by Bonham-Carter (1994), and therefore only a short summary is given here.

Processing

The fuzzy-logic procedure consists of five steps (Fig. 3.8);

1. **Classify raw values and assign fuzzy membership values.** Fuzzy membership values, in the range $[0, 1]$, are assigned to classes of cell values for each input map layer. The membership values are assigned subjectively, according to how favourable the parameter values are for mineralization. Classes of variable values and the corresponding membership values are shown in Table 4.3 (Chapter 4).
2. **Create map layers containing fuzzy membership values.** A new fuzzy membership map layer was created for each variable using values in Table 4.3.
3. **Design fuzzy-logic net.** Maps containing membership values are combined using map algebra functions (e.g. addition, subtraction, multiplication, and division) or fuzzy membership operators (fuzzy AND, fuzzy OR, algebraic sum, algebraic prod-

uct and the gamma operator; Zimmermann, 1984; An *et al.*, 1991; Bonham-Carter, 1994). The fuzzy-logic inference net refers to the combination of primary and derived map layers and the choice of map algebra and fuzzy operators used to combine maps. The fuzzy inference net used in the pilot study is shown in Figure 3.9.

4. **Combine layers to create favourability map.** At each grid cell location, fuzzy membership values from different map layers were combined using fuzzy operators to produce a single output membership value representing the overall favourability for mineralization. The procedure is the same as that described in point 7 on page 7.
5. **Model selection.** A variety of different fuzzy membership value assignments, inference nets, choice of fuzzy operators for the final map combination step, and, in the case of the gamma operator, different values of the gamma operator (in the range 0–1), were tested. The prospectivity map that best accounts for the known deposit locations, while minimizing the area of the highest prospectivity classes, was chosen as the final fuzzy-logic model.

The relationship between the deposit points and the magnetic intensity map is ambiguous, and therefore the magnetic map was not used as an input map in the fuzzy-logic and weights-of-evidence methods. The map algebra addition-operator was used to combine the gamma-ray U- and Th-channel maps. The fuzzy gamma operator with $\gamma = 0.95$ was used to combine membership values in the final step (refer to Fig. 3.9).

3.4.2 Comparing Mineral Prospectivity Map Quality

This section describes work performed as part of this pilot study to determine how to assess the results of the different prospectivity mapping methods. In order to quantitatively compare the quality of maps produced using different methods, verification of the results using some form of ground truth would normally be required. This is not feasible here, since prospectivity maps do not represent a classification of an extensive and continuously measurable category, such as agricultural crop type, that can be readily checked. Instead, prospectivity maps were quantitatively compared by measuring the extent to which high prospectivity areas of the maps include the locations of known mineral deposits and occurrences. A variety of statistical and probability indices of map quality was used.

The chi-squared statistic measures the extent to which observed and expected numbers of deposits differ. As noted previously, although the chi-squared statistic cannot be used to make statistical tests of significance of spatial associations, it can provide explorative and

Figure 3.8. Processing steps used to create fuzzy-logic mineral prospectivity maps in pilot study

Figure 3.9. Fuzzy inference net used in the mineral prospectivity map shown in Fig. 4.11 b.

descriptive measures of spatial correlation (Bonham-Carter, 1994) and is used here as a measure of the quality of a prospectivity map.

The observed number of deposits in the map classes with the highest favourability should be much higher than the number that would be expected if the map class areas were distributed randomly with respect to deposits. The chi-squared statistic has a lower limit of zero when the patterns of the map class areas and deposits are completely independent of one another, and it increases in value as the differences between observed and expected numbers of deposits become larger. A problem with the chi-squared statistic is that it is only sensitive to the total difference between observed and expected numbers of deposits for all the map classes and not to whether it is the higher prospectivity map classes that contain higher than expected numbers of the known deposits.

The non-parametric rank-order tests of Spearman's ρ and Kendall's τ were used to measure the degree of correlation between the probability of occurrence of known mineral deposits with prospectivity map class. Both tests measure the degree of independence between random variables. The hypotheses for a one-tailed test of positive correlation between variables are (Macfarlane, 1998);

H_0 : X_i and Y_i are mutually independent, i.e. there is no correlation

H_1 : there is a tendency for larger values of X and Y to be paired together

Spearman's and Kendall's rank correlation coefficients were chosen because they are suitable where a monotonic, rather than a strictly linear, trend is of interest, and they are robust with respect to outliers and inexact measurement (Rock, 1988). For both these statistics, a value of zero indicates that no correlation exists and a value of one indicates

a perfect correlation.

Conditional probabilities $P(D/C_k)$ of the occurrence of a known mineral deposit, given the grid cell is located within a particular prospectivity class C_k were calculated for each prospectivity map class, using the numbers of grid cells. Each deposit is assumed to occupy only a single cell. A disadvantage of conditional probabilities is that they are very small numbers and depend on the total number of known deposits in a region.

The ratio of the conditional probability of a deposit $P(D/C_k)$, given that the area of interest is restricted to a particular prospectivity-map class C_k , to the prior probability of a deposit, $P(D)$ results in numbers that can be more simply compared (Brown *et al.*, 2000a). This ratio, $P(D/C_k)/P(D)$, is equivalent to an intuitive notion of a successful prospectivity map; that is, a high prospectivity map class should define an area in which a high proportion of the known deposits ($n(D_{C_k})/n(D_{total})$) are predicted in a small proportion of the total map area ($n(C_k)/n(T)$). This can be expressed as the following ratio:

$$\frac{n(D_{C_k})/n(D_{total})}{n(C_k)/n(T)} = \frac{P(D/C_k)}{P(D)} \quad (3.14)$$

where $n(D_{C_k})$ represents the number of deposits in map class C_k , $n(D_{total})$ is the total number of deposits, $n(C)$ is the area of map class C_k , and $n(T)$ is the total area. It is interesting to note that Mihalasky & Bonham-Carter (2001) use the same ratio as the one shown in Equation 3.14 but refer to it as the normalized density, ρ_i for class i . When the unit cell is infinitely small, ρ is related to weights by:

$$W = \ln(\rho) \quad (3.15)$$

They use ρ to measure the spatial association between lithodiversity-map classes and deposit points. Mihalasky & Bonham-Carter (2001) have pointed out that ρ as a measure of association is skewed because the range of ρ for negative associations is compressed into $[0, 1]$, whereas the range for positive associations is $[1, +\infty]$. They solve this by using the natural logarithm of ρ which is symmetrical about the null value of $\ln \rho = 0$.

If a prospectivity map is to be useful, then the probability of discovery of a deposit in the highest group of prospectivity map classes should be significantly upgraded compared to selecting a grid cell at random. Consequently, the ratio in Equation 3.14 should be greater than one for high prospectivity-map classes. Conversely, map classes representing

the lowest prospectivity classes should have ratios significantly less than one, indicating that the probability of discovery of a deposit is much lower than average. In the middle group of map classes, the ratio should be approximately equal to one, indicating that cells in these areas are no more likely to contain a deposit than cells chosen at random.

Another simple measure that can be used to assess the final map is the contrast, $C_W = W^+ - W^-$, and the studentized contrast, $C_W/S(C_W)$, for each prospectivity-map class (Bonham-Carter, pers. comm.; where $S(C)$ is the standard deviation of contrast).

3.5 Choice of GIS Databases for Pilot and Case Studies

This section provides a summary of the source, location and content of the GIS databases used in this study, together with the reasons for using the database and a description of the role the database plays in the study. GIS databases used in this study are summarized in Table 3.4 below. Detailed descriptions and metadata for the two databases are given in Appendices C and D.

Table 3.4. Summary of GIS databases used in this study. The Tenterfield database is used for the pilot study in Chapter 4 and the Kalgoorlie database is used for experiments described in Chapters 5 to 7.

Database	Deposit Type	Location	Rows×Cols	Cell Size ^a	Deposits ^b
Tenterfield	Intrusion-related Au	Tenterfield, N.E. NSW	280×240	200 m	63
Kalgoorlie	Archaean lode-Au	Eastern Goldfields, WA	1140×1100	100 m	100

^aRows, columns and grid size after converting all GIS layers to a standard size

^bTotal includes deposits and mineral occurrences

3.5.1 Intrusion-Related and Placer Gold Deposits, Tenterfield, N.S.W.

The Tenterfield database was compiled by Robert Barnes at the NSW Geological Survey in Armidale (Barnes, 1993; Barnes *et al.*, 1995; Barnes, 1995; Barnes & Suppel, 1995; Barnes, 1997a,b). The data set corresponds to the Tenterfield 1:100000 map sheet area (9339), an area, located in north-eastern NSW.

Although a wide variety of mineralization types exist in the area (e.g. Mo-W-Bi, Sn±W, and Sn placer), intrusion-related primary and associated placer gold deposits are the

largest group (63 deposits) and were chosen for the pilot study in Chapter 4. The area corresponds to part of the southern portion of the New England Orogen.

GIS thematic layers supplied as ARCVIEW polygon coverages and BIL images include solid geology (compiled at 1:100000 and 1:250000 scale), regional faults and shear zones, a regional stream-sediment geochemistry survey, and airborne magnetic and gamma-ray survey (1986 data on 1500 m flight-line spacing) and mineral deposits and occurrences. Data were converted to a raster grid with 280 rows $\times$ 240 columns and a 200 m cell size.

The database was chosen for the pilot study in Chapter 4 because;

1. there is complete coverage over the area for all data sets,
2. there are abundant gold deposits and mineral occurrences (63 primary and placer),
3. the data are in the public domain,
4. there was no major post-mineralization structural deformation or metamorphism.

The Tenterfield database is not suitable for the detailed investigations in other chapters because;

1. the data were not collected specifically to explore for intrusion-related gold deposits,
2. the resolution of the geophysics data is low collected in 1986 using a flight-line spacing of 1500 m,
3. geophysics data are only available as grey-scale images, and
4. the regional faults and shear zone data are incomplete, as indicated by the number of faults apparent as topographic features on a high resolution DEM produced after the compilation of the geological map (unpublished data of the NSW Geological Survey).

A detailed description of the GIS database is given in Appendix C.

3.5.2 Archaean Orogenic Gold Deposits, Kalgoorlie, W.A

The Kalgoorlie data set was provided by Dr Scott Halley at Placer Dome (formerly Goldfields Exploration Pty Ltd). The data set is currently being used for exploration for Archaean lode-gold deposits in the Kalgoorlie district.

The area covers part of the Bardoc Tectonic Zone within the Norseman-Wiluna belt of the

Yilgarn Block. The data set covers an approximately square area with sides of 110 km and corresponds to the eastern half of the Kalgoorlie 1:250000 geological map sheet (SH51-9). Data compilation was mainly performed at a scale of 1:100000. In raster format, the map grid consists of 1140 rows $\times$ 1100 columns with a cell size of 100 m.

Data consist of solid geology (a compilation of mapping by the Geological Survey of Western Australia and Goldfields Exploration geologists using field mapping and aeromagnetic interpretation), structure, Bouguer gravity anomaly, total magnetic intensity (RTP), drill-hole geochemistry, and regolith geochemistry. All vector data layers were originally supplied in MAPINFO format.

This database is used for experiments in the methodology part of the thesis because;

1. it is a current and high-quality compilation and contains one of the best syntheses of geological mapping presently available,
2. it was compiled specifically for exploration for Archaean lode-gold deposits,
3. there is a large amount of expertise within the Centre for Global Metallogeny on this deposit type,
4. the database contains a large number of gold deposits and occurrences, and
5. the deposit database is well attributed and includes tonnage and grade information.

A detailed description of the GIS database is given in Appendix D.

3.6 Software

3.6.1 Pre-Processing (C++ Programs)

Pre-processing steps shown in Figure 3.3 were performed with a series of C++ programs. The functions performed by these programs and other commercial software used in the project are shown in Table 3.5. The code for the C++ programs is listed in the attached CD-ROM (vol. 1), and the processing procedure for the MLP network is documented in Appendix E. All input and output data supplied to the C++ programs are in ASCII format.

3.6.2 Neural Network Simulation Packages

A teaching package called the GIS prospectivity analysis package (GEODIPS), developed by Jusmady & Taylor (1997), was used to implement the weights-of-evidence and fuzzy-logic methods in the pilot study in Chapter 4 only. A tutorial description of the GEODIPS package is given by Taylor (1997). All other neural network processing was performed using the MATLAB software package. Experiments in Chapters 6–7 were conducted using MATLAB, which is a software package suited to manipulating large arrays, an extension package referred to as the Neural network Toolbox, and functions written in a C-like script language.

3.7 Hardware

Most of the work in this study was performed using a Dell 410 Precision workstation with a 650 MHz Intel Pentium III processor, 512 MB of ECC RAM, 32 MB of video memory and a 27.2 GB hard drive. Peripherals included external 40 GB and 80 GB IEEE 1394/Firewire hard drives. The main requirement for this study is a large main memory. This allowed all the large matrices representing GIS map layers (up to 18 at a time) to be stored in RAM simultaneously, rather than have to be transferred from disk using paged memory. The ARC/INFO GIS was run on a Sun Sparc 20 workstation.

3.8 Summary

The main points discussed in Chapter 3 are listed below.

1. Derived layers (layers derived from primary geoscientific data) are important because they represent a means of incorporating expert knowledge into the neural network input.
2. In this study, derived layers were prepared using the in-built functions of either the ARC/INFO and ARCVIEW GIS systems.
3. All GIS thematic layers in vector format (i.e., polygon coverages in ARC/INFO) were converted to raster format prior to further processing because; 1) a raster format is compatible with neural network packages, and 2) most derived GIS layers and geophysical data are stored in raster format.

4. The main processing steps in a neural network approach to mineral prospectivity mapping are; 1) convert GIS data to ASCII raster format, 2) produce derived GIS thematic layers (feature extraction), 3) combine GIS layers to create input feature vectors, 4) scale data to range [0,1], 5) create training data sets, 6) train network and collect test-set performance statistics, 7) process entire study area using trained network, 8) scale and classify outputs, 9) produce prospectivity map, and 10) analyze the quality of that prospectivity map.
5. In the pilot study, performance of the trained network is assessed using; 1) the mean square error, and 2) the percentage correct classification of an independent test set.
6. In the case study, the area under a receiver operating characteristic (ROC) curve is used as an additional measure of the classification performance of the trained

Table 3.5. Programs and software packages used in this study

Processing step	Program Name
GIS Pre-Processing	
Clipping and re-gridding (geophysics)	ERMAPPER
Conversion to raster format	MAPINFO, ARC/INFO, ARCVIEW
Create derived layers	ARCVIEW
Neural Network Pre-Processing^a	
Create feature vectors, scaling	merge_sls
Create training data sets	rand_select
Scale and classify output	map_class
Calculate map quality statistics	map_qstats
Calculate deposit statistics	deposit_locns
Data integration	
Neural network processing	MATLAB, bp ^b
Weights-of-Evidence	MATLAB, GEODIPS ^c
Fuzzy Logic	MATLAB, GEODIPS
Post-Processing	
Preparation and display of maps	GEODIPS <i>Oasis Montaj</i>

^aThese are C++ programs. Listings are given on the attached CD-ROM (vol. 1).

^bThe *bp* program is a MLP neural network trained with the back-propagation algorithm and was written by McClelland & Rumelhart (1988).

^cThe GEODIPS software package was developed by Jusmady & Taylor (1997) and Taylor (1997).

network on an independent test set. The area is calculated using all of the data (rather than the test set only) and varies from a minimum of 0.5 to a maximum of 1.0.

7. A plot designed by Harris & Pan (1999) is also used as a measure of classification performance in the case study. The plot shows the percentage of total cells that must be retained to ensure that different percentages of mineralized cells are retained when various cutoff probabilities for mineralization are applied to neural-network output probabilities.
8. Weights-of-evidence maps and fuzzy-systems maps in the pilot study were prepared using the GEODIPS GIS prospectivity analysis package developed by Jusmady & Taylor (1997).
9. Prospectivity maps produced using different methods are quantitatively compared by measuring the extent to which high prospectivity areas of the maps account for the locations of known deposits.
10. The following measures of map quality are used to compare mineral prospectivity maps produced using different methods; 1) the chi-squared statistic, which measures the extent to which the observed number of deposits in the highest prospectivity map class differs from the number of deposits expected due to chance, 2) Spearman's ρ and Kendall's τ rank correlation coefficients which are used as measures of the correlation between increasing prospectivity map class and the probability of occurrence of known deposits within the region corresponding to that class, and 3) $P(D/C_k)/P(D)$, which represents the ratio of the conditional probability of finding a deposit given that the cell is located in the highest prospectivity class (i.e., in a prospectivity map converted to nine-classes) compared to the prior probability of finding a deposit for the map area as a whole.
11. The ratio $P(D/C_k)/P(D)$ is a measure of the performance of the prospectivity map. The ratio represents the posterior conditional probability that a known deposit is located in the area corresponding to class k of the prospectivity map to the prior probability of a deposit (i.e., the probability that any cell selected at random contains a deposit). It is equivalent to the ratio, D/A , where D = the percentage of the total number of deposits located in the highest prospectivity class and A = the percentage of the total area of the map represented by the highest prospectivity class.
12. The pilot study is based on intrusion-related primary gold and associated placer gold deposits in the Tenterfield area of north-eastern NSW. The map grid has 280 rows

× 240 columns and a 200 m cell size. This database was chosen because; 1) there is complete coverage over the area for all data sets, 2) there are abundant deposits and mineral occurrences (63 primary and placer), 3) the data are in the public domain, and 4) there was no major post-mineralization structural deformation, such that the map represents the geological scenario at the time of primary gold mineralisation.

13. The case study is based on a database provided by Goldfields Exploration Pty Ltd., used in a current exploration program for orogenic lode-gold deposits in the Archaean Kalgoorlie Terrane, Western Australia. The map grid consists of 1100 rows × 1100 columns with a cell size of 100 m. The database was chosen because; 1) it is a current, comprehensive and high-quality compilation, and 2) the timing of gold is late within the deformational history of the host terrane, and, therefore, the geometry of the structures associated with deposits is essentially similar to that at the time of mineralization. Consequently, spatial relationships between the structures and known gold deposits displayed in the geological map can be analyzed using a GIS to predict the location of new gold deposits.
14. Experiments in Chapters 6-7 were performed using MATLAB, which is a software package suited to manipulating large arrays.

Chapter 4

Pilot Study based on Intrusion-Related, Granite-Hosted Gold Deposits, Tenterfield, New South Wales: Testing the Viability of an MLP Neural Network Method

4.1 Introduction

The pilot study described in this chapter was performed to test whether it is possible to produce a multiclass mineral-prospectivity map using a neural network, and if so, then how it compares to established methods. Although Bonham-Carter (1994) refers to neural networks as a possible method for mineral-prospectivity mapping, there are very few papers on the use of neural networks in mineral exploration, and only two papers described the use of neural networks for mineral prospectivity at the time this study commenced (Singer & Kouda, 1996; Clare *et al.*, 1997). In the case of Clare *et al.* (1997), a proprietary commercial system is briefly reported and no information is given on the type of network used, methods or exact nature of the output from the network.

It is difficult to assess from the study by Singer & Kouda (1996) whether neural networks

could be used to produce mineral prospectivity maps similar to those produced with the weights-of-evidence and fuzzy-logic methods. The reason for this is that both the deposit type and the study area appear to represent special cases, which allowed Singer & Kouda (1996) to express mineral prospectivity in terms of the distance to the nearest VMS deposit rather than as probability or favourability that a cell contains mineralization.

Singer & Kouda (1996) trained an MLP neural network using semi-quantitative X-ray analyses of four minerals in drill holes to predict the distance to Kuroko-type massive sulphide deposits in the Hokuroku district, Japan. In that study, the neural network is used as a function approximator rather than as a classifier, since the target output is a continuous variable representing the distance to the nearest ore deposit. The results were presented in the form of a map showing contours indicating the distance to ore deposits. Contours were not shown for areas greater than three kilometres from any drill hole. It is possible to present the results in this way because the abundance of the alteration minerals (used as input variables) display a distance relationship on a regional scale to the sites of hydrothermal vent on the sea-floor that originally produced the deposits (Agterberg *et al.*, 1993).

In contrast, the weights-of-evidence method and fuzzy-logic methods produce results in the form of the probability of occurrence of deposits and a fuzzy membership value in the range $[0, 1]$, indicating favourability for mineralization. Data used to determine weights in the weights-of-evidence method and to validate models in the fuzzy-logic method are the presence or absence of deposits.

The area analysed by Singer & Kouda (1996) is unusually well explored. The Hokuroku district is the most thoroughly studied Kuroko-bearing district in the world. This has important implications for the application of neural networks. First, the density of drill holes is such that it is possible to be very sure that no undiscovered deposits exist in areas used to obtain training data, and therefore, that the distances used in the training data are correct. Generally, areas for which mineral prospectivity maps are prepared are not so well explored, and therefore, it is not possible to have the same degree of confidence that some of the apparently barren areas selected for use as training data do not contain deposits. Second, in most areas under exploration, the amount of training data available for deposits are very small relative to non-deposit data. This pilot study was intended to determine whether a neural-network approach could be applied to a more general situation in which;

1. GIS data sets typical of those used in mineral exploration are used,
2. the area contains known deposits but has not been the subject of intense scientific

exploration or study, and

3. output in the form of a map showing probability or favourability for mineralization is required.

A particular problem related to this last point is whether a neural network method can be used to produce a *multiclass* mineral prospectivity map. The problem is that if the presence and absence of deposits are used as target values to train a neural network, the network is being required to perform as a binary classifier. However, in this mode, the output of the network should approach one and zero for inputs corresponding to deposits and non-deposit areas, respectively. This presents a problem if the task is to produce a multiclass (and therefore multicoloured) mineral prospectivity map, since the output must be in the form of a continuous variable that spans a wide range of values. This pilot study was intended to resolve some of these problems and compare the performance of a neural-network approach to the weights-of-evidence and fuzzy-logic methods in producing mineral prospectivity maps.

4.2 GIS Database

The GIS database for the trial study corresponds to the area of the Tenterfield 1:100000 sheet (map 9339), and was compiled by the Geological Survey of New South Wales (Barnes, 1993; Barnes *et al.*, 1995). Metadata, including the sources, preparation of the data layers and an explanation of the attributes and codes used in each layer, are given in Appendix C. An explanation of the metadata standards used to document the GIS data in this thesis is given in Appendix B.

The database comprises the following thematic layers; solid geology, regional-scale faults, airborne total magnetic intensity (classed-image data), airborne gamma-ray spectrometry (U, Th, K and total count, classed-image data) and deposit locations (Fig. 4.2). The mineral deposit layer includes mineral occurrences, and small and medium sized mines. The Tenterfield 1:100,000 map grid contains 69,440 cells in 280 rows and 248 columns. Each cell in the grid data represents a 200 metre square on the ground. The Tenterfield GIS database is well suited for a pilot study to test the application of neural networks to prospectivity mapping for the reasons listed below.

1. The data are well documented and in the public domain.
2. The area has a uniform and complete coverage for all thematic layers.

Figure 4.1. GIS thematic layers used as inputs in the pilot study: a) simplified solid geology, b) major faults and shear zones, c) total magnetic intensity (RTP), d) U channel gamma-ray survey data (classified), e) Th-channel, f) K-channel, g) total count, h) 200m fault buffers (only first 5 shown), i) deposit points; vertical crosses = primary, intrusion-related, disseminated, Au deposits, diagonal crosses = placer deposits, and open circles = disseminated deposits with unknown form).

3. There are a sufficiently large number of mineral deposits and occurrences to provide training data for the neural network method and to apply the statistical weights-of-evidence method used to provide a comparison.
4. Although some of the older sedimentary basement sequences are highly deformed, Permo-Triassic granites (which are the main hosts to mineralization) and volcanic units are relatively undeformed. Thus, present-day structures are a good guide to those that existed when the deposits formed. This is an important requirement for applying the fuzzy-logic method, because it is based on a deposit model and relies on a correspondence between the spatial relationships of geological structures and the features of the deposit model. This correspondence would be obscured in an area that had undergone strong post-mineralization structural deformation.
5. The thematic layers in the Tenterfield GIS are representative of those that would be available in a typical regional exploration program.

A disadvantage of the data set is that the geophysical data (airborne magnetic and four gamma-ray survey channels) are only available as grey-scale images. Consequently, the raw data have been converted to the range [0, 255]. Although this represents a potential disadvantage in the case of neural network analysis, because information available in the raw data are reduced, it does not represent a problem for the weights-of-evidence method, and the implementation of the fuzzy-logic method used in this pilot study, since both methods involve steps where the input data are reduced to classes.

4.3 Geology

4.3.1 Regional Geological Setting

The study area is located in the southern portion of the New England Orogen, N.S.W. (Fig. 4.2). The area of the New England Orogen was part of a major Devonian-Permian fore-arc basin-accretionary prism complex that formed during westward subduction of the paleo-Pacific plate beneath a convergent Australian continental margin (Cross *et al.*, 1987; Blake & Murchey, 1988; Cawood & Leitch, 1985). Extensive synorogenic Carboniferous-Permian S-type and postorogenic Permian-Triassic I-type granitoids intrude the complexly deformed siliclastic sedimentary sequences that form the accretionary complexes (Gilligan & Barnes, 1990). A major period of igneous activity occurred in the Permian-Early Triassic producing Middle- to Late Permian intermediate to felsic calc-alkaline volcanic rocks,

represented by the Wandsworth Volcanic Group in the study area, and comagmatic felsic to intermediate granitoids (Barnes & Willis, 1989). The sedimentary and volcanic rocks were intruded by Late-Permian granodiorites and Triassic leucogranites during a Middle Permian to Early Triassic episode of plutonism. They were emplaced late in the orogenic sequence following major thrusting and folding in the New England Orogen (Barnes *et al.*, 1995). Several hundred plutons extend throughout the central New England area, forming the New England Batholith (Shaw & Flood, 1981).

The study area consists of three main lithostratigraphic units: 1) a Silurian to Carboniferous metasedimentary and volcanic basement, 2) the Mid to Late Permian Wandsworth Volcanic Group, comprising intermediate to felsic volcanic rocks and comagmatic felsic intrusions, and 3) Late Permian to Early Triassic leucogranitoids. The main granitoids in the subject area are those of the Clarence River and Moonbi Suites and an undifferentiated group of leucogranitoids.

4.3.2 Mineralization

The New England Orogen contains a wide variety of magmatic, hydrothermal and granite-derived mineralization. The leucogranites of the Moonbi Supersuite are the most important hosts to mineralization in this area. They contain the important Timbarra gold deposits as well as deposits of tin, tungsten, molybdenum and bismuth. Additional commodities include silver, arsenic, copper, lead, fluorite, beryl and topaz (Gilligan & Barnes, 1990; Blevin & Chappell, 1992).

4.3.3 Leucogranitoids

The Permian-Triassic (245–238 Ma) high-K leucogranites of the Tenterfield-Stanthorpe region form a distinct group within the Moonbi Supersuite, and are informally referred to as the Stanthorpe Granite group by Mustard (1999). The granites previously have been referred to as leucoadamellites, and were grouped separately from the Moonbi Plutonic Suite by previous workers (Barnes & Willis, 1989; Barnes, 1993; Barnes *et al.*, 1995). They are highly fractionated I-type granitoids and formed as high level intrusions. The intrusions of the Stanthorpe Granite group contain chilled zones and porphyritic phases and are intruded by pegmatite and numerous gently-dipping and flat-lying aplite dykes. These features suggest that the present weathering surface intersects the upper levels of the granite bodies. Mustard (1999) recognized three main granite types within the

Figure 4.2. Location and simplified geology of the Tenterfield 1:100000 sheet area, adapted from an unpublished regional digital map supplied by the Geological Survey of New South Wales.

Stanthorpe Granite group, termed the Bungulla (referred to by Barnes *et al.*, 1995 as the Bungulla Porphyritic Adamellite), Stanthorpe and Ruby Creek types. These form a compositional and textural continuum, and are interpreted by Mustard (1999) to represent a differentiated magma series.

The mid-Triassic Stanthorpe Granite has intruded the Bungulla Granite and lies directly over the top of the Bungulla Granite in the Timbarra area. The Stanthorpe Granite, in plan view, forms a semi-circular body east of the Demon Fault in the north of the study area (Fig. 4.2).

4.3.4 Intrusion-Hosted Gold Mineralization

The Stanthorpe Granite hosts gold mineralization as low-grade disseminations within poorly-defined irregular lenses near the upper surface of the granite body (e.g. Timbarra-Poverty Point deposits) and as minor sheeted veins. The Timbarra deposits contain a resource of 14 Mt at an average grade of 0.82% (de Graaf, 1999). Gold is located within, or immediately below, the aplitic carapace in the Surface Hill granite, which is a late-stage fractionated phase of the Stanthorpe granite (Mustard, 1999). The granite is described by Simmons *et al.* (1996) as a magnetite-series, metaluminous to peraluminous granite, which comprises two porphyritic to equigranular phases cut by pegmatite, fine-grained granite, and highly fractionated microgranite dykes. Barnes *et al.* (1995) report that, throughout the area in which the Stanthorpe granite type is exposed, gold is also locally structurally controlled along fractures, joints and faults. Previously, gold has been mined from pegmatite sheets. Many alluvial and eluvial gold deposits occur in the Stanthorpe Granite.

A characteristic feature of the disseminated deposits in the Timbarra goldfield is that the gold is very fine-grained (<1 to 100 μm ; Bampton, 1988, Mustard, 1999). Gold is located in miarolytic cavities, disseminations between granitic minerals, and in dissolution cavities within K-feldspar (Simmons *et al.*, 1996).

Numerous alluvial gold occurrences are scattered across the Bungulla Granite, which forms an arcuate body on the eastern margin of the Stanthorpe Adamellite (Barnes *et al.*, 1995). Forty-seven secondary, thirteen primary and three spatially-associated granitoid-hosted gold deposits of unknown form were selected as the basis for the prospectivity analysis in this study.

The use of placer deposits in the training data is reasonable because of the very close

genetic and spatial association of those placer and primary deposits. Gold in the placer deposits in the Stanthorpe Adamellite was derived from the disseminated deposits. Bampton (1988) concluded that the alluvial gold from the Stanthorpe Adamellite had not been transported very far, because the faceted morphology of some grains reflects the shape of crystals around which they had deposited. The fineness of the alluvial and primary gold reported by Barnes *et al.* (1995), the flat and poorly-drained top of the plateau formed by the Stanthorpe Adamellite, and the fact that much of the historical production from the Timbarra-Poverty Point goldfield came from eluvial deposits also supports this conclusion. Thus, locations of these disseminated gold deposits are likely to be favourable indicators for undiscovered primary as well as secondary deposits.

Similarly, the use of both primary mineral occurrences and deposits, which contain predominantly disseminated gold within a Late Permian to Early Triassic leucogranitoid host, in the training data set is reasonable because both groups appear to represent the same population. A number of studies show that the alluvial deposits were derived from the primary deposits. In addition, gold present in alluvial deposits formed very locally, and appears to have formed at a similar time (Barnes *et al.*, 1988; Barnes & Willis, 1989; Barnes *et al.*, 1995). The largest deposit in the area, Timbarra-Poverty Point, is quite small and low grade (de Graaf, 1999), and Barnes *et al.* (1995) report that it appears very similar to a large number of smaller deposits and occurrences throughout the Tenterfield area. Although these studies have shown that variation exists in terms of the form of mineralization (e.g. disseminations, sheeted veins), and accessory mineral assemblages, the disseminated gold deposits have been distinguished from the epigenetic $\text{Au} \pm \text{Sb} \pm \text{Hg}$ mineralization, exemplified by the Lionsville-Solferino deposits to the east of Tenterfield sheet area, and from the Drake-style $\text{Cu} \pm \text{base metal} \pm \text{Ag} \pm \text{Au}$ epithermal mineralization located to the north of the area.

The Timbarra and other similar disseminated gold deposits in the Stanthorpe granite group belong to a recently proposed, globally widespread class of intrusion-related gold deposits, which are associated with W-Sn-bearing magmatic provinces. The Au-Bi-Te-Mo signature, spatial association with a Sn-W province and felsic intrusions with intermediate oxidation states (spanning the boundary between the ilmenite-magnetite series), the sheeted-vein and disseminated mineralization style, close association of gold with bismuth and tectonic setting at a cratonic margin are all characteristic features of this type of deposit (Sillitoe, 1991; Hollister, 1992; Lang *et al.*, 1997; Thompson *et al.*, 1999; Lang *et al.*, 2000).

A group of primary and closely-associated alluvial deposits near the north-west contact of

the Dumbudgery Creek Granodiorite (Clarence River Plutonic Suite) were excluded from the prospectivity analysis because they represent a genetically different group to those described above. The deposits belong to the historic Lionsville-Solferino goldfields. The primary deposits represent a type of $\text{Au} \pm \text{Ag} \pm \text{W} \pm \text{Sb} \pm \text{Hg}$ epigenetic mineralization, which grades from gold to gold-antimony to antimony in a south-easterly direction. Quartz reefs, veins and breccia fills occur in faults and shear zones, which cut all rock types. Barnes *et al.* (1988) refer to these deposits as metahydrothermal, because their relationship to the granites is unclear.

4.3.5 Exploration Criteria

Exploration criteria for intrusion-related gold deposits, proposed by Lang *et al.* (2000), mainly on the basis of their studies of deposits in the Yukon and eastern Alaska, include the following observations.

1. Prospective intrusions correspond to a short time interval within a protracted and commonly episodic period of magmatism.
2. Prospective intrusions are mostly metaluminous to weakly peraluminous, calc-alkalic and subalkalic, with the inferred oxidation state on the boundary between strongly oxidized magnetite-series and strongly reduced ilmenite-series intrusions, although intrusions at Timbarra are considered by Lang *et al.* (2000) to be a more highly oxidized exception due to emplacement into older oxidized calc-alkaline intrusions,
3. A high degree of differentiation is favourable. For intrusions in the Fairbanks area of Alaska, McCoy *et al.* (1997) suggest that most gold is associated with intrusions with a differentiation index above 80. A $\text{Fe}_2\text{O}_3/\text{FeO}$ value below 0.5 is favourable (Mutschler *et al.*, 1985; Leveille *et al.*, 1988).
4. In the Yukon, pre-existing faults and fractured zones adjacent to intrusive contacts are favourable sites for mineralization.
5. Deposits formed at greater than 1.5 kbar do not have a large lateral extent. Lang *et al.* (2000) estimated that Timbarra formed at a depth of about 5 km; that is, at approximately 1.5 kbar.
6. Age of the host rock is unimportant.
7. The geochemical signature recorded by Lang *et al.* (2000) in deeper systems from the Yukon and eastern Alaska consists of $\text{Au-Bi-W} \pm \text{As} \pm \text{Te} \pm \text{Mo}$, whereas Au occurs

together with Mo, Bi, and Sn in the leucogranites of the Tenterfield area (Bampton, 1988).

8. Deeper systems, like Timbarra, display a very good correlation between Au and both Bi and Te.
9. Bismuth geochemical anomalies are located proximal to deposits, whereas As is more widely dispersed and yields large geochemical haloes.
10. The most prospective systems were first recognized from associated placer deposits.

Unfortunately, much of the data required to apply the criteria of Lang *et al.* (2000), such as the geochemistry and geochronology of the granitoids, are lacking for the study area. In detailing the exploration potential of the Tenterfield 1:100000 sheet area, Barnes *et al.* (1995) noted the following aspects of gold mineralization that have implications for exploration.

1. Gold occurs as large low-grade disseminations in poorly-defined irregular lenses in the upper part of the granite bodies, and is widespread throughout the Stanthorpe granite group.
2. Other leucogranites contain very low-grade gold in association with tin, molybdenum, bismuth and tungsten, and therefore have moderate potential for low-grade high-tonnage gold deposits.
3. Gold mineralization occurs in close proximity to cogenetic aplite dykes within the Stanthorpe granite group.
4. The Stanthorpe granite has very low magnetic intensities.
5. The Bungulla granite is associated with high magnetic intensities.
6. Leucogranitoids have high radiometric responses in all channels.
7. Intrusions of the Bungulla granite by the Stanthorpe granite or locations where the Stanthorpe granite underlies the Bungulla granite at shallow depth, identified by the magnetic intensity images, may indicate prospective areas for disseminated gold mineralization.

4.4 Experimental Procedure

4.4.1 Preparation of Neural-Network Maps

Pre-Processing of Input Data

All thematic layers in the GIS database were converted to raster format prior to further processing. The original solid geology layer contained 41 rock units, many of which contain zero or very few deposits. The reliability of probability estimates used in the weights-of-evidence method depends on the existence of a statistically significant number of known deposits. Therefore, units belonging to the same rock suite or stratigraphic group were combined, resulting in a simplified geology layer consisting of 12 rock units (Fig 4.3). The GIS database layer containing regional faults was converted to a grid in which the cell values indicate the distance to the nearest fault.

The thematic layers in the Tenterfield GIS database were combined into a set of input feature vectors. At each cell location in the Tenterfield 1:100000 sheet grid, values from each thematic layer were combined to form a vector as shown in Chapter 3 (Fig. 3.2). These vectors, known as input feature vectors, formed the input to the neural network.

Linear scaling, based on the maximum and minimum values contained in each thematic layer, was applied to all input feature vectors. The logistic activation function, which is used in the hidden and output layer units of a neural network, has a squashed S-shape shown in Figure 2.7. The output values of this function approach limits of 1 and 0 asymptotically. Although the actual output produced by the network can theoretically reach these limits, in practice, the values that can be achieved by the network are limited to the range $[0.1, 0.9]$. Consequently, training is facilitated if the target values are scaled to this range (Masters, 1993b). The input values were also scaled to this range. Masters (1993b) demonstrated that this improves the stability of the network and reduces the time required for training, since the network does not need to adjust weights to extreme values to compensate for the diverse range of the input data.

Apart from the preparation of the map layers, all processing was performed outside the GIS using a series of utility programs written in C++ and the neural network simulation program, bp (McClelland & Rumelhart, 1988). Data processing in the neural network method consisted of three main stages: 1) pre-processing of data to a format suitable as inputs to the neural network, 2) training and processing the entire data set after training, and 3) post-processing to convert the output values to a map. The data processing pro-

cedures are shown schematically in Figures 3.3, 3.7, and 3.8. C++ programs used in the neural network method in this chapter are listed and briefly explained in Appendix E and the code is included on the CD-ROM (vol. 1) that accompanies the thesis.

Figure 4.3. Simplified solid geology of the Tenterfield 1:100000 map sheet area. The three main rock units in the area are a Silurian-Carboniferous accretionary complex (yellow), the Early-Permian Wandsworth Volcanic group (light green), and a series of Late-Permian to Early-Triassic granitoids (red colours). The two leucogranitoids in the north-east of the area (inner semi-circle: Stanthorpe Adamellite, and Bungulla Porphyritic Adamellite: outer semi-circle) are the main hosts to mineralization.

Input Layers

The 18 input units shown in Figure 4.4 correspond to; Quaternary alluvium, Tertiary volcanic rocks, Clarence-Moreton Basin sedimentary rocks, undifferentiated leucogranitoids (Stanthorpe Granite), granitoids of the Moonbi, Uralla, and Clarence River Plutonic Suites, undifferentiated Permian granitoids, undifferentiated Permian porphyritic granitoids, rocks of the Wandsworth Volcanic Group, Permian sedimentary rocks, Silurian-Carboniferous sedimentary rocks, uranium, thorium, potassium and total count channels of airborne gamma-ray survey data, airborne magnetic data (total magnetic intensity, reduced to pole) and distance to the nearest fault.

Input Coding

The solid geology GIS layer represents the only categorical data type used as an input to the neural network in this study. A 1-of-n coding scheme was applied to the solid geology

Figure 4.4. Architecture of the MLP neural network used in the pilot study. The network has an 18-2-1 topology (where the numbers refer to input, hidden, and output units, respectively). Each map layer in the GIS database was assigned an input unit except the geology layer, for which a 1-of-n coding scheme was used.

layer, so that each of the 12 rock types in the simplified geology layer was assigned a separate input layer unit in the neural network. For example, if the current rock type is basalt, then the input unit for basalt is set to one and all other input units allocated to rock types are set to zero. A single input unit was assigned to each of the magnetic, four radiometric and fault-proximity layers. Binary coding was used for the single output unit, with one and zero representing the presence and absence of deposits, respectively.

Training Data

Training data were randomly divided into training, training-stop¹ and test sets². As noted in Chapter 3, the training data set is used to adapt the weights in the network and the training-stop data set is used to determine when to stop training (see description of neural network training in Section 4.4.1). The test data set plays no role in training and is

¹The name *training-stop* data set is sometimes referred to as the *stop* set in tables in subsequent chapters

²There is some confusion in the literature concerning the nomenclature of these data sets. Some authors refer to the data set used to determine when to stop training as the test set whereas others refer to this as the validation set. If only two data sets are used, the data sets are sometimes referred to as the training and validation sets. However, the second set in this case is not independent because training is stopped at the point at which the error for the data set is at a minimum value. Consequently, the nomenclature used here is call the data set used to determine when to stop training as the training-stop data set and the data set used to assess the generalization performance of the network after training as the test set.

used assess the generalization performance of the trained network when new data are processed. Only the independent test data can provide a guide to the performance of the trained network on new data, since the network is biased to perform well on the training and training-stop data sets (Masters, 1993b).

Although the ratio of deposit to non-deposit cells in the Tenterfield grid is approximately 1:1000, the ratio of deposit to non-deposit vectors used in the training set is close to 1:1. This is necessary because the learning algorithm minimizes the TSS error over all the patterns in the training set. If deposit patterns were represented in the training set in the same proportion as they appear in the total data population, the learning algorithm would optimize the performance for non-deposit patterns (Masters, 1993b). The network would not learn to recognize the rare deposit patterns at all or would perform very poorly for this class of patterns. Learning in MLP networks is improved by selecting equal numbers of training vectors from each class irrespective of the *a priori* probability of occurrence of the classes (Zaknich, 1999). Consequently, the training, training-stop and test data sets were randomly assigned one third of the available deposit vectors (21 each), and two non-deposit vectors were randomly selected for each of the 12 main rock units, giving a total of 24 non-deposit vectors in each training set. Table 4.1 shows the composition of the training sets.

Table 4.1. Number of patterns in the training data sets

Class	Training set	Stop set	Test set
Deposit	21	21	21
Barren	24	24	24
Total	45	45	45

Since there are only 63 gold deposits of the required type in the Tenterfield area, compared with 69,377 non-deposit cells. Since the size of the training data sets are limited by the number of known deposits, the available training data is too small for a third of the data to be reserved as a test data set in the statistically-based weights-of-evidence method. The weights-of-evidence method includes a test for correlations between evidence maps. Using only deposit cells, the chi-squared statistic is calculated for all possible pairs of input layers. However, at least five deposits are required in each of the four possible overlap combinations involving the pair of binary maps (e.g. pattern 1 present, pattern 2 absent). Otherwise the chi-squared test is very unreliable. To avoid this problem, all of the available data was used to estimate the value of the the weights in the weights-of-evidence method.

The training patterns were presented to the network in a randomly permuted order.

Network Topology and Parameters

The number of units in the hidden layer of the network was determined experimentally. A heuristic for estimating the number of hidden units that works for many practical problems has been suggested by Masters (1993b). The number of units should decrease from the input to the output layer with the number of hidden layer units roughly given by:

$$h = \sqrt{mn} \quad (4.1)$$

where h = number of hidden units, m = number of input units, and n = number of output units.

Applying this rule of thumb to the network here, which has 18 input units and a single output, suggests that four hidden units should be used. If too many hidden layer units used in combination with a small training set, this can result in a network that is too complex, leading to over-fitting of the data (Bishop, 1995). In order to minimize the effective complexity of the network, as few hidden units as possible were used. Consequently, the procedure used here was to experiment with one to five hidden units using identical training sets and network parameters. The smallest number of hidden units giving the best generalization performance on the test data set was used. This procedure resulted in a 18-2-1 network topology.

A constant learning rate of 0.5 was used for all networks. Weights were randomly initialized in the range $[-0.5, +0.5]$. The values of the momentum parameter (used to add a fraction of the previous weight change to the current weight change) and the weight-update frequency (i.e. whether the weights are updated after the presentation of each training pattern or after all the patterns in the training set are processed) are indicated in Table 4.4.

Neural Network Training

A series of networks were trained using ten different random sets of initial weights. The purpose of using different random initial weights is to prevent the network converging at a local rather than a global minimum TSS error in multidimensional weight space (Fig. 2.9). Whether this has occurred can only be determined if training with some other set of random initial weights results in a significantly lower TSS error for both the

training and test sets. Thus, the weights in the network after training is completed depend on the starting point in multidimensional weight space, which is determined by the set of initial weights. Each of these random initializations effectively results in a different trained network. In each case the initial weights were saved. In some cases, training was repeated for a given set of initial weights using different network parameters (Table 4.4). Training runs with identical random initial weights are labelled with the same run number in Table 4.4.

Although the training error decreases during training, the test error initially decreases to a minimum and then begins to increase as training continues. This occurs because the network starts to learn the idiosyncrasies of the training set. To avoid this, the procedure known as early stopping was used (Bishop, 1995). The total sum of squares (TSS) error was monitored for both the training and test data sets and training is stopped at the number of epochs corresponding to the minimum TSS error for the test data set. To achieve this, the test data set is processed and the TSS error is recorded at intervals of 10 or 100 training cycles (depending on the rate at which the error is decreasing). Weights are not modified during the test data set cycle. This continued until a clear increase in the TSS error for the test data set occurs. Once the number of cycles corresponding to the minimum test set error is known, the values of the weights are reset to their random initial values and the network is re-trained for the optimal number of cycles using the training data set only. The neural network giving the best classification performance for the independent test data set was used to process the input vectors for the entire Tenterfield grid (network 10a in Table 4.4).

Post-Processing

Output values, produced by the trained network used to process the complete Tenterfield data set, were re-scaled to the range $[0, 8]$ and then classified into integer values to produce a nine-class prospectivity map. The percentages of correctly classified deposits and non-deposit cells were determined by applying a threshold of 0.5 to the activation of the single output unit. Cells corresponding to values greater or equal to 0.5 were classified as deposits, otherwise the cells were classified as barren.

A C++ program, *map-class* was used to convert the output file produced by the neural network simulation package, *bp*, consisting of a list of floating point values in the range $[0.1, 1.0]$, to an integer grid with values representing nine prospectivity classes (code included on CD-ROM (vol.1)). Inputs were scaled to a range $[0, 1]$.

4.4.2 Preparation of Weights-of-Evidence Maps

The input maps depicting solid geology, buffered regional faults and shear zones (25 buffer zones at 200 m intervals), airborne total magnetic intensity, U, Th, K and total count gamma-ray survey data channels were reclassified using threshold classes which maximize the spatial association between the evidence pattern and deposit point pattern (known deposits). Thresholds were selected from the tables of weights and contrasts produced by the GEODIPS system.

Pairwise tests of all possible binary evidence maps from the weights-of-evidence method showed that the assumption of conditional independence is violated for nearly all map pairs. Only the proximity-to-faults map did not exceed the χ^2 limit of 5.4 at the 95% confidence level for 1 degree of freedom. This means the other binary map pairs are not conditionally independent, which would lead to the predicted number of deposits being significantly greater than the observed number of deposits (Bonham-Carter, 1994; Singer & Kouda, 1999a). The following steps were taken in order to reduce the conditional dependence;

1. The solid geology map was re-classified to produce a new binary evidence map. The map algebra operations used to produce the initial and modified binary solid geology maps are as follows:

```

Geol_1 = recode_class(If Classold = Leucogranitoid, Moonbi Suite Granitoids
                        THEN Classnew = 1,
                        ELSE Classnew = 0)

```

```
Geol_2 = recode_class(IF Classold = Leucogranitoid, Moonbi Suite Granitoids,  
Permian Granitoids, Clarence River Suite  
THEN Classnew = 1,  
ELSE Classnew = 0)
```

2. All airborne gamma-ray survey maps except the one for the uranium channel were discarded. The U-channel map was retained because it was associated with the highest value of W^+ . This did not solve the problem as the U-channel binary radiometric map is conditionally dependent on the geology and magnetic maps. Since leucogranitoids associated with gold deposits are highly fractionated (Blevin & Chappell, 1996a,b) and have high radiometric responses (Barnes, 1993), a number of combinations of the uranium- and thorium-channel radiometric and magnetic maps were tested. The $U \times Th$ map showed a combination of a strongest association with known deposit and occurrence points and a lower degree of variability between adjacent cells in the raster grid.
3. The airborne total magnetic intensity map was discarded because the statistical relationship between magnetic intensity and deposit points is unclear. The magnetic intensity data were not used in the final weights-of-evidence map that is compared with the fuzzy-logic and neural network methods in the conclusions section below.

The steps above resulted in the seven original input maps being reduced to the following three maps; *bin_flt*, *bin_geol2*, *bin_uxth* and *magnetic*. Since these new derived geology and radiometric map pairs were also conditionally dependent, different ways of combining the maps using the Boolean *AND* and *OR* operators were tested. The operations that were used to combine the maps are shown in terms of map algebra in Table 4.2 below.

In each case, the weight calculated for the binary output map in Table 4.2 was combined with the weight for the binary proximity-to-fault map, *bin_flt* to create a prospectivity map. The resulting maps are shown in Figures 4.5 and 4.6. The prospectivity map that best accounted for the known deposit locations, while minimizing the area of the highest prospectivity classes, was chosen as the final map to be compared with the fuzzy-logic and neural network methods in the results section below (Fig. 4.5b; *add2*).

Table 4.2. Map algebra operations used to combine conditionally dependent input maps in weights-of-evidence method. All maps in Figures 4.5, 4.6 and 4.11 were produced using the layer depicting the distance to the nearest major fault or shear zone as an additional input.

Map	Map algebra operation
add1	$\text{geology} + (U \times Th) + \text{magnetic}$
add2	$\text{geology} + (U \times Th) + \text{magnetic}^a$
max1	$\min[\text{geology}, (U \times Th)]$
max2	$\min[\text{geology}, (U \times Th)^b]$
max3	$\min[\text{geology}, (U \times Th), \text{magnetic}]$
min1	$\min[\text{geology}, (U \times Th)]$
min2	$\min[\text{geology}, (U \times Th)^b]$
min3	$\min[\text{geology}, (U \times Th)/\text{magnetic}]$
min4	$\min[\text{geology}, (U \times Th)^b/\text{magnetic}]$
min5	$\min[\text{geology}, (U \times Th), \text{magnetic}]$
min6	$\min[\text{geology}, (U \times Th \times K)/\text{magnetic}]$
min7	$\min(\text{geology}, (U + Th))$

^aIn *add1* the geology binary input map consists of leucogranites only whereas in *add2* it consists of additional lithological units; i.e. Permian Undifferentiated Granitoids, Moonbi Granite and Clarence River Granite.

^bThe $U \times Th$ evidence map was recoded using a different set of class thresholds to produce a new binary map.

(a) add1

(b) add2

(c) max1

(d) max2

(e) max3

(f) min1

Figure 4.5. Weights-of-evidence mineral prospectivity maps for intrusion-related disseminated gold mineralization, Tenterfield 1:100000 map sheet area, north-eastern NSW. Refer to Table 4.2 on page 115 for an explanation of the map names.

Figure 4.6. Weights-of-evidence mineral prospectivity maps for intrusion-related disseminated gold mineralization, Tenterfield 1:100000 map sheet area, north-eastern NSW. Refer to Table 4.2 on page 115 for an explanation of the map names.

4.4.3 Preparation of Fuzzy-Systems Maps

The GEODIPS GIS prospectivity analysis package, developed by Jusmady & Taylor (1997), was also used to prepare maps based on the fuzzy-logic method. Fuzzy membership values, in the range $[0, 1]$, were assigned on the basis of subjective judgement according to how favourable the parameter values are for mineralization. Parameter value classes and the corresponding membership values are shown in Table 4.3 below. These are the final values chosen after experimentation. Some of the membership values were varied so that the two highest prospectivity map classes included as many of the known mineral deposits in as small an area as possible. A new layer containing fuzzy membership values was created for each input map using the values in Table 4.3.

A variety of different fuzzy membership value assignments, inference nets, and choices of fuzzy operators for the final map combination step were tested. In the case of the gamma operator, a range of values of gamma (in the range $[0, 1]$) was tested. The results of the tests showing the mineral prospectivity maps together with the inference net, are shown in Figures 4.7-4.10. The relationship between the deposit points and the magnetic intensity map was ambiguous, and therefore the magnetic map was not used as an input map in the fuzzy-logic and weights-of-evidence methods.

The areas of the fuzzy systems maps, which represent the highest favourability, are very sensitive to small changes in gamma in the range $0.90 \leq \gamma \leq 1.0$. Large gamma values result in larger areas being assigned a high prospectivity due to the effect of the fuzzy algebraic sum component in the gamma function (see equation 2.15 and the left-hand factor in equation 2.16). For example, in Figure 4.10b ($\gamma = 0.95$), the highest prospectivity class (favourability index ≥ 0.90) connects the two main groups of deposit points in the northern part of the map in a north-south direction, whereas in Figure 4.9b ($\gamma = 0.90$), the two groups of deposits are separated by a lower prospectivity area. The second map represents a more conservative estimate of prospectivity, in which the gap between deposit points (shown in yellow-green) is assigned the next lower prospectivity class (favourability ≥ 0.80).

Modifying the fuzzy membership values and the inference net also has a significant effect on the resulting prospectivity map. The effect of slight differences in the fuzzy membership functions and inference nets (for a given gamma value) can be illustrated by comparing Figures 4.7a, 4.7b and 4.10b ($\gamma = 0.95$ for the three maps). The effect of using a different

The effect of using different values in the fuzzy membership functions is evident in Figures 4.7b and 4.10b. For Figure 4.7b (and Fig. 4.7a), fuzzy membership values for the fault buffer classes where *distance to the nearest fault* ≤ 2000 m are set to 0.1, whereas a value of 0.5 is used in Figure 4.10b. The same fuzzy inference net is used in both cases.

The prospectivity map that best accounted for the known deposit locations, while minimizing the area of the highest prospectivity classes, was chosen as the final fuzzy-logic model. (Fig. 4.7c). This fuzzy-logic map is compared with the weights-of-evidence and neural-network maps in the results section in Figure 4.11b. It was produced by using the gamma fuzzy-membership operator ($\gamma = 0.95$) in the final integration step. The fuzzy inference net corresponding to this map is shown in Figure 4.11b. The map algebra addition-operator was used to combine the gamma-ray U- and Th-channel maps.

[illegible]

(a) $\gamma = 0.95$, 4 inputs. Fuzzy membership values in Table 4.3 except *distance-to-faults* layer (class $>2000\text{ m} = 0.70$, rest = 0.05 instead of 0.75 and 0.01, respectively).

(b) $\gamma = 0.95$, 4 inputs. Fuzzy membership values in Table 4.3 except *UplusTh* layer (classes 1-6 = 0.1 instead of 0.1, 0.1, 0.3, 0.3, & 0.3 and classes 7-11 = 0.2 instead of 0.3, 0.6, 0.6, 0.6, & 0.9).

(c) $\gamma = 0.95$, 3 inputs. Fuzzy membership values in Table 4.3 except *dist.-to-faults* layer (class $>2000\text{ m} = 0.90$, instead of 0.75) and *geology* layer (Leuco- & Moonbi Granites = 0.90 instead of 0.75).

Figure 4.7. Fuzzy mineral prospectivity maps for the Tenterfield 1:100000 map sheet area.

(a) $\gamma = 0.0$, 4 inputs. Fuzzy membership values are those given in Table 4.3 except for the *distance-to-faults* layer (class <2000 m = 0.50 instead of 0.1).

(b) $\gamma = 0.90$, 4 inputs. Fuzzy membership values are those given in Table 4.3 except for the *distance-to-faults* layer (class <2000 m = 0.50 instead of 0.1).

(c) $\gamma = 0.91$, 4 inputs. Fuzzy membership values are those given in Table 4.3 except for the *distance-to-faults* layer (class <2000 m = 0.50 instead of 0.1).

Figure 4.9. Fuzzy mineral prospectivity maps for the Tenterfield 1:100000 map sheet area.

(a) $\gamma = 0.95$, 3 inputs. Fuzzy membership values are those given in Table 4.3 except for the *distance-to-faults* layer (class >2000 m = 0.70, rest = 0.05 instead of 0.75, rest = 0.1, respectively).

(b) $\gamma = 0.96$, 3 inputs. Fuzzy membership values are those given in Table 4.3 except for the *distance-to-faults* layer (class >2000 m = 0.70, rest = 0.05 instead of 0.75 and 0.01, respectively).

(c) $\gamma = 0.975$, 3 inputs. Fuzzy membership values are those given in Table 4.3 except for the *distance-to-faults* layer (class >2000 m = 0.70, rest = 0.05 instead of 0.75 and 0.01, respectively).

Figure 4.8. Fuzzy mineral prospectivity maps for the Tenterfield 1:100000 map sheet area.

(a) $\gamma = 0.925$, 4 inputs. Fuzzy membership values are those given in Table 4.3 except for the *distance-to-faults* layer (class <2000 m = 0.50 instead of 0.1).

(b) $\gamma = 0.95$, 4 inputs. Fuzzy membership values are those given in Table 4.3 except for the *distance-to-faults* layer (class <2000 m = 0.50 instead of 0.1).

(c) $\gamma = 1.0$, 4 inputs. Fuzzy membership values are those given in Table 4.3 except for the *distance-to-faults* layer (class <2000 m = 0.50 instead of 0.1).

Figure 4.10. Fuzzy mineral prospectivity maps for the Tenterfield 1:100000 map sheet area.

4.4.4 Comparing Mineral Prospectivity Map Quality

Several statistical and probability measures were used to compare the quality of maps produced using the different methods. These are explained in Chapter 3.

The chi-squared statistic measures the extent to which observed and expected numbers of deposits differ. It is used here as a measure of the quality of a prospectivity map. Due to autocorrelation in spatial data and the fact that clustering of deposit cells means that deposits do not represent independent samples Bonham-Carter (1994) has recommended that the chi-squared statistic be used without reference to confidence limits.

For each class within a prospectivity map, the chi-squared statistic measures the degree to which the numbers of deposits differs from the number that would be expected if the distribution of the deposits through the different prospectivity map class areas were random. Due to the limitations of the chi-squared statistic explained in Section 3.3.1. Spearman's and Kendall's rank correlation coefficients are also used as measures of map quality. These statistics are very similar and are used to determine whether the probability of the occurrence of known deposits increases monotonically with increasing prospectivity map class. For both these statistics, a value of zero indicates that no correlation exists and a value of one indicates a perfect correlation (Stoodley *et al.*, 1980; Harnett, 1982; Rock, 1988).

Conditional probabilities of the occurrence of a known mineral deposit, given the grid cell is located within a particular prospectivity class and the ratio of the conditional probability, $P(D/C_k)/P(D)$, of a deposit (given a prospectivity class k), to the probability of a deposit for the map area as a whole, were calculated. The probability ratio increases as the proportion of known deposits increases in comparison to the proportion of the total area occupied by the prospectivity class decreases. Consequently, the ratio should increase from a value smaller than one to a number greater than one with increasing map prospectivity class.

The fuzzy-logic and neural-network maps were reclassified from nine to four classes of favourability prior to calculating the probability-based statistics to allow a more direct comparison with the weights-of-evidence map, which, due to problems of conditional independence, contains only four prospectivity classes.

4.5 Results

Mineral prospectivity maps produced using the weights-of-evidence, fuzzy-logic and neural network methods are shown together with known gold occurrence and deposit points

in Figure 4.11. Both the neural network and fuzzy-logic favourability results are classified into nine prospectivity classes. The weights-of-evidence map (Fig. 4.11a) displays only three colours corresponding to three discrete probability levels because input maps were combined to avoid problems of conditional dependence. Converting the values into classes gave a four-class prospectivity map. However, one of the classes (class 3 in Fig. 4.11 a and Table 4.6) does not correspond to any cells on the map.

Table 4.4 shows the percentages of correct classifications for training, training-stop and test sets for training runs using different random initial weights. Values over the threshold of 0.5 are classified as deposit vectors and those below 0.5 as non-deposit vectors. An estimate of how well the network performs at generalization is provided by the error rate for the classification of deposit and non-deposit vectors from the test data set. The trend of successively lower success rates for training, training-stop and test data sets shown in Table 4.4 is typical for back-propagation-trained MLP networks, and reflects the degree to which each of the data sets was used in training the network.

Values of the statistics used to quantify map quality are shown in Tables 4.5 and 4.6. The chi-squared statistic and Spearman's and Kendall's rank correlation coefficients are shown for each of the three prospectivity-mapping methods. Table 4.6 shows probability-based measures of map quality in which favourability values for the fuzzy-logic and neural network methods are reclassified from nine to four classes. Although no cells in the weights-of-evidence map correspond to class 3, in order to calculate the statistics shown in Tables 4.5 and 4.6, it was assumed that just one cell value corresponds to this class. The upper part of Table 4.6 shows the conditional probability that a cell contains a known deposit, given that the area of interest is restricted to a particular prospectivity class. The lower part of Table 4.6 shows the ratio of conditional probability for a given map class area to the prior probability for the study area as a whole.

Table 4.4. Classification accuracy for deposit and non-deposit vectors in training, training-stop and test data sets.^a A series of networks were trained using ten different sets of random initial weights. Training was repeated, in some cases, using the same set of initial weights, but different network parameters. The weight sets are labelled numerically and repeated training runs are labelled alphabetically.

Training run	Weight update	Momentum	Training cycles	Classification results (% correct)		
				Training	Training-stop	Test
1a	batch	0.0	206	83	76	71
1b	sequential	0.0	1536	93	83	74
1c	sequential	0.5→0.0 ^c	700	95	81	74
2	sequential	0.0	700	93	81	74
3	sequential	0.7→0.0 ^c	4278	95	79	76
4	sequential	0.0	65	79	74	74
5a	sequential	0.0	300	90	81	76
5b	sequential	0.5	195	90	81	74
5c	batch	0.3	104	83	79	74
6	batch	0.3	250	90	79	76
7a	batch	0.3	28	79	74	71
7b	sequential	0.3	39	79	74	71
8a	batch	0.3	1186	95	83	74
8b	batch	0.3→0.0 ^c	1704	95	79	74
8c	sequential	0.3	2050	95	79	74
9a ^d	sequential	0.3	817	93	79	71
9b	sequential	0.0	400	90	79	74
10a ^e	sequential	0.0	33	84	79	84
10b ^f	sequential	0.0	200	79	77	79

^aA threshold of 0.5 was applied to the network output values in order to make a classification. Inputs corresponding to an output below 0.5 were classified as non-deposits; otherwise the vector was classified as a deposit.

^bbatch = weights update after each training set cycle, sequential = after each pattern

^cMomentum was reduced during training within the range shown.

^dStopped training before minimum TSS error for test data set was reached.

^eThis network was used to process vectors from the entire Tenterfield map grid.

^fEight deposit and eight non-deposit training patterns taken from the test data set and added to the training data set.

Figure 4.11. Prospectivity maps for the Tenterfield 1:100000 area. a) Weights-of-evidence method, b) Fuzzy-logic method. c) Neural network method. Crosses, dots, and open squares represent known primary, alluvial and undifferentiated gold deposits and occurrences, respectively. The weights-of-evidence map contains only three colours corresponding to three probability classes (see Figure 4.5b). This is due to combining inputs maps to eliminate problems of conditional dependence which resulted in only two input maps.

Table 4.5. Statistical measures of map quality. Chi-squared statistic, and Spearman's and Kendall's rank correlation coefficients, for prospectivity maps produced using different methods

Statistic	Wts of Evidence	Fuzzy Logic	Neural Network
Chi-squared	66	63	83
Spearman's ρ	0.80	0.50	0.93
Kendall's τ	0.67	0.53	0.83

4.6 Discussion

4.6.1 Validation of the Neural Network Results

The close similarity of the neural-network map to the fuzzy-logic map, and the broad similarity to the weights-of-evidence map, indicates that the neural network method produces geologically meaningful results. The similarity of the neural network and conceptually-based fuzzy-logic maps indicates that the neural network result conforms to current understanding of geological factors important for gold mineralization in the Tenterfield area. The broad similarity between the neural network and empirically-derived weights-of-evidence maps indicates that the neural network result accounts for observed spatial relationships between known gold deposits and the parameters of the GIS database.

4.6.2 Interpretation of Output Values

The output of the neural network is suitable for producing multiclass prospectivity maps. Although the network was trained as a classifier using binary target values (0 = deposit absent and 1 = deposit present), it is possible to produce a multiclass map because the trained network produces output values in the range [0.1, 0.9]. Rescaled to the range [0, 1], the network output approximates the posterior conditional probability $p(C_{deposit}|\mathbf{x})$ that the input vector $\mathbf{x}$ belongs to the class of deposits $C_{deposit}$ given that the input vector is $\mathbf{x}$ (White, 1989; Richard & Lippmann, 1991; Bishop, 1995). The output of the trained network can also be interpreted as a measure of how similar the input vector is to a composite of all deposit vectors presented to the network during training. The degree of similarity can also serve as a measure of how favourable the area is for mineral deposits of the type included in the training data set. This interpretation of the network output fits with the intuitive notion that a prospective area has characteristics that closely resemble

Table 4.6. Probability measures of map quality for prospectivity maps produced using different methods

Map Class	Wts of Evidence	Fuzzy Logic ^a	Neural Network ^a
$P(D/C_k) \times 10^4$			
4	2.53	2.85	2.60
3	0.00	1.65	2.15
2	8.67	6.89	11.66
1	23.45	18.91	26.74
$P(D/C_k)/P(D)$			
4	0.28	0.31	0.29
3	0.00	0.18	0.24
2	0.96	0.76	1.29
1	2.58	2.08	2.95

^aThe fuzzy-logic and neural-network maps were reclassified from nine to four classes to enable a direct comparison with the weights-of-evidence map.

areas known to contain mineral deposits. Since the training data comprise both deposits and mineral occurrences, what is being estimated here is favourability for mineralization rather than for deposits. In order to analyse these two groups separately, a GIS database with larger numbers of both deposits and occurrences would be required.

4.6.3 Response to Critical Combinations of Favourable Parameters

The main difference between the prospectivity maps is that the neural network contains much-smaller high-prospectivity areas (classes 1 and 2 in Fig. 4.11c) compared to the other two maps (Fig. 4.11a & b). This is interpreted to be due to the ability of the neural network to respond in a highly non-linear way to combinations of input parameters, so that a high favourability value is only assigned to areas where a combination of the critical favourable parameters is present. This contrasts with the weights-of-evidence and fuzzy-logic methods, where, for a given grid location, each favourable input-parameter value automatically results in an increase in the prospectivity estimate. For example, if three parameters are favourable for mineralization and one parameter is essential for mineralization, then, for an area where only the three favourable parameters are present, the overall favourability estimated by the weights-of-evidence and fuzzy-logic methods is

(a) Airborne gamma-ray survey, Th-channel.

(b) Fuzzy-logic mineral prospectivity map.

(c) Neural network mineral prospectivity map for the Tenterfield 1:100000 map sheet area.

Figure 4.12. Contrasting response of the fuzzy-logic and neural network methods to input maps containing highly correlated or redundant data. Gold deposit types: crosses = primary, dots = alluvial and squares = un-differentiated. The high prospectivity band in the north-eastern part of the fuzzy-logic map (b) is due to the U- and Th-channel airborne gamma-ray input maps, which contain high counts in the area labelled A. The fuzzy-logic method is sensitive to inputs containing similar or redundant information. The high prospectivity band is absent in the neural-network map because the neural network method is quite robust with respect to redundant inputs.

high. The estimated favourability would be high despite the absence of the one essential parameter. The fuzzy-logic method is quite sensitive to data layers that are strongly correlated; that is, contain similar information and produce spuriously-high favourability estimates. Such data are, however, common in data sets used for geological exploration, particularly those involving geochemistry.

4.6.4 Response to Redundant Input Parameters

The broad high prospectivity band in the north-eastern part of the fuzzy-logic map appears to be an example of the additive character of the fuzzy-logic method for combining evidence maps (red and orange area in Fig. 4.12b). The high favourability estimate is the result of high radiometric responses in all channels of the gamma-ray survey data (Fig. 4.12a).

This area is not highlighted in the neural-network map (Fig. 4.12c), where both a favourable leucogranite host and a high radiometric response are required to produce a high favourability estimate. The high prospectivity band doesn't appear in the weights-of-evidence map (Fig. 4.11a) because gamma-ray survey map layers, which contain very similar information, violate the assumption of conditional independence and were therefore converted to a single input layer. The uranium and thorium channels were combined and the potassium and total count channels were discarded.

A neural-network approach overcomes problems related to the assumption of conditional independence in the weights-of-evidence method. To deal with conditional dependence, dependent data sets must either be rejected or combined in some way. However, Boolean and multiple regression methods of combining data sets reduce multiple parameters to a single parameter and therefore result in a loss of information. However, Masters (1993b) warns that, although the first few principal components may explain the majority of the variation in the data, the information that is important for the classification may reside in the last principal component.

4.6.5 Loss of Information through Re-Classification of Input Data

The neural network method allows data sets to be combined without the loss of information inherent in the weights-of-evidence and some implementations of the fuzzy-logic method. Although the weights-of-evidence method can be used with multiclass maps (Bonham-Carter *et al.*, 1988, 1998a,b; Bonham-Carter & Agterberg, 1999), in many studies multiclass evidence maps are converted to a binary format prior to integration (e.g. Watson:1990;Raines:1999;Venkataraman:2000;Harris:2001;Scott:2001). Values below the threshold used to reclassify multiclass maps to binary maps play no role in determining prospectivity, and values above the threshold (included in the binary evidence map) are treated as though they are equal because they are assigned the same weight. Thus, information available in the raw data, which might otherwise have contributed to the prospectivity estimate, may be lost prior to integration.

The fuzzy-logic method overcomes the problem of applying a fixed cut-off value by assigning fuzzy membership values to raw data on a continuous scale from zero to one. However, loss of information also occurs with the fuzzy-logic method if single fuzzy-membership values are applied to a whole class or range of values, as in the case of studies by An *et al.* (1991), Eddy *et al.* (1995), Donaldson (1996), D'Ercole (1998) and in this pilot study. In contrast to the weights-of-evidence, and most implementations of the fuzzy-logic method, the neural network method does not require ratio data to be classed prior to combining data sets.

4.6.6 Response to Irrelevant or Misleading Input Parameters

Inconsistent or misleading data are unlikely to represent as serious a problem for neural networks as for statistical methods, such as the weights-of-evidence methods and combinations of statistical and fuzzy-logic methods. The GIS thematic layer containing regional faults and lineaments is an example of a possibly spurious data set (Fig 4.13a). An examination of the digital elevation model (DEM) for the Tenterfield area reveals many major lineaments not present in the structural layer. Thus, the structural map represents incomplete information. The weak inverse relationship between deposit points and faults that emerged from the statistical analysis performed in the weights-of-evidence method is likely to be misleading. Subjective judgement was used in estimating the cut-off value used to convert the multiclass map showing distances to the nearest fault, to a binary evidence map.

The effect of this input on the estimated prospectivity is clearly illustrated in the weights-of-evidence prospectivity map in the form of elongate zones of moderate prospectivity throughout the map (Fig 4.13b). In contrast, the neural network prospectivity map does not show any evidence that major faults have played an important role in determining prospectivity (Fig 4.13c). A property of neural networks is the ability to respond to spurious input data by adjusting the weights connected to the relevant input to very low values, and thereby reducing or eliminating the contribution made by those data to the output.

(a) Regional-scale faults and shear zones.

(b) Weights-of-evidence mineral prospectivity map.

(c) Neural network mineral prospectivity map for the Tenterfield 1:100000 map sheet area.

Figure 4.13. Contrasting response of the WofE and neural network methods to input maps containing spurious or irrelevant data. Gold deposit types: crosses = primary, dots = alluvial and squares = undifferentiated. The weak inverse relationship between faults and deposit points apparent in a) is misleading because the structural map does not include many of the faults that are apparent on a recent high resolution DEM produced by the NSW Geological Survey. Note that the WofE map reflects the effect of the structural input map in the form of orange bands where the prospectivity has been significantly downgraded due to proximity to faults. In contrast, the neural-network map does not show any evidence that proximity to faults has played an significant role in determining mineral prospectivity.

4.6.7 Comparison of Map Quality

The statistical measures of prospectivity map quality (Table 4.5) are all highest for the neural-network map. The chi-squared statistic indicates greater differences between number of deposits observed in the class areas of the neural-network map than those that would be expected if the class areas were located at random, compared with maps produced by the fuzzy-logic and weights-of-evidence methods. The larger values of both Spearman's and Kendall's rank correlation coefficients show that there is a stronger correlation be-

tween map class and probability of a cell containing a known deposit than for the other two methods.

The probability and probability ratio measures of map quality (Table 4.6) indicate that the highest prospectivity map classes in the neural-network map are stronger predictors of deposits than the highest prospectivity map classes in the fuzzy-logic map, and slightly stronger than those in the weights-of-evidence map. As noted above, in an ideal prospectivity map, the ratio $P(D/C_k)/P(D)$ should be greater than one in the high prospectivity class, approximately equal to one for the middle prospectivity class, and considerably less than one for the low prospectivity class (where C_k represents map class k ; Brown *et al.*, 2000b,a). Mihalasky & Bonham-Carter (2001) interpret a normalized density measure, ρ for lithodiversity classes in a similar way. However, since the ranges for negative and positive spatial associations have unequal ranges ($[0,1]$ and $[1,+\infty]$, respectively) they use the natural logarithm of ρ so that negative and positive spatial associations are symmetrical about the null value of $\ln \rho = 0$.

The prospectivity map produced using the neural network method is based on approximately two thirds of the data that are used in the weights-of-evidence method. Approximately one third of the available data were reserved as a test data set in the neural network method, and used to check the generalization performance of the network after it had been trained. Only one third of the available data, the training data set, were used directly in training the network and a further third, the test data set, were used indirectly. The test data set played no role in training. In contrast, all of the available deposit points were used in the weights-of-evidence method, as there were an insufficient number of deposit and occurrence points available to allow a third of the data to be reserved as a test data set.

One important issue that has not been addressed here is the uncertainty associated with the prospectivity map. Bonham-Carter has noted that one of the advantages of the weights-of-evidence method over other methods such as logistic regression is that uncertainty can be estimated using the; 1) variance due to the weights (usually controlled by the number of deposits), 2) variance due to missing data (Agterberg *et al.*, 1990) and 3) variance such as kriging variance and other sources of error in the explanatory variables (pers. comm.; Bonham-Carter & Agterberg, 1999). To calculate the variances due to the weights, Bonham-Carter (1994); Bonham-Carter & Agterberg (1999) use the expressions from Bishop *et al.* (1975):

$$\rho^2(W^+) = \frac{1}{B_j \cap D} + \frac{1}{B_j \cap \bar{D}} \text{ and} \quad (4.2)$$

$$\rho^2(W^-) = \frac{1}{\bar{B}_j \cap D} + \frac{1}{\bar{B}_j \cap \bar{D}} \text{ and} \quad (4.3)$$

which assume that the number of deposit cells is large. The uncertainty at each cell is given by Bonham-Carter *et al.* (1989); Bonham-Carter & Agterberg (1990) as:

$$\rho^2(P_{post}) = \left[\frac{1}{\bar{D}} + \sum_{j=1}^m \rho^2(W_j^k) \right] * P_{post}^2 \quad (4.4)$$

where $1/D$ is the variance of the prior odds $O(D)$ (based on the assumption that the prior probability of a deposit is given by D/T), D is the number of deposit cells, T is the total number of cells, and B_j is the number of cells with the favourable pattern present in the j -th binary input map. Bars indicate that the favourable or deposit patterns are absent. Bonham-Carter & Agterberg (1999) has also pointed out that, because standard deviation of the posterior logit is correlated with the logit magnitude, the studentized ratio of the posterior logit, $\ln(O_{post})/s(\ln(O_{post}))$, is a better measure of uncertainty than the standard deviation.

Although these methods can not be applied to prospectivity estimates made with neural networks, a Monte Carlo simulation could be applied to obtain uncertainty estimates (Section 8.3.5, page 396).

4.7 Conclusion

A neural-network approach, using a simple implementation of the most commonly-used neural network architecture (i.e. the multilayer perceptron), is successful in integrating geological and geophysical data sets, representative of those used in a regional exploration program, to produce a mineral prospectivity map. The neural-network map is consistent with both the spatial relationships in the data and with geological knowledge about factors important for gold mineralization in the Tenterfield area. The results of this study indicate that the neural network method has several advantages over existing methods. These include the ability to:

1. respond to critical combinations of parameters, rather than automatically increasing the prospectivity due to all favourable parameters,
2. combine data sets without the loss of information inherent in existing methods, and
3. produce results that are relatively unaffected by redundant data, spurious data and data containing multiple populations.

Statistical measures used to compare map quality indicate that the neural network method performs as well, or better, than existing methods while using approximately a third less data than the weights-of-evidence method.

As noted in Section 3.5.1, the Tenterfield database is not ideal for a detailed investigation. A larger more detailed and recently compiled database, which is being used for exploration for Archaean orogenic lode-gold deposits around Kalgoorlie is used for all further investigations in the methodology part of the thesis. The advantage of this database is that it is representative of geoscience GIS databases used in modern, large-scale regional exploration programs.

Chapter 5

Compilation of Case Study GIS Database: Orogenic Gold Deposits, Kalgoorlie Area, Western Australia

5.1 Introduction

This chapter describes the layers in a GIS database for Archaean orogenic lode-gold deposits in the Kalgoorlie area of Western Australia. It is used in subsequent chapters as the basis for experiments on a neural-network approach to mineral prospectivity mapping. All the layers referred to are included on the attached CD-ROM (vol. 2) in both the ARCVIEW and MATLAB directories¹. Layers that are used as inputs to neural networks in experiments in Chapter 7 are shown in Figures 5.7–5.35 at the end of the chapter.

Although the results of Chapter 4 illustrate the effectiveness of Multi-Layer Perceptron (MLP) neural networks for combining exploration data into prospectivity maps and highlight several advantages of neural networks over the weights-of-evidence and a simple fuzzy-systems method, the Kalgoorlie data set can provide a more realistic test of a neural network method because the controls on the location of Archaean lode-gold deposits

¹ARCVIEW layer names differ from those in MATLAB in some cases due to the restriction on file-name length in ARCVIEW. In all cases, however, the number (1–46) in the first part of the name is the same in both ARCVIEW and MATLAB directories

are better understood and possibly more complex than those for intrusion-related disseminated gold deposits in the Tenterfield area. For example, the location of lode-gold deposits in the Kalgoorlie area depends on a complex combination of structural and host-rock rheology and geochemistry, whereas gold deposits in the Tenterfield are largely restricted to two main lithological units, which represent the most highly-differentiated intrusions and can be discriminated on the basis of the high airborne radiometric responses in the uranium, thorium and total-count channels. In contrast, the Kalgoorlie area contains gold deposits that formed at a wide range of crustal depths ($\sim 5 - > 15$ km), with correspondingly varied metamorphic grades, structural styles, host rocks and mineralogy (Groves, 1993; Groves *et al.*, 1998). It is therefore likely that there are wide variations in the data that characterize deposits and that multiple deposit populations exist within the multi-dimensional data.

The Kalgoorlie data set was chosen because;

1. the data set was recently compiled (i.e. 2000-2001),
2. it is in current use in exploration by Placer Dome,
3. it is based on a single recent high-resolution airborne geophysical survey (flight-line spacing: 200 m) that covers the entire study area,
4. the data set consists of a variety of data types (geology, structure, airborne magnetic, radiometric drill-hole geochemistry, and Bouguer gravity anomaly maps),
5. the Kalgoorlie area has been well explored and has been well mapped,
6. the solid geology and structural geology maps, the primary sources for many of the derived GIS layers, were produced by interpretation of airborne magnetic survey maps and existing geological maps by an experienced geologist (Dr Scott Halley, Placer Dome) so that the interpretation is uniform and the geological legend is consistent across the study area, and
7. the area contains a large number of known gold deposits available for training neural networks.

The Kalgoorlie study area covers an approximately 100×100 km area located in the Norseman-Wiluna greenstone belt of the Yilgarn Block, Western Australia (Fig. 5.1). Metadata for the GIS data are given in Appendix D. The Kalgoorlie data set is typical of the sort of geoscience data sets used by companies in modern exploration programs and provides a good test of the general applicability of the neural-network approach to mineral prospectivity mapping.

Figure 5.1. Location of the Kalgoorlie case study area. The data set covers an approximately 110×110 km area within Norseman-Wiluna greenstone belt of the Yilgarn Block near Kalgoorlie, Western Australia. The northern margin of the area is about 25 km north of Bardoc and the southern margin is located approximately 12 km south of Coolgardie. The area corresponds to the eastern half of the Kalgoorlie 1:250000 geological map sheet (SH51-9), with a small proportion of the data set extending into the Kurnalpi, Boorabbin and Widgiemooltha 1:250000 sheet areas (SH51-10, SH51-13, & SH51-14).

5.2 Geology of Archaean Orogenic Gold Deposits

The purpose of this section is to describe the main features of orogenic lode-gold deposits, particularly those in the Kalgoorlie area of the Norseman-Wiluna belt of the Yilgarn Block, Western Australia, and to summarize the essential features of the deposit model relevant to exploration on a regional scale. In the following section, these features are translated into exploration criteria that are likely to be captured in the sort of data that are contained in a regional-scale GIS database or which can be obtained from the primary GIS data layers and incorporated explicitly as a derived layer.

5.2.1 Deposit Characteristics

Orogenic lode-gold deposits are a widespread epigenetic type of gold deposit, which form structurally-hosted quartz-dominant vein systems and are located in Archaean greenstone-granitoid and Phanerozoic sedimentary-rock dominated (e.g. slate) belts within deformed metamorphic terranes (Groves *et al.*, 2000). Although orogenic lode-gold deposits can be hosted in a large variety of rocks and their structural style, alteration, ore mineralogy, and metamorphic grade is also variable, they are now recognized as a coherent group with a common origin (Groves *et al.*, 1995, 2000), in which the deposit characteristics vary due to the large range of crustal depths and temperatures over which the deposits can form (i.e. 180 °C at 2–5 km depth to > 700 °C at 15–20 km depth; the crustal continuum model; Groves *et al.*, 1992; Groves, 1993).

Gold mineralization occurs in quartz vein systems, which in greenschist-facies host rocks contain $\leq 3\text{--}5\%$ sulphides and $\leq 5\text{--}15\%$ carbonates. Arsenopyrite is the most common sulphide in metasedimentary country rocks and pyrite and pyrrhotite predominate in igneous host rocks. In addition to the quartz veins, gold can be located in sulphidized wall rocks. Gold:silver ratios are normally about 10 but range to less than 1.

Lateral alteration zoning is on the scale of centimetres to tens of metres. At greenschist facies, alteration zones are enriched in CO_2 , S, K, H_2O , SiO_2 , $\pm \text{Na}$ and LILE, leading to the development of carbonates (ankerite, dolomite, or calcite) alkali metasomatism (sericitization, fuchsite, biotite, K-feldspar), and albitization. Mafic minerals are highly chloritized.

Vein-forming fluids in orogenic gold deposits are low salinity $\text{H}_2\text{O} - \text{CO}_2 \pm \text{CH}_4 \pm \text{N}_2$ fluids with a high CO_2 content and minor H_2S content. The high CO_2 content is responsible for widespread carbonate alteration zones and the low chloride ($< \sim 6$ wt% equiv. NaCl)

content is responsible for high Au:Ag ratios and a lack of base metal enrichment and low Sn content in orogenic deposits. Although O- and H-isotope work indicates a deep crustal source for the fluids, it is not known if the fluids are metamorphic, magmatic or from a mantle-fluid source (Groves *et al.*, 2000).

5.2.2 Tectonic Setting

Orogenic lode-gold deposits are associated with either plate subduction below continental crust (accretionary terranes) or the collision of terrains on to older blocks of continental crust (collisional terranes). An important aspect of the tectonic setting is association of orogenic deposits with large thermal anomalies due to thrusting of the crust due to thickening of relatively radiogenic crustal material in the orogen core or to upwelling of the asthenosphere (Goldfarb *et al.*, 2001). Tectonic setting and depth of formation distinguish them from other gold deposit types. For example, epithermal-vein, gold-rich porphyry and skarn deposits form at shallow depths (commonly <3 km) in both island and continental arcs in compressional to extensional regimes. In continental arcs in which these deposit types coexist, porphyry and epithermal gold deposit types are sited above, and landward of, orogenic lode-gold deposits (Groves *et al.*, 1998). Intrusion-related gold deposits have many similar characteristics to orogenic lode gold deposits (Sillitoe, 1991; Thompson *et al.*, 1999) and intrusion-related gold mineralization does occur in Archaean granitoids (Qui & McNaughton, 1999). However the tectonic setting appears to be different to that of orogenic deposits. Intrusion-related gold deposits are located in old continental crust well to the landward side of convergent plate boundaries (e.g. continental-margin Andean batholiths). Additionally, the deposits show a clear association with magmatic intrusions, occurring as sheeted veins and disseminated mineralization within plutons or their contact metamorphic aureoles. This type of deposit is also associated with regional extension and form at relatively shallow depths (<6 km).

There is a heterogeneous distribution of ages of orogenic lode-gold deposits. Peaks in the number of deposits occur around 2800–2555 Ma (a period which includes the giant Kalgoorlie and Timmins gold fields) and at 2100–1800 Ma (including the Ashanti and Homestake gold fields, Goldfarb *et al.*, 2001) attributed to during episodes of, possibly plume-driven, crustal growth while the Earth was hotter (before ca. 1800 Ma), and subsequently preserved in the interiors of cratons. Abundant major gold provinces also exist with ages from ca. 450 to ca. 50 Ma. and include the gold fields of the circum-Pacific and the giant gold placers.

5.2.3 Timing of Gold Deposits within Orogens

Both structural and geochronological studies show that the timing of gold deposition is typically late within the tectonic evolution of its host terranes. A variety of structural studies indicate, that the relative timing of gold is slightly later than regional metamorphism, plutonism, and early phases of orogenic deformation in mid-crustal level greenschist facies host rocks. At deeper levels in the crust, closer to the source of the gold-bearing fluids, mineralization is earlier and may be coeval with metamorphism and magmatism (Groves, 1995). In both the Yilgarn and elsewhere, gold was generally deposited during the D_2 or D_3 events in a D_1 – D_4 deformational sequence.

Absolute ages for gold mineralization in the Yilgarn have been established from pre-mineralization granitoid and felsic porphyry dykes and sills that are cut by gold-bearing veins, post-mineralization cross-cutting dykes and sills, which are not mineralized, and by direct dating of gold deposits using alteration minerals. These data show that most of the gold was deposited from 2645–2630 Ma (Yeats & McNaughton, 1997), a period which corresponds to a widespread gold-mineralizing event in the Yilgarn. Most of the deposits were formed 60–70 m.y. after the end of widespread basic-ultrabasic volcanism and towards the end of the craton-wide emplacement of felsic magmas.

Late timing of gold within the deformational history of the host terranes has important implications for the use of GIS-based methods in mineral exploration. It means that the geometry of the structures associated with deposits (i.e. faults and shear zones) and rock sequences hosting the deposits on geological maps are essentially similar to those that existed during mineralization. It is significant that the location of ore deposits are related to repeated and predictable structural geometries. In addition, Hronsky *et al.* (1990) record that the vast majority of the gold-hosting structures in the Yilgarn are near vertical. Consequently, it means the spatial relationships between the structures and known deposits displayed in a geological map can be analysed using a GIS to predict the location of new deposits (Groves *et al.*, 2000).

5.2.4 Structural Controls

Regional structures are the main structural control on the location of orogenic deposits. Although a broad spatial association between crustal- and regional-scale first-order structures exists, these structures rarely host gold deposits. Deposits are generally located in nearby second and third-order structures (Eisenlohr *et al.*, 1989; Witt, 1993; Groves *et al.*, 2000). Possible reasons for the lack of mineralization associated with first-order structures,

which are generally crustal to regional shear zones, are that the translational movements along these shear zones did not produce permeability or that the shear zones are barriers to fluid flow (S.Halley, pers.comm., 2001)

Examples of favourable structural sites include;

1. Large, linear greenstone belts with major bounding shear zones which are favourable because the high structural permeability associated with thin bands of relatively reactive rock (compared to the surrounding granitoids) can result in high fluid-rock ratios. Reactivation of the major bounding structures may create second and third-order structures, and associated dilational zones, which are potential sites of gold mineralization.
2. Suitably-oriented structures in heterogenous stress fields around rigid granitoid plutons and complex batholith margins (e.g. Knight *et al.*, 1993; Ojala *et al.*, 1993; Phillips *et al.*, 1996; Groves *et al.*, 2000).
3. Pressure shadows at the terminations of elongate batholiths (Groves *et al.*, 1995).
4. Irregularities in strike (and large rheological contrasts) along crustal and regional-scale faults or shear zones (Sibson, 1987; Phillips *et al.*, 1996; Groves *et al.*, 2000). According to Hronsky *et al.* (1991), only minor variations in strike along shear zones are required to produce a heterogenous stress distribution and thereby affect fluid flow. This is due to potential for compressional and dilational zones within the same domain (Groves *et al.*, 2000).
5. Dilational jogs along strike-slip faults and overstepping faults (Hagemann *et al.*, 1992).
6. Dilational zones where shear zones and faults are more gently dipping than elsewhere, for example, Granny Smith (Ojala *et al.*, 1993) and Sons of Gwalia (Smith & Gardoll, 1997) deposits.
7. Cross faults between first-order faults (Goldfarb *et al.*, 1997).
8. Reactivated, locked-up fold-thrust structures and tightly-folded, overturned anticlines. The giant Golden Mile deposit, Kalgoorlie, is located in a zone where early-formed thrust faults, involving competent units surrounded by less competent units, were later folded and faulted (Groves *et al.*, 1995; Phillips *et al.*, 1996).
9. Structurally isolated blocks of more competent volcanic rocks surrounded by less competent volcanic or sedimentary rocks. These blocks are formed where late NE-

trending faults cross-cut NW-trending competent units enclosed in less competent units (Fig. 4, Groves *et al.*, 2000). Isolated blocks of this type at all scales represent favourable sites for gold mineralization since the competent units within these blocks preferentially fail and become sites of enhanced structural permeability. Groves *et al.* (2001) have suggested that the cross-cutting faults tend to act as barriers to fluid flow, thereby greatly increasing fluid-flux ratios required to form larger deposits.

10. Isolated curvilinear blocks, which are closed off at one or both ends may also form where early thrust faults within competent units, which are enclosed by less competent units are later folded and faulted. Fluids reach supralithostatic pressure in these blocks causing fracturing in competent units and the formation of large vein arrays; the anomalous fluid fluxes produced in such blocks can produce giant ore deposits; for example, Mt Charlotte, Golden Mile deposits (Ridley & Mengler, 2000), Kalgoorlie and Timmins, Canada (Fig. 5, Groves *et al.*, 2000).
11. Anticlinal hinges and domes formed by doubly plunging anticlines. In the Kalgoorlie Terrane, the location of anticlines are often inferred to be between synclines. Anticlinal axes are favourable sites for mineralization because they are often the sites of thrust faults and therefore may represent areas where fluids have been focussed. Anticlinal folds may also have the effect of trapping upward moving fluids if the overlying lithologies (e.g. shale) form an impermeable cap.
12. Dykes and small bodies of syenite and porphyritic intermediate to mafic intrusions are, in places, associated with gold mineralization (Halley, Groves, Cassidy, pers. comm., 2000). Halley (2000; pers. comm.), argues that porphyritic felsic intrusions, which contain up to 200 ppb gold, have moved gold from the lower crust to higher levels and that later events pump fluid through these to produce deposits. Alternatively, most of the porphyritic intrusions are quartz-bearing and therefore very brittle. Consequently, they may correspond to sites of selective failure and high structural permeability.
13. Large to giant deposits are more common in greenschist facies terranes than in higher-grade metamorphic settings (Phillips *et al.*, 1996). This may be due to the greater effectiveness of mean stress variations as a fluid focussing mechanism at depths corresponding to greenschist facies metamorphism (Ridley, 1993) or, as Sibson (1987) has proposed, that fluid fluctuations in faults may be greatest at these crustal depths.
14. Magnetite-bearing rocks may be particularly favourable hosts for gold deposition. Phillips *et al.* (1996) has suggested that while Fe-silicate-rich (chlorite, actinolite)

host rocks greatly facilitate the destabilization of gold complexes in solution (Neall & Phillips, 1987), the presence of magnetite may promote gold deposition. Carbonation of magnetite to form siderite leads to oxidation of the fluid, in contrast to carbonation of Fe-silicates which do not involve a change in redox state. Reaction of the oxidized fluid would lead to gold deposition by lowering the activity of reduced sulphur species which complex with gold. Evidence from ore and alteration mineral assemblages suggests that the fluids which deposited gold in the Golden Mile Dolerite were relatively oxidized and that magnetite was relatively abundant compared with other deposits in the same terrane. The reactions envisaged by Phillips *et al.* (1996) are shown below;

Alteration zones containing leucoxene and pyrite formed by the replacement of magnetite (see the first of the two reactions shown above) extend well beyond the carbonate alteration. Groves *et al.* (2001) have noted that this destruction of magnetite leads to a magnetically depleted core of the deposit and that some deposits have a magnetic rim due to the precipitation of magnetite by spent fluids. Strong positive and negative aeromagnetic anomalies may indicate sites of magnetite production and destruction, respectively. Although ore-forming fluids produce strong carbonate alteration, it is so widespread throughout the Norseman-Wiluna greenstone belt that the presence of alteration cannot be used as a simple vector to ore.

Further structural geometries that are favourable for gold deposition have been identified using a technique called stress mapping. This is a computer-based structural analysis that models paleo-stress patterns using the geometry of the lithological units, regional-scale structures and estimates of rock strength and fault friction properties and the far-field stress orientation (Holyland & Ojala, 1997; Groves *et al.*, 2000). The low stress anomalies (low mean stress and low minimum principal stress) identified using this technique correlate well with the location of all the known gold fields in the Kalgoorlie Terrane (Groves *et al.*, 2000).

A requirement of this method is that fluid pressures locally exceed lithostatic pressures resulting in focussing of fluids, generally upwards, to zones of low mean stress. Such zones are commonly sites of selective failure, high fluid flux and resultant gold deposition (Groves *et al.*, 1997). Evidence for high or supralithostatic pressures occurs throughout

the Yilgarn block at all crustal depths in the form of flat extensional veins containing crack-seal textures

Gold deposits associated with low stress anomalies were identified in the following locations (Groves *et al.*, 2000);

1. changes in strike of first-order faults from dominant the NNW to a NW trend,
2. intersections of two or more first-order faults, and
3. intersections of first- and second-order faults.

Groves *et al.* (1995, 2000) noted that reactivation of suitably-oriented, pre-existing structures in response to a change in the far-field stress direction may also provide favourable sites for gold deposition and suggest that multiple episodes in response to repeated reactivation may be an important ingredient in the formation of giant ore deposits.

At a mine scale, work by Hronsky *et al.* (1990) and Witt (1993) demonstrates that all kinematic types of structure such as strike-slip, oblique-slip, reverse, and normal faults may host gold mineralization. These local structures containing the gold mineralization vary with crustal depth (from brittle-ductile faults to ductile shear zones), lithology of host rocks, and rheological contrasts between the host and enclosing rocks units. In ductile sequences, where fluid flow was mainly within a fault or shear zone, structures vary from tensional quartz veins and breccias, quartz-vein sets, laminated quartz reefs and broad ductile shear zones. In more competent rocks, where fluid flow was in sub-vertical zones of fractured rock, gold is generally hosted in tensional quartz-vein sets.

5.2.5 Host Rocks

Highly competent and chemically reactive host rocks are the most common hosts to gold mineralization. On a regional scale, most of the gold deposits are sited in competent units or at contacts between layers of contrasting competency, which are oriented at high angles to the maximum principal far-field stress. Ridley (1993) has noted that the reason for this is that the more competent units tend to fail selectively in this orientation and hence become sites of increased structural permeability and fluid focussing. In the Yilgarn, this means that competent layers, which are oriented between NNW and NNE, are selectively mineralized, since the far-field maximum principal stress at the time of gold mineralization is estimated to have been approximately E-W (Phillips & Groves, 1983; Witt, 1993). According to this criterion, most of the greenstone belt is prospective as most of the units have this orientation.

Although a number of reports suggest that rheological contrasts across lithological boundaries are an important control on the location of larger deposits (Groves *et al.*, 1995, 1997, 2000; Holyland & Ojala, 1997), there have been few studies that test this hypothesis on a regional scale. One study by Yun (2000) confirms that this concept does apply well to the Kalgoorlie Terrane. Yun (2000) used subjective estimates of the relative competency, based on the degree of fabric development and modal mineralogy and ranked 15 rock types using integers in the range, 1–5. For example, BIF, porphyry, quartz dolerite and basalt were ranked as very competent (1) and ultramafic schists as very incompetent (5).

Rocks with high Fe and/or high Fe/(Fe + Mg) such as dolerite, tholeiitic basalt, Banded Iron Formation (BIF), and some mafic porphyries are also the most chemically reactive host rocks and therefore the most likely to be mineralized. However, in the Norseman-Wiluna Belt, banded iron formations are negligible and mafic rocks such as dolerite sills are associated with most large deposits (Phillips & Groves, 1983; Phillips *et al.*, 1996). Much of the Golden Mile Dolerite especially the granophyre has high Fe/(Fe + Mg + Ca) (Phillips, 1986).

Iron-rich rocks react with the ore-bearing fluids to produce pyrite, thereby destabilizing the reduced sulphur complexes (see equations 5.2.4 & 5.2.4 above; Phillips & Groves, 1983; Mikucki, 1998) and depositing gold. Due to the high CO_2 content of the fluids, reaction with calcium and magnesium-rich wall rocks will form Fe-bearing carbonates (i.e. ankerite and dolomite) which prevents the formation of Fe-sulphides leading to gold deposition. For this reason, BIF and Fe-rich mafic rocks represent ideal host rocks for gold deposition, as evidenced by the sometimes extreme sulphide alteration in places (Groves *et al.*, 2000), because iron content is very high (~40–55%) and calcium contents are very low.

5.2.6 Mechanism of Gold Precipitation

The main mechanism for the precipitation of gold is fluid-wall-rock reaction. Reduced S-rich fluids containing the $Au(HS)_2$ complex react with Fe-bearing host rocks (Phillips & Groves, 1983; Mikucki, 1998). Gold deposition is thought to occur through coupled reactions such as (Mikucki, 1998):

and

Phase separation due to brittle failure and a concomitant sudden reduction of pressure and fluid mixing of ore fluid with near surface fluids are other possible means by which gold can be precipitated. However, they appear to have played a minor role in the Yilgarn (Groves *et al.*, 1997; Mikucki, 1998).

5.2.7 Simplified Model of an Orogenic Gold System

A simplified model of an orogenic gold system is one in which an anomalous heat source in the middle crust (due to mantle plume activity, subduction of a oceanic arc, subduction roll-back or mantle delamination) causes upward migration of low-salinity fluids carrying reduced sulphur species through first-order crustal-scale and regional-scale channel ways, which are associated with heterogenous stress fields. These primary structures may focus fluids into second and third -order structures. Large fluid fluxes and high fluid-rock ratios in thick units of competent, chemically-reactive host rocks are required for the formation of large gold deposits. High structural permeability results from complex geometries in volcanic rocks and strong contrasts in rock strength (so that a competent unit fails and is surrounded by other less competent units that do not). In the Yilgarn, reactive host rocks are generally mafic with high-Fe or high Fe/(Fe+Mg+Ca) contents. The main mechanism of gold deposition is through fluid-wall rock reactions in which the iron-rich minerals in the host rocks react with sulphide complexes which carry gold in solution to form Fe-sulphides (Phillips & Groves, 1983; Mikucki, 1998).

5.3 Exploration Criteria

This purpose of this section is to derive exploration criteria based on the model for orogenic deposits described above. Only criteria that are applicable to regional-scale exploration and which can be applied to the data available for the Kalgoorlie study area are considered here.

The approach used in this study was developed by Wyborn *et al.* (1994c, 1995b) and involves converting the essential ingredients of a mineral systems model to features that are likely to have been mapped and compiled in a regional scale GIS database. Wyborn emphasized the need to consider the entire mineralizing system, including source region, metal and ligand sources, pathways, and trap zone, and outflow zone rather than just the characteristics of the deposit itself, as the mineral system provides a larger target and is more applicable to the type of data that are captured in a regional-scale GIS.

Regional-scale exploration criteria are listed together with a description of how the criteria are modelled as a GIS map layer in Table 5.1 below.

5.4 Primary GIS Layers

This section gives a brief explanation of the primary data used in the Kalgoorlie case study. The data set comprises geology, gravity and airborne geophysics, a composite LANDSAT Thematic Mapper image and whole-rock geochemical analyses from soil samples and drill holes. These data sets were supplied by Dr Scott Halley, Placer Dome. The data sets were compiled in the period 1999–2000 and were part of an active exploration program. Additional data sets, such as the deposit and regional whole-rock geochemical databases and the rock strength data, came from other sources, which are explained briefly below. Detailed information, such as metadata and data dictionaries for the digital GIS data sets, are given in Appendix D. Digital copies of all ARCVIEW GIS layers and MATLAB arrays are included on the CD-ROM (vol.2) attached to the thesis.

5.4.1 Geology Layer

The solid geology GIS layer was compiled in November 2000 and incorporates a combination of mapping by Goldfields Exploration geologists and an interpretation of a high-resolution airborne magnetic survey (200 m flight-line spacing). The GIS layer supplied by Goldfields Exploration Pty Ltd maps comprises a number of non-contiguous areas along the NNE-trending Bardoc Tectonic Zone (BTZ; refer to Fig. 5.1 in Appendix D).

Solid geology and structural geology maps supplied by Goldfields Exploration Pty Ltd in MapInfo format were imported first into ARCVIEW and then clipped to conform to the boundaries of the Kalgoorlie study area. The solid geology GIS layer was then exported from ARCVIEW as a plain ASCII file, which was then imported into MATLAB (a software package containing the neural network programs). A similar procedure was applied to other data sets (except for geophysics data sets). The steps are illustrated in Figure 5.2.

Once the data were imported into ARCVIEW, the legend used by Goldfields Exploration Pty Ltd was simplified from 108 to 25 rock types (Table 5.2 and Section 5.5.1 below).

Table 5.1. Regional-scale exploration criteria for orogenic gold deposits in the Kalgoorlie Terrane

Exploration Criteria	Corresponding GIS Database Layer
Proximity to crustal & regional-scale faults	Distance to nearest crustal fault Distance to nearest regional NNW fault Distance to nearest regional NNE fault
Heterogenous stress fields around granitoid margins	Not modelled
Pressure shadows at ends of elongate batholiths	Not modelled
Irregularities in strike of faults or shear zones	Strike of nearest fault, types 1–4
Dilational jogs along strike-slip faults	Strike of nearest fault, types 1–4
Dilational zones where dip of fault locally flattens	Not modelled
Cross faults between first-order faults	Distance to intersection of crustal and regional faults
Intersections of two or more first-order faults	As above
Intersections of first- and second-order faults	As above
Reactivated locked-up fold-thrust structures & tightly-folded, overturned anticlines	Not modelled
Structurally isolated blocks (late NE faults cross-cut NW trending competent units)	Not modelled
Anticlinal hinges & domes formed by doubly plunging anticlines	Distance to nearest regional-scale anticlinal axis
Syenite intrusions (weak association with gold mineralization)	Binary syenite layer (i.e.; presence-absence of syenite) Distance to nearest syenite intrusion
Porphyritic felsic intrusions (weak association with gold mineralization)	Binary porphyritic felsic intrusion layer Distance to nearest porphyritic felsic intrusion
Quartz dolerite & leucocratic dolerite (highly prospective host rocks)	Binary quartz dolerite/leucocratic dolerite layer Distance to nearest quartz dolerite/leucocratic dolerite
Isolated curvilinear blocks formed by folding & faulting of early thrust faults	Not modelled
Most prospective metamorphic grade is greenschist facies	Metamorphic-grade map
Chemically reactive host rocks with high Fe and/or high Fe/(Fe + Mg + Ca)	Maps of Fe^{3+}/Fe^{2+} , $Fe_{tot}/(Fe_{tot}+Mg+Ca)$, $Fe_{tot}*Fe_{tot}/(Fe_{tot}+Mg+Ca)$, & $Fe_2O_3/(Fe_2O_3 + FeO)$ ratios
Highly competent host rocks	Subjective rock strength, Young's modulus, UTS, UCS & fracture toughness
Host rock sequences containing layers with strong competency contrasts	Maps with rheological contrast at nearest lithological boundary Cell values = absolute value of difference in rock strength at nearest rock boundary
Alteration related to ore-forming fluids	Positive & negative magnetic anomaly maps show domains of magnetite destruction & production
Changes in strike of first-order faults from dominant the NNW to a NW trend	Strike of nearest fault, types 1–4
Reactivated crustal & regional-scale faults and shear zones	Not modelled

Figure 5.2. Steps required to convert data sets obtained from Goldfields Pty Ltd in MAPINFO vector GIS format to MATLAB arrays.

Table 5.2: Simplified rock type legend for the solid geology GIS layer. The geological legend used by Goldfields Exploration Pty Ltd was reduced to 25 rock types (listed in order of simplified legend rock names).

New Code	Simplified Legend (25 rock types)	Old Code	Goldfields Exploration Pty Ltd legend (108 rock types)	Count
Hm	Amphibolite (Undivided)	Hof	Alkali-rich Ortho Amphibolite (f.g. felsic)	11346
Hm	Amphibolite (Undivided)	Hpc	Calcic Para Amphibolite (diopside almandine)	
Hm	Amphibolite (Undivided)	Homc	Fe-rich Ortho Amphibolite (c.g. mafic)	
Hm	Amphibolite (Undivided)	Hom	Fe-rich Ortho Amphibolite (f.g mafic)	
Hm	Amphibolite (Undivided)	Homh	Fe-rich Ortho Hornfels (mafic derived)	
Hm	Amphibolite (Undivided)	Hm	Mafic Amphibolite (undivided)	
Hm	Amphibolite (Undivided)	Hou	Mg-rich Ortho Amphibolite (f.g. ultramafic)	
Hm	Amphibolite (Undivided)	Houh	Mg-rich Ortho Hornfels (ultramafic derived)	
Hm	Amphibolite (Undivided)	Hpt	Para Amphibolite (mafic)	
Mb	Basalt	Mb	Basalt	117529
Mb	Basalt	Mbbx	Mafic Pyroclastic Breccia	
Mb	Basalt	Mb-mg	Mount Goode Basalt	
Mb	Basalt	Mbp	Porphyritic Basalt (plagioclase phyric)	
Mb	Basalt	Mbx	Undivided Basaltic Autoclastic Rocks	
Mb	Basalt	Mby	Undivided Mafic Pyroclastic Rock	
Mb	Basalt	M	Undivided Mafic Rocks (often altered)	
Shcc	Carbonaceous Shale	Shcc	Carbonaceous Shale	22755
Sct	Chert	Sct	Chert	0
Sc	Conglomerate	Sc	Conglomerate	8530
Sc	Conglomerate	Scpf	Jones Creek Conglomerate	
Sc	Conglomerate	Scxm	Monomict Conglomerate	
Sc	Conglomerate	Scxp	Polymict Conglomerate (Kurrawang)	
Sc	Conglomerate	Scvm	Volc.-derived Conglomerate (mafic-u/mafic)	
Md	Dolerite	Md	Dolerite	15161
Md	Dolerite	Mdl	Leucocratic Dolerite (pyroxene, phyric)	
Md	Dolerite	Mb-m	Magnetic Basalt	
Md	Dolerite	Mdp	Porphyritic Dolerite (plagioclase, phyric)	
Pf	Feldspar Porphyry	Pfbh	Feldspar Hornblende Biotite Porphyry	14998
Pf	Feldspar Porphyry	Pf	Feldspar Porphyry	
Pf	Feldspar Porphyry	Pfqh	Feldspar Quartz Biotite Porphyry	
Pf	Feldspar Porphyry	Pfqh	Feldspar Quartz Hornblende Porphyry	
Pf	Feldspar Porphyry	Pfq	Feldspar Quartz Porphyry	
Pf	Feldspar Porphyry	Pfh	Plagioclase $\pm$ Hornblende Porphyry	
Hgf	Felsic Gneiss	Hgf	Felsic Gneiss	0
Mg	Gabbro	Mg	Gabbro	56944
Mg	Gabbro	Mg1	Gabbro - Kundana unit 1	
Mg	Gabbro	Mg2	Gabbro - Kundana unit 2	
Mg	Gabbro	Mg3	Gabbro - Kundana unit 3	
Mg	Gabbro	Mg5	Gabbro - Kundana unit 5	
Mg	Gabbro	Mg6	Gabbro - Kundana unit 6	
Mg	Gabbro	Mg6A	Gabbro - Kundana unit 6A	
Mg	Gabbro	Mgl	Leucocratic Gabbro (pyroxene, phyric)	
Mg	Gabbro	Mgm	Melanocratic Gabbro - amphibole rich	
Mg	Gabbro	Mgp	Porphyritic Gabbro (plagioclase phyric)	
Gt	Granitoid	Gr	Granite	331673
Gt	Granitoid	Gt	Granitoid	

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Table 5.2: *continued*

New Code	Simplified Legend (25 rock types)	Old Code	Goldfields Exploration Pty Ltd legend (108 rock types)	Count
Gt Gt Gt Gt Gt Gt Gt Gt	Granitoid Granitoid Granitoid Granitoid Granitoid Granitoid Granitoid Granitoid	Gdi Gmo Gp Gmoq Gsy Gsdi Gto Gdi-wee	Granodiorite Monzonite Pegmatite Quartz Monzonite (cf Adamellite) Syenite Syenodiorite Tonalite Weebo Granodiorite	
Sif Sif	Iron Formation Iron Formation	Bif Sif	Banded Iron Formation Iron Formation	0
Mmb Mmb	Magnesian Basalt Magnesian Basalt	Mmb Mbu	Magnesian Basalt (variolitic $\pm$ pyx.) Mafic Ultramafic (Greenstone)	49249
Perm Pmd Pmd	Permian Sedimentary Rock Proterozoic Dolerite Proterozoic Dolerite	Perm Pmd Pd	Permian Sedimentary Rock Proterozoic Dolerite Proterozoic Mafic & Ultramafic Dyke	– – –
Mdq Qv	Quartz Dolerite Quartz Vein	Mdq Qv	Quartz Dolerite Stacked Plutonic-Style Lodes	117
Hpq Us Us Us Hpqh	Quartzite Serpentinite Serpentinite Serpentinite Si-Rich Hornfels	Hpq Usk Uspd Us Hpqh	Quartzite Serpentinised Komatiite Serpentinised Peridotite Serpentinite Si-rich Hornfels (qtz, minor Al-silicate)	15489 139
Utc Utc	Talc-Chlorite Ultramafic Talc-Chlorite Ultramafic	Uac Utc	Amphibole-Chlorite Ultramafic Rock Talc-Chlorite Ultramafic Rock	589
Zu	Ultramafic Schist	Zu	Ultramafic schist	2
Zls Zls Zls Zls Zls	Undiff'd Felsic Schist Undiff'd Felsic Schist Undiff'd Felsic Schist Undiff'd Felsic Schist Undiff'd Felsic Schist	Zac Zf Zm Zs Zls	Actinolite Schist Fuchsite schist Muscovite schist Sericite schist Undifferentiated Felsic Schists	15
Fv Fv Fv Fv Fv Fv Fv Fv Fv Fv Fv	Undivided Felsic Volcanic Undivided Felsic Volcanic Undivided Felsic Volcanic Undivided Felsic Volcanic Undivided Felsic Volcanic Undivided Felsic Volcanic Undivided Felsic Volcanic Undivided Felsic Volcanic Undivided Felsic Volcanic Undivided Felsic Volcanic Undivided Felsic Volcanic	Svcf Fd Fpbx Ftc Svff Svmf Ft Fvx Fvy Fv	Coarse-grained Fragmental Dacite (even grained) Felsic Pyroclastic Breccia (agglomerate) Felsic Tuff (crystal lithic) Fine-grained Fragmental Medium-grained Fragmental Metamorphosed Felsic Tuff (lava dominant) Undivided Felsic Autoclastic Rocks Undivided Felsic Pyroclastic Rocks Undivided Felsic Volcanic Rocks	18131
Ia Iv Ia Iv Iv	Undivided Int. Volcanic Undivided Int. Volcanic Undivided Int. Volcanic Undivided Int. Volcanic Undivided Int. Volcanic	Ia Ipbx Ifp Ivx Iv	Andesite (even grained) Intermediate Pyroclastic Breccia Porphyritic Andesite (plag. phyr. biotite) Undivided Intermediate Autoclastic Rocks Undivided Intermediate Volcanic Rock	384
S S S	Undivided Sed. Rock Undivided Sed. Rock Undivided Sed. Rock	Sslh Shl Sha	Interbedded Siltstone - Shale Shale Shale (altered)	56462

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Table 5.2: *continued*

New Code	Simplified Legend (25 rock types)	Old Code	Goldfields Exploration Pty Ltd legend (108 rock types)	Count
S	Undivided Sed. Rock	Ssl	Siltstone	
S	Undivided Sed. Rock	San	Undivided Arenite (sandstone, matrix <15%)	
S	Undivided Sed. Rock	S	Undivided Sedimentary Rocks	
U	Undivided Ultramafic Rock	Uk	Komatiite	95067
U	Undivided Ultramafic Rock	Upd	Peridotite (olivine cumulate)	
U	Undivided Ultramafic Rock	Upx	Pyroxenite	
U	Undivided Ultramafic Rock	Uxa	Ultramafic Autobreccia	
U	Undivided Ultramafic Rock	U	Undivided Ultramafic Rocks	
?	Unknown/Unclassified	X	Mylonite	217
?	Unknown/Unclassified	?	Unknown/Unclassified Unit	
Svg	Volcanogenic Rock	Sfw	Feldspathic Wacke (>75% feldsp. <25% lithic)	167123
Svg	Volcanogenic Rock	Ivs	Intermediate Volcanogenic Sedimentary Rock	
Svg	Volcanogenic Rock	Sw	Undivided Wacke (15-75% matrix)	
Svg	Volcanogenic Rock	Svfw	Volcanic Feldspathic Wacke (% qtz < feldsp.)	
Svg	Volcanogenic Rock	Svw	Volcanic Wacke	
Svg	Volcanogenic Rock	Svg	Volcanogenic Sediments	

5.4.2 Structural Layer

The primary structural GIS layer is a synthesis of published mapping by the Geological Survey of Western Australia (Swager, 1989; Swager & Griffin, 1990; Swager *et al.*, 1990), mapping by company geologists at Goldfields Exploration Pty Ltd, and an interpretation of airborne magnetic data by Dr Scott Halley. The final structural GIS coverage is the result of combining the Kalgoorlie area and the BTZ structural maps using the same procedure described for the geology layer above. The structural GIS layer, *faults.shp* containing all faults, shear zones and magnetic trend lines (ARCVIEW vector format) is shown in Figure 5.8 below.

5.4.3 Fold Axis Layer

GIS layers, which show the ground traces of major anticlinal and synclinal axes are based on an interpretation by Prof. David Groves of geology and structural maps of the Kalgoorlie area (Swager & Griffin, 1990; Swager *et al.*, 1990; Yun, 2000). Whilst many of the synclinal locations are mapped, the site of anticlinal hinge zones are generally the locations of thrust faults and are inferred. The fold-axis layer, (*folds.shp*; ARCVIEW vector format) is shown in Figure 5.9 below.

5.4.4 Aeromagnetic and Gamma-Ray Layer

The airborne geophysics survey covering the Kalgoorlie study area is a high-resolution (200 m flight-line spacing) multi-client survey flown by World Geoscience in 1989. The data comprise total magnetic intensity (TMI) with reduction-to-pole (RTP) corrections, first vertical derivative of magnetic intensity, and radiometric survey data (i.e. U, Th, K and total-count channels). Due to poor outcrop and the widespread and thick regolith layer in the Kalgoorlie area, the radiometric data were not used. The total magnetic intensity layer, *l5_m_rtp* is a raster layer which was converted from a ERMAPPER file (*.ers*; *BIL format*) by importing it into GEOSOFT.¹ The data set were re-gridded to convert the original 25 m grid spacing to 100 m and then converted from a GEOSOFT *.grd* file to an ARCVIEW binary raster grid file, which was then imported into ARCVIEW (Fig. 5.10).

5.4.5 Gravity Layer

The gravity GIS layer shows Bouguer gravity anomalies calculated from data collected by AGSO in 1971. The original data has an 11 km station spacing, which was re-gridded to a 100 metre grid by Dr Mike House, geophysicist, Goldfields Pty Ltd. The Bouguer anomaly layer, *l12_grav*, was converted from an ERMAPPER *.ers* file to an ARCVIEW grid using the procedure described for the TMI magnetic layer above (Fig. 5.11).

5.4.6 Deposit Layer

The locations and sizes of gold deposits in the Kalgoorlie study area were obtained from the Mines and Mineral Deposits database (MINEDEX) compiled by the Geological Survey of Western Australia (Townsend et al., 2000). The data relevant to gold deposits in the Kalgoorlie study area were extracted from the original ACCESS 97 database and converted to an ARCVIEW point coverage by Paul Hodkiewicz and Stephen Gardoll at the Centre for Global Metallogeny, University of Western Australia.

For each deposit, an estimate of pre-mining resource (kg total contained gold, TCG) was calculated by adding the largest resource category corresponding to the Australian Institute of Mining and Metallurgy (AusIMM) JORC code (inferred, indicated, and measured) available to any historic and recent production. Hodkiewicz (2002) notes that, although

¹The software package referred to as GEOSOFT is the *OASIS montaj* geoscience data processing and analysis system (Release 4.3) produced by GEOSOFT.

pre-1980 production was typically from underground operations that could only support average grades greater than ~ 30 g/t, current large-scale open pit operations now mine average grades of less than 5 g/t. Consequently, Hodkiewicz concluded that a combination of historic production and current resources is the best way to provide order-of-magnitude estimates of the district-scale pre-mining gold endowment for the comparison purposes of a mineral prospectivity study (see ARCVIEW vector format layers *deps_all.shp* and *deps_1000tcg*, which show all gold deposits and occurrences, and deposits with resource of ≥ 1000 kg TCG, respectively in Figs. 5.12 and 5.13).

5.4.7 OZCHEM Database

Whole-rock geochemical data were used to calculate five different indices representing the chemical reactivity of potential host rocks in the Kalgoorlie region.

The data used to calculate the chemical ratios are a subset of a spatial representation of the Australian Government Survey Organization's (AGSO) OZCHEM whole-rock geochemistry database (Kilgour & Hazell, 1998). The Yilgarn Block data set comprises 4473 analyses, which were obtained from the database of the CSIRO Division of Exploration Geoscience, PhD theses, rocks collected as part of joint AGSO-Geological Survey of Western Australia (GSWA) mapping projects, and from the bottom of AGSO seismic shot holes.

The database was supplied as an Microsoft EXCEL spreadsheet and an ARCVIEW shape file showing sample locations. Table D.8 in Appendix D shows the OZCHEM analyses used to calculate the reactivity ratios for each rock type in the solid geology legend. The ratio values were calculated in an EXCEL spreadsheet and then exported as an ASCII file together with AMG coordinates of the sample locations. The ASCII file was imported into ARCVIEW. Using the ARCVIEW *spatial join* function, the attributes of the point data set containing the chemical ratios were added to the geology attribute table. The chemical ratio attributes were then used to create raster GIS layers corresponding to each of the five indices. In a further step, chemical contrasts at lithological boundaries were calculated to produce a derived GIS layer. The procedure is described in Section 5.5.12 below.

The chemical ratios tested together with the corresponding layer names (refer to the GIS database on the attached CD-ROM (vol.2)) are shown in Table 5.3. In the first two ratios, $\text{Fe}/(\text{Fe}+\text{Mg}+\text{Ca})$ is a ratio of weight percentages of metals and Fe represents the total iron; i.e. $\text{Fe}^{2+} + \text{Fe}^{3+}$. Work by Yun (2000) using the first two ratios has shown

that chemical reactivity of the host rocks is one of the parameters useful in estimating the prospectivity for orogenic gold deposits. The two ratios describe how much iron is available in the host rock for sulphidation reactions (see Equations 5.2.6 & 5.2.6) which are proposed as the primary means of gold precipitation (Mikucki, 1998). Magnesium and calcium in the host rocks inhibit the precipitation of gold by reducing the amount of iron due to reaction with the CO₂ – rich fluids to produce carbonates (e.g. calcite, dolomite, magnesite or in low Fe/(Fe+Mg+Ca) conditions, ankerite). In addition to the ratio of iron to iron, magnesium and calcium, the total amount of iron is important. Consequently, total iron in weight percent was multiplied by the Fe/(Fe+Mg+Ca) ratio in row 1 of Table 5.3. The last two ratios in Table 5.3 show the Fe³⁺/Fe²⁺ ratios as oxide and molar ratios, respectively, and are included to check if the oxidation state of the rocks could be used to estimate the prospectivity for gold mineralization. The layers, *l3_lch2-5* are in the ARCVIEW directory on the attached CD-ROM (vol. 1).

Table 5.3. Chemical reactivity layers, which were evaluated as potential input GIS layers for neural network analyses

Layer name	Rock chemical reactivity ratio
l3_lch1	$\text{Fe}_{wt\%} \times \text{Fe}_{total} / (\text{Fe}_{total} + \text{Mg} + \text{Ca})$
l3_lch2	$\text{Fe}_{total} / (\text{Fe}_{total} + \text{Mg} + \text{Ca})$
l3_lch3	$\text{Fe}_2\text{O}_3 / (\text{Fe}_2\text{O}_3 + \text{FeO})$
l3_lch4	$\text{Fe}_2\text{O}_3 / (\text{FeO})$
l3_lch5	$\text{Fe}^{3+} / \text{Fe}^{2+}$

The values of these five different methods of calculating a chemical reactivity index based on iron ratios are shown in Table 5.4 below.

Table 5.4: Chemical reactivity ratios for the Kalgoorlie study area, arranged in order of decreasing Fe×Fe/(Fe+Mg+Ca).

Rock Code	Rock Type/Description	$\text{Fe}_{wt\%} \times \frac{\text{Fe}}{\text{Fe} + \text{Mg} + \text{Ca}}$	$\frac{\text{Fe}}{\text{Fe} + \text{Mg} + \text{Ca}}$	$\frac{\text{Fe}_2\text{O}_3}{\text{Fe}_2\text{O}_3 + \text{FeO}}$	$\frac{\text{Fe}_2\text{O}_3}{\text{FeO}}$	$\frac{\text{Fe}^{3+}}{\text{Fe}^{2+}}$
Bif	Banded Iron Formation	22.65	0.78	0.54	1.15	1.04
Sif	Iron Formation	22.65	0.78	0.54	1.15	1.04
Md	Dolerite	4.75	0.44	0.25	0.62	0.56
Mdl	Leucocratic Dolerite	4.75	0.44	0.25	0.62	0.56
Mb-m	Magnetic Basalt	4.75	0.44	0.25	0.62	0.56

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Table 5.4: *continued*

Rock Code	Rock Type/Description	$\text{Fe}_{wt\%} \times \frac{\text{Fe}}{\text{Fe}+\text{Mg}+\text{Ca}}$	$\frac{\text{Fe}}{\text{Fe}+\text{Mg}+\text{Ca}}$	$\frac{\text{Fe}_2\text{O}_3}{\text{Fe}_2\text{O}_3+\text{FeO}}$	$\frac{\text{Fe}_2\text{O}_3}{\text{FeO}}$	$\frac{\text{Fe}^{3+}}{\text{Fe}^{2+}}$
Mdp	Porphyritic Dolerite	4.75	0.44	0.25	0.62	0.56
Sslh	Interbedded Sst/Shale ¹	4.11	0.68	0.37	0.78	0.70
Ssl	Siltstone	4.11	0.68	0.37	0.78	0.70
Zf	Fuchsite Schist	3.54	0.31	0.17	0.20	0.18
Zm	Muscovite Schist	3.54	0.31	0.17	0.20	0.18
Zs	Sericite Schist	3.54	0.31	0.17	0.20	0.18
Zls	Undiff. Felsic Schists	3.54	0.31	0.17	0.20	0.18
Sc	Conglomerate	3.30	0.38	0.14	0.38	0.34
Scxm	Monomict Conglomerate	3.30	0.38	0.14	0.38	0.34
S	Undivided Sed. Rocks	3.30	0.38	0.14	0.38	0.34
Shcc	Carbonaceous Shale	3.02	0.45	0.71	2.44	2.19
Mg	Gabbro	2.58	0.29	0.13	0.15	0.13
Mg1	Gabbro - Kundana unit 1	2.58	0.29	0.13	0.15	0.13
Mg2	Gabbro - Kundana unit 2	2.58	0.29	0.13	0.15	0.13
Mg3	Gabbro - Kundana unit 3	2.58	0.29	0.13	0.15	0.13
Mg5	Gabbro - Kundana unit 5	2.58	0.29	0.13	0.15	0.13
Mg6	Gabbro - Kundana unit 6	2.58	0.29	0.13	0.15	0.13
Mg6A	Gabbro - Kundana unit 6A	2.58	0.29	0.13	0.15	0.13
Mgl	Leucocratic Gabbro	2.58	0.29	0.13	0.15	0.13
Mgm	Melanocratic Gabbro	2.58	0.29	0.13	0.15	0.13
Mgp	Porphyritic Gabbro	2.58	0.29	0.13	0.15	0.13
Hof	K-rich Ortho Amphibolite	2.52	0.29	0.17	0.21	0.19
Hpc	Ca-rich Para Amphibolite	2.52	0.29	0.17	0.21	0.19
Hm	Mafic Amphibolite	2.52	0.29	0.17	0.21	0.19
Mb	Basalt	2.38	0.29	0.18	0.24	0.22
Mbbx	Mafic P/clastic Breccia	2.38	0.29	0.18	0.24	0.22
Mbmng	Mount Goode Basalt	2.38	0.29	0.18	0.24	0.22
Mbp	Porphyritic Basalt	2.38	0.29	0.18	0.24	0.22
Mbx	Basaltic A/clastic Rock	2.38	0.29	0.18	0.24	0.22
Mby	Mafic P/clastic Rock	2.38	0.29	0.18	0.24	0.22
M	Undivided Mafic Rocks	2.38	0.29	0.18	0.24	0.22

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Table 5.4: *continued*

Rock Code	Rock Type/Description	$\text{Fe}_{wt\%} \times \frac{\text{Fe}}{\text{Fe}+\text{Mg}+\text{Ca}}$	$\frac{\text{Fe}}{\text{Fe}+\text{Mg}+\text{Ca}}$	$\frac{\text{Fe}_2\text{O}_3}{\text{Fe}_2\text{O}_3+\text{FeO}}$	$\frac{\text{Fe}_2\text{O}_3}{\text{FeO}}$	$\frac{\text{Fe}^{3+}}{\text{Fe}^{2+}}$
Sct	Chert ²	2.14	0.30	0.31	0.69	0.62
X	Mylonite ²	2.14	0.30	0.31	0.69	0.62
?	Unknown/Unclassified unit ²	2.14	0.30	0.31	0.69	0.62
Upx	Pyroxenite	2.12	0.24	0.14	0.18	0.16
Mbu	Mafic U/mafic (Greenstone)	1.74	0.21	0.18	0.24	0.21
Mmb	Magnesian Basalt	1.74	0.21	0.18	0.24	0.21
San	Undivided Arenite	1.61	0.33	0.28	0.42	0.38
Hou	Mg-rich Ortho Amphibolite	1.56	0.21	0.14	0.16	0.15
Houh	Mg-rich Ortho Hornfels	1.56	0.21	0.14	0.16	0.15
Sfw	Feldspathic Wacke	1.53	0.39	0.40	0.96	0.86
Ivs	Int. Volcanogenic Sed. Rock	1.53	0.39	0.40	0.96	0.86
Sw	Undivided Wacke	1.53	0.39	0.40	0.96	0.86
Svfw	Volcanic Feldspathic Wacke	1.53	0.39	0.40	0.96	0.86
Svw	Volcanic Wacke	1.53	0.39	0.40	0.96	0.86
Svg	Volcanogenic Sed. Rock	1.53	0.39	0.40	0.96	0.86
Zac	Actinolite Schist	1.49	0.20	0.17	0.20	0.18
Gsdi	Syenodiorite	1.39	0.31	0.30	0.51	0.46
Mdq	Quartz Dolerite	1.27	0.30	0.41	0.72	0.65
Utc	Talc-Chl. U/mafic Rock	1.26	0.17	0.21	0.26	0.24
Uac	Amph.-Chl U/mafic Rock	1.23	0.17	0.16	0.20	0.18
Shl	Shale	1.16	0.44	0.37	0.78	0.70
Sha	Shale (altered)	1.16	0.44	0.37	0.78	0.70
Homc	Fe-Ortho Amphibolite (c.g.)	1.15	0.20	0.40	0.67	0.61
Hom	Fe-Ortho Amphibolite (f.g.)	1.15	0.20	0.40	0.67	0.61
Homh	Fe-rich Ortho Hornfels	1.15	0.20	0.40	0.67	0.61
Hpt	Para Amphibolite (mafic)	1.15	0.20	0.40	0.67	0.61
U	Undivided Ultramafic Rock	0.93	0.13	0.29	0.49	0.44
Hpq	Quartzite	0.91	0.29	0.38	0.62	0.56
Usk	Serpentinised Komatiite	0.90	0.12	0.11	0.15	0.13
Uspd	Serpentinised Peridotite	0.90	0.12	0.11	0.15	0.13
Us	Serpentinite	0.90	0.12	0.11	0.15	0.13

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Table 5.4: *continued*

Rock Code	Rock Type/Description	$\text{Fe}_{wt\%} \times \frac{\text{Fe}}{\text{Fe}+\text{Mg}+\text{Ca}}$	$\frac{\text{Fe}}{\text{Fe}+\text{Mg}+\text{Ca}}$	$\frac{\text{Fe}_2\text{O}_3}{\text{Fe}_2\text{O}_3+\text{FeO}}$	$\frac{\text{Fe}_2\text{O}_3}{\text{FeO}}$	$\frac{\text{Fe}^{3+}}{\text{Fe}^{2+}}$
Zu	Ultramafic Schist	0.89	0.14	0.22	0.18	0.16
Uk	Komatiite	0.88	0.13	0.39	0.73	0.66
Uxa	Ultramafic Autobreccia	0.88	0.13	0.39	0.73	0.66
Gto	Tonalite	0.84	0.34	0.42	0.75	0.67
Upd	Peridotite	0.83	0.12	0.30	0.52	0.47
Fd	Dacite (even grained)	0.82	0.29	0.38	0.76	0.68
Ia	Andesite (even grained)	0.80	0.25	0.43	2.25	2.02
Ifp	Porphyritic Andesite	0.80	0.25	0.43	2.25	2.02
Scvm	Volc.-derived Conglomerate	0.70	0.23	0.25	0.52	0.47
Hgf	Felsic Gneiss	0.69	0.36	0.46	1.02	0.92
Gdi	Granodiorite	0.69	0.32	0.44	0.89	0.80
Gdiwee	Weebo Granodiorite	0.69	0.32	0.44	0.89	0.80
Pfbh	Felds. Hbl. Bio. Porphyry	0.67	0.40	0.40	0.78	0.70
Pf	Feldspar Porphyry	0.67	0.40	0.40	0.78	0.70
Pfqh	Feldspar Qtz Bio. Porphyry	0.67	0.40	0.40	0.78	0.70
Pfqh	Feldspar Qtz Hbl. Porphyry	0.67	0.40	0.40	0.78	0.70
Pfq	Feldspar Qtz Porphyry	0.67	0.40	0.40	0.78	0.70
Gmo	Monzonite	0.67	0.30	0.59	1.45	1.31
Pfh	Plag. $\pm$ Hbl. Porphyry	0.67	0.40	0.40	0.78	0.70
Hpqh	Si-rich Hornfels	0.67	0.61	0.86	6.33	5.70
Gsy	Syenite	0.65	0.38	0.54	1.95	1.76
Svcf	Fragmental (c.g.)	0.63	0.37	0.40	1.62	1.46
Fpbx	Felsic Pyroclastic Breccia	0.63	0.37	0.40	1.62	1.46
Ftc	Felsic Tuff (crystal lithic)	0.63	0.37	0.40	1.62	1.46
Svff	Fragmental (f.g.)	0.63	0.37	0.40	1.62	1.46
Svmf	Fragmental (m.g.)	0.63	0.37	0.40	1.62	1.46
Ft	Meta-. Felsic Tuff & Lava	0.63	0.37	0.40	1.62	1.46
Fvx	Undiv. Fels. A/clastic Rock	0.63	0.37	0.40	1.62	1.46
Fvy	Undiv. Fels. P/clastic Rock	0.63	0.37	0.40	1.62	1.46
Fv	Undivided Felsic Volc. Rock	0.63	0.37	0.40	1.62	1.46
Ipbx	Int. P/clastic Breccia	0.56	0.42	0.38	0.63	0.57

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Table 5.4: *continued*

Rock Code	Rock Type/Description	$\text{Fe}_{wt\%} \times \frac{\text{Fe}}{\text{Fe}+\text{Mg}+\text{Ca}}$	$\frac{\text{Fe}}{\text{Fe}+\text{Mg}+\text{Ca}}$	$\frac{\text{Fe}_2\text{O}_3}{\text{Fe}_2\text{O}_3+\text{FeO}}$	$\frac{\text{Fe}_2\text{O}_3}{\text{FeO}}$	$\frac{\text{Fe}^{3+}}{\text{Fe}^{2+}}$
Ivx	Undiv. Int. A/clastic Rock	0.56	0.42	0.38	0.63	0.57
Iv	Undivided Int. Volc. Rock	0.56	0.42	0.38	0.63	0.57
Gt	Granitoid	0.50	0.37	0.46	1.03	0.93
Gr	Granite	0.48	0.40	0.43	0.82	0.74
Scpf	Jones Creek Conglomerate	0.36	0.34	0.44	0.78	0.70
Scxp	Polymict Conglomerate	0.36	0.34	0.44	0.78	0.70
Gmoq	Quartz Monzonite	0.35	0.36	0.51	1.40	1.26
Gp	Pegmatite	0.07	0.31	0.67	2.00	1.80
Perm	Permian Sedimentary Rock ³	-999	-999	-999	-999	-999
Pmd	Proterozoic Dolerite ³	-999	-999	-999	-999	-999
Pd	Proterozoic Dykes ³	-999	-999	-999	-999	-999

5.4.8 Rock Strength Data Sets

Although it is generally recognized that competency contrasts across lithological boundaries are an important control on the location of deposits, there are little data on how to model these rheological contrasts. Yun's study (Yun, 2000) employed subjective estimates and Holyland's work (Holyland *et al.*, 1993; Groves *et al.*, 1997) is based on proprietary software and few details on how the calculations are performed have been published. To help determine the best way to model rheological contrast, a number of different rock strength parameters were tested (i.e. two different compilations of Young's Modulus, uniaxial compressive and tensile strength, and fracture toughness). Subjective estimates of rock competency, expressed as classes and fuzzy membership values, were also used to prepared layers depicting rheological contrasts at lithological boundaries layers. These rheological-contrast layers are described in Section 5.5.11 below.

¹Abbreviations: a/clastic = autoclastic, amphib. = amphibolite, bio = biotite, c.g. = coarse-grained, fels. = felsic, f.g. = fine-grained, hbl = hornblende, int. = intermediate, m.g. = medium-grained, meta- = metamorphosed, p/clastic = pyroclastic, plag. = plagioclase, qtz = quartz, sst = sandstone, sed. = sedimentary, undiff. = undifferentiated, undiv. = undivided, & u/mafic = ultramafic.

²Chemical ratios for these rock units represent area weighted averages for all rock units.

³Rock units formed after gold mineralization (~ 2.6 Ga) are represented in raster format GIS layers with the value -999, which is the default *no data* value for ARCVIEW.

Measured Rock Strength and Deformational Properties

Rock strength and deformational data for Young's modulus, uniaxial compressive and tensile strengths and fracture toughness were provided by M. Lee (unpublished data from Australian Mining Consultants, 2000; abbreviated as AMC). Some of the data supplied by AMC originated from Szwedzicki & Jiang (1994). Although these data refer to rocks from mines in the Yilgarn Terrane, many of the 108 rock types in the simplified lithology legend derived from the solid geology map obtained from Goldfields Exploration Pty Ltd were not available. In such cases, an estimate of the rock strength properties was made selecting a rock type with similar deformational properties. The parameter values used to calculate the rheological contrast at lithological boundaries represent the average value in the AMC data set for a specific rock type from different mine sites. In addition, Young's Modulus data from a compilation of rock properties by Hatheway & Kiersch (1989) have also been tabulated (Table 5.5).

Subjective Estimates of Rock Competency

There is an overall lack of rock strength properties for many specific rock types in the Kalgoorlie Terrane. The properties that are available commonly apply only to a particular unit with a specific alteration assemblage and fracture density at a particular mine. Thus, subjective estimates of relative rock strength were also made in this study.

Rocks in the detailed geology legend (108 rock types) are ranked according to their tendency for brittle or ductile failure, based on the field observations by Prof. David Groves. The primary criterion used to estimate rock competency on a regional-scale is silica content and mineralogy. The following minerals are associated with decreasing strength (from left to right);

quartz → plagioclase → hornblende → biotite → sericite → talc

Quartz-rich rocks are more competent than rocks which are rich in mafic minerals. In addition to silica content, subjective estimates of the relative competency of host rocks are based on (in decreasing order of importance); modal mineralogy, grain size, fabric development, texture, and metamorphic grade. For example, banded iron formation and basalt are ranked as very competent, whereas ultramafic schists are ranked as very incompetent under greenschist facies conditions. There may be reversals in rheology at amphibolite facies. Figure 5.3 illustrates how the criteria were applied.

Figure 5.3. Criteria used for subjective estimates of rock strength. The importance of the criterion decreases from top to bottom and the competency of rocks decreases from left to right. Provided that the rocks are compared under conditions of equal lithostatic and hydrostatic pressures and temperature and assuming the rock does not contain pre-existing fractures, silica content and modal mineralogy are the most significant factors in determining the rock strength

Rock units later in age than gold deposits were assigned the value -9999 and excluded from rheology contrast calculations. The steps used to produce the rheology contrast layers are described in Section 5.5.11 below.

A percentile transformation was then applied and the values scaled to the range [0,1]. The resultant parameter is a fuzzy membership value. Two GIS rheology layers were prepared; one containing a continuous, fuzzy-membership variable (layer *l2.L1*), and the other containing values in the range [1,10] representing ten classes of rock competency (layer *l2.L2*). Values in the subjectively estimated layers for each rock type are shown in Table 5.5 below. The rock strength layers, *l2.Lrh1-5* correspond to the subjective fuzzy membership layer, subjective ten-class layer, Young's modulus (AMC data), Young's modulus (Hatheway & Kiersch, 1989 data), uniaxial compressive strength, tensile strength, and fracture toughness and are included in the ARCVIEW directory on the attached CD-ROM (vol. 1). The layer, *l2.Lrh5*, depicting fracture toughness is shown in Figure 5.14

5.4.9 Metamorphic Grade

A metamorphic-grade map was prepared from a combination of maps by Binns *et al.* (1976) and Witt (1993). Scanned images of the maps, which covered different parts of

the Kalgoorlie study area, were digitized in ARCVIEW. Boundaries of the metamorphic domains were adjusted slightly so that they matched the crustal-scale faults and shear zones of the solid geology map of the study area. There are four classes of rock in the metamorphic-grade map, which were assigned the numeric codes shown in brackets; granite (0), amphibolite (1), upper greenschist (2), and lower greenschist facies (3). The numeric codes were assigned so that the code increases with increasing favourability for gold deposits. A raster version of the metamorphic grade map is shown in Figure 5.15.

Table 5.5: Rock strength and deformational properties of rocks in the Kalgoorlie study area: rocks listed in order of decreasing strength. Values in brackets in the comments column indicate the number of samples used to calculate averages.

Rock Code	Rock Type/ Description	Rock Strength		Young's Modulus		UCS ³ (MPa)	UTS (MPa)	Fract. Tough. $MPa \cdot m^{\frac{1}{2}}$	Comments
		Fuzzy	Class	CRC ¹ (GPa)	AMC ² (GPa)				
Sct	Chert	1.00	10	53.4	85.0	156	8.0	1.61	CRC (1) Chalcedonic chert. AMC: (1) vein quartz, except fracture toughness set to granite value.
Hpq	Quartzite	0.99	10	84.2	85.0	156	8.0	1.61	CRC:(3) Unaltered rocks. AMC: (1) as above
Hpqh	Si-rich Hornfels	0.98	10	95.8	76.0	217	20.6	3.12	CRC:(1) Hornfels. AMC:(2) Ave. of metasediment & metasilstone
Sif	Iron Formation	0.97	9	67.1	64.0	152	13.6	1.76	CRC:(1) Hematite ore. AMC: (1) BIF, Bounty Mine
Bif	Banded Iron Formation	0.96	9	67.1	64.0	152	13.6	1.76	CRC:(1) As above.
Homh	Fe-rich Ortho Hornfels	0.95	9	95.8	76.0	217	20.6	3.12	CRC:(1) Hornfels. AMC:(2) Ave. of metasediment & metasilstone
Houh	Mg-rich Ortho Hornfels	0.94	9	95.8	76.0	217	20.6	3.12	CRC:(1) Hornfels. AMC:(2) As above.
Pfq	Feldspar Qtz Porphyry	0.93	9	64.7	63.3	250	17.2	2.37	CRC:(20) Ave. of all granites excluding altered & foliated samples
Pfqh	Felds. Qtz Hbl. Porphyry ⁶	0.92	9	64.7	63.3	250	17.2	2.37	CRC:(20) As above. AMC:(7) Two extreme UCS values were omitted from the average calculation.
Pfqh	Felds. Qtz Bio. Porphyry	0.91	9	64.7	63.3	250	17.2	2.37	CRC:(20) As above. AMC:(7) As above.
Pf	Feldspar Porphyry	0.90	9	64.7	63.3	250	17.2	2.37	CRC:(20) As above. AMC:(7) As above.
Pfh	Plag. $\pm$ Hbl. Porphyry	0.90	9	64.7	63.3	250	17.2	2.37	CRC:(20) As above. AMC:(7) As above.
Pfbh	Felds. Hbl. Bio. Porphyry	0.89	9	64.7	63.3	250	17.2	2.37	CRC:(20) As above. AMC:(7) As above.
Gr	Granite	0.88	9	75.7	48.2	141	10.8	1.61	CRC:(10) Ave. of upper 50 percentile of 20 granites AMC: (1) Zarnitain, USSR
Gmoq	Quartz Monzonite	0.87	9	72.1	48.2	141	10.8	1.61	CRC:(5) AMC: (1) Used value for granite, Zarnitain, USSR
Gdi	Granodiorite	0.86	9	69.9	48.2	141	10.8	1.61	CRC:(6) AMC: (1) Used value for granite, Zarnitain, USSR
Gdi-wee	Weebo Granodiorite	0.85	9	69.9	48.2	141	10.8	1.61	CRC:(6) Granodiorite AMC: (1) Used value for granite, Zarnitain, USSR
Gto	Tonalite	0.84	9	69.9	48.2	141	10.8	1.61	CRC:(6) Ave. of 6 granodiorites AMC: (1) Used value for granite, Zarnitain, USSR
Gsy	Syenite	0.83	9	72.4	51.0	172	16.7	1.61	CRC:(2) AMC: (2) Used granite value for fracture toughness.

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Table 5.5: *continued*

Rock Code	Rock Type/ Description	Rock Strength		Young's Modulus		UCS ³ (MPa)	UTS (MPa)	Fract. Tough. $\text{MPa m}^{\frac{1}{2}}$	Comments
		Fuzzy	Class	CRC ¹ (GPa)	AMC ² (GPa)				
Gmo	Monzonite	0.82	9	72.1	48.2	141	10.8	1.61	CRC:(5) Quartz Monzonite. AMC: (1) Used value for granite, Zarmitain, USSR
Gsdi	Syenodiorite	0.81	9	68.8	48.2	141	10.8	1.61	CRC:(6) Ave. of 6 diorites. AMC: (1) Used value for granite, Zarmitain, USSR
Gt	Granitoid	0.80	9	64.7	48.2	141	10.8	1.61	CRC:(20) Ave. of all granites excluding altered & foliated samples. AMC: (1) Used value for granite, Zarmitain, USSR
Fd	Dacite (even grained)	0.79	8	64.6	80.3	215	16.7	2.96	CRC:(1) Used value for andesite. AMC (8) Used value for dolerite
Ia	Andesite (even grained)	0.78	8	64.6	80.3	215	16.7	2.96	CRC:(1) AMC:(8) Used value for dolerite
Mdq	Quartz Dolerite	0.77	8	90.9	76.5	223	17.9	2.96	CRC:(7) Ave. of 7 diabases. AMC (1) Qtz dolerite from Darlot mine (Fracture toughness = ave. of 5 dolerites.)
Md	Dolerite	0.76	8	90.9	80.3	215	16.7	2.96	CRC:(7) As above. AMC (8) Dolerite
Mdp	Porphyritic Dolerite	0.75	8	90.9	80.3	215	16.7	2.96	CRC:(7) As above. AMC (8) Dolerite
Mdl	Leucocratic Dolerite	0.74	8	90.9	80.3	215	16.7	2.96	CRC:(7) As above. AMC (8) Dolerite
Ifp	Porphyritic Andesite	0.73	8	64.6	80.3	215	16.7	2.96	CRC:(1) Andesite. AMC (8) Used value for dolerite
Fv	Undiv. Fels. Volc. Rock	0.72	8	60.0	64.3	152	19.0	1.42	CRC: Median value for medium compressibility range, p-689 after Deere & Miller (1966). AMC: (6)
Iv	Undiv. Int. Volc. Rock	0.71	8	64.6	57.8	141	20.6	2.29	CRC:(1) Used value for andesite. AMC: (15) Int. volcanic rocks & tuff. Used ave. of granite and dolerite for Frac. toughness.
Gp	Pegmatite	0.70	8	61.6	63.6	192	7.9	1.70	CRC:(1). AMC: (2)
Mg5	Gabbro - Kundana unit 5	0.70	8	86.2	85.4	216	17.5	2.67	CRC:(2) Gabbro. AMC: (2)
Mg6	Gabbro - Kundana unit 6	0.69	8	86.2	85.4	216	17.5	2.67	CRC:(2) Gabbro. AMC: (2)
Mb	Basalt	0.68	7	58.9	72.0	191	20.4	3.31	CRC:(19) Ave. of 19 non-vesicular basalts. Excl. one sample with very high value. AMC: (28)
Mb-m	Magnetic Basalt	0.67	7	58.9	80.3	215	16.7	2.96	CRC:(19) As above. AMC:(8) Used value for dolerite
Mb-mg	Mount Goode Basalt	0.66	7	58.9	72.0	191	20.4	3.31	CRC:(19) As above. AMC: (28) Used basalt value
Mbp	Porphyritic Basalt	0.65	7	58.9	72.0	191	20.4	3.31	CRC:(19) As above. AMC: (28) Used basalt value
Mbu	Mafic U/mafic	0.64	7	35.0	88.3	212	16.9	3.65	CRC:(4) Ave. of 4 olivine basalts. AMC: (1) Used value for high magnesium basalt.

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Table 5.5: *continued*

Rock Code	Rock Type/ Description	Rock Strength		Young's Modulus		UCS ³ (MPa)	UTS (MPa)	Fract. Tough. $\text{MPa m}^{\frac{1}{2}}$	Comments
		Fuzzy	Class	CRC ¹ (GPa)	AMC ² (GPa)				
Mmb	Magnesian Basalt	0.64	7	35.0	88.3	212	16.9	3.65	CRC:(4) As above. AMC: (1) High magnesium basalt.
Mg	Gabbro	0.63	7	50.0	79.0	216	14.6	2.67	CRC:(4) Gabbro. AMC: (2)
Mg1	Gabbro - Kundana unit 1	0.62	7	50.0	79.0	216	14.6	2.67	CRC:(4) Gabbro. AMC: (2)
Mg2	Gabbro - Kundana unit 2	0.61	7	50.0	79.0	216	14.6	2.67	CRC:(4) Gabbro. AMC: (2)
Mg3	Gabbro - Kundana unit 3	0.60	7	50.0	79.0	216	14.6	2.67	CRC:(4) Gabbro. AMC: (2)
Mg6A	Gabbro - Kundana unit 6A	0.59	7	65.0	79.0	216	14.6	2.67	CRC: Known as quartz-rich brittle unit, therefore value for porphyry was used. AMC: (2)
Mgp	Porphyritic Gabbro	0.58	7	50.0	79.0	216	14.6	2.67	CRC:(4) Gabbro. AMC: (2)
Mgl	Leucocratic Gabbro	0.57	7	50.0	79.0	216	14.6	2.67	CRC:(4) Gabbro. AMC: (2)
Mgm	Melanocratic Gabbro	0.56	7	50.0	79.0	216	14.6	2.67	CRC:(4) Gabbro. AMC: (2)
Mbbx	Mafic P/clastic Breccia	0.55	7	47.0	72.0	191	20.4	3.31	CRC:(9) Lower 50 percentile of basalts, incl. altered & amygdaloidal rocks
Hgf	Felsic Gneiss	0.54	6	56.3	63.6	205	7.5	1.70	CRC:(12). AMC: (2) Used value for pegmatite.
Hof	K-rich Ortho Amphibolite	0.51	6	60.8	76.0	217	20.6	3.12	CRC:(2) Amphibolite. AMC: (2) Ave. of metasilstone & metasedimentary rock.
Hom	Fe-Ortho Amphib. (f.g.)	0.50	6	60.8	76.0	217	20.6	3.12	CRC:(2) Amphibolite. AMC: (2)
Homc	Fe-Ortho Amphib. (c.g.)	0.50	6	60.8	76.0	217	20.6	3.12	CRC:(2) Amphibolite. AMC: (2)
Hpc	Ca-rich Para Amphibolite	0.49	6	60.8	76.0	217	20.6	3.12	CRC:(2) Amphibolite. AMC: (2)
Hpt	Para Amphibolite (mafic)	0.48	6	60.8	76.0	217	20.6	3.12	CRC:(2) Amphibolite. AMC: (2)
Hou	Mg-rich Ortho Amphibolite	0.47	6	60.8	76.0	217	20.6	3.12	CRC:(2) Amphibolite. AMC: (2)
Hm	Mafic Amphibolite	0.46	6	60.8	76.0	217	20.6	3.12	CRC:(2) Amphibolite. AMC: (2)
M	Undivided Mafic Rocks	0.45	6	47.5	72.0	191	20.4	3.31	CRC:(23) Used area weighted ave. of basalts & olivine basalts. AMC: (28) Used value for basalt.
San	Undivided Arenite	0.44	5	17.5	74.2	219	21.7	2.92	CRC:(21) Sandstone. AMC (1) Used sample of Black Flag Beds sedimentary rock, Junction Mine.
Ft	Meta. Felsic Tuff & Lava	0.43	5	33.9	64.3	152	19.0	1.42	CRC:(5) In Berkman (1995), tuff values at low end of granite range so used lower 25 percentile of CRC granite data. AMC:(6) Used value for felsic volcanic rock.
Fpbx	Felsic P/clastic Breccia	0.42	5	33.9	64.3	152	19.0	1.42	CRC:(5) As above. AMC: (6) Used value for felsic volcanic rock.
Ftc	Felsic Tuff (crystal lithic)	0.41	5	33.9	64.3	152	19.0	1.42	CRC:(5) As above. AMC: (6) Used value for felsic volcanic rock.

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Table 5.5: *continued*

Rock Code	Rock Type/ Description	Rock Strength		Young's Modulus		UCS ³ (MPa)	UTS (MPa)	Fract. Tough. $\text{MPa m}^{\frac{1}{2}}$	Comments
		Fuzzy	Class	CRC ¹ (GPa)	AMC ² (GPa)				
Fvx	Undiv. Fels. A/clastic	0.40	5	33.9	64.3	152	19.0	1.42	CRC:(5) As above. AMC: (6) Used value for felsic volcanic rock.
Fvy	Undiv. Fels. P/clastic Rock	0.39	5	33.9	64.3	152	19.0	1.42	CRC:(5) As above. AMC: (6) Used value for felsic volcanic rock.
Ivx	Undiv. Int. A/clastic Rock	0.38	5	33.9	57.8	141	20.6	2.29	CRC:(5) As above. AMC: (15) Ave. of value intermediate volcanics and tuff values. Frac. toughness value calculated as the average of granite and dolerite.
Ipbx	Int. P/clastic Breccia	0.37	5	33.9	57.8	141	20.6	2.29	CRC:(5) As above. AMC: (15) As above.
Sc	Conglomerate	0.36	5	77.9	75.1	114	14.4	2.87	CRC:(1) Conglomerate. AMC: (4) Conglomerate.
Scxm	Monomict Conglomerate	0.35	5	77.9	75.1	114	14.4	2.87	CRC:(1) Conglomerate. AMC: (4) Conglomerate.
Sexp	Polymict Conglomerate	0.34	5	77.9	75.1	114	14.4	2.87	CRC:(1) Conglomerate. AMC: (4) Conglomerate.
Scpf	Jones Creek Conglomerate	0.33	5	77.9	75.1	114	14.4	2.87	CRC:(1) Conglomerate. AMC: (4) Conglomerate.
Scvm	Volc.-derived Conglomerate	0.32	5	33.9	75.1	114	14.4	2.87	CRC: Set to same value estimated for tuff (see above). AMC: (4) Conglomerate
Sfw	Feldspathic Wacke	0.31	4	33.9	61.6	123	16.2	1.10	CRC: As above. AMC: (3) Ave. of arkosic grit, felsic grit and felsic clastic, Black Swan mine.
Svfw	Volcanic Feldspathic Wacke	0.30	4	43.4	64.3	152	19.0	1.42	CRC:(2) Average of 2 argillites. AMC (6) Used value for undivided felsic volcanic rock above.
Svff	Fragmental (f.g.)	0.30	4	33.9	61.6	123	16.2	1.10	CRC: Set to value as undivided felsic & intermediate clastic rocks
Svmf	Fragmental (m.g.)	0.29	4	43.4	64.3	152	19.0	1.42	CRC:(2) Average of 2 argillites. AMC (6) Used value for undivided felsic volcanic rock above.
Svcf	Fragmental (c.g.)	0.28	4	43.4	64.3	152	19.0	1.42	CRC:(2) Average of 2 argillites. AMC (6) Used value for undivided felsic volcanic rock above.
Mbx	Basalt. A/clastic Rock	0.27	4	47.0	72.0	191	20.4	3.31	CRC:(9) Used lower 50 percentile of basalt values, incl. altered & amygdaloidal rocks. AMC: (28) Used value for basalt.
Mby	Mafic P/clastic Rock	0.26	4	47.0	72.0	191	20.4	3.31	CRC: As above. AMC: (28) Used value for basalt.
Ivs	Int. Volcanogenic Sed. Rock	0.25	4	33.9	61.6	123	16.2	1.10	CRC: Set to value estimated for tuff (see above). AMC: (3) Ave. of arkosic grit, felsic grit and felsic clastic, Black Swan mine.
Svg	Volcanogenic Sed. Rock	0.24	4	33.9	61.6	123	16.2	1.10	CRC: As above. AMC: (3) As above.
Ssl	Siltstone	0.23	4	26.3	61.1	168	18.5	2.61	CRC:(4). AMC: (2) Black Flag Beds sedimentary rock.

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Table 5.5: *continued*

Rock Code	Rock Type/ Description	Rock Strength		Young's Modulus		UCS ³ (MPa)	UTS (MPa)	Fract. Tough. $\text{Mpa m}^{\frac{1}{2}}$	Comments
		Fuzzy	Class	CRC ¹ (GPa)	AMC ² (GPa)				
Sw	Undivided Wacke	0.22	4	33.9	61.6	123	16.2	1.10	CRC: Set to value estimated for tuff (see above). AMC: (3) Ave. of arkosic grit, felsic grit and felsic clastic, Black Swan mine.
Sslh	Interbedded Sst/Shale	0.21	4	24.0	61.1	168	18.5	2.61	CRC: Average of values for siltstone and shale. AMC: (2) Black Flag Beds sedimentary rock.
Svw	Volcanic Wacke	0.20	4	33.9	61.6	123	16.2	1.10	CRC: Set to value estimated for tuff (see above). AMC: (3) Ave. of arkosic grit, felsic grit and felsic clastic, Black Swan mine.
S	Undivided Sed. Rocks	0.19	4	27.3	60.2	154	16.9	1.28	CRC: Area weighted average of values for volcanogenic sediments (tuff) & shale. AMC: (8) Ave of all sedimentary rocks.
Uk	Komatite	0.18	4	70.2	82.0	207	17.1	3.90	CRC: Carbonate-altered Komatiitic basalt from the Bounty mine AMC: (3) Ave of 3 komatiitic basalts.
Upx	Pyroxenite	0.17	4	17.6	70.8	118	19.3	2.61	CRC:(2) Excluded. 2 very high values as most rocks in Kalgoorlie area are altered. AMC: (1) Used value for peridotite (below).
Upd	Peridotite	0.16	4	70.8	70.8	118	19.3	2.61	CRC: non-serpentinized Peridotite from the Bounty mine. AMC: (1)
Usk	Serpentinised Komatiite	0.15	3	38.8	47.8	95	8.3	1.76	CRC: Serpentinite-talc u/mafic rock, Perseverance mine. AMC: (3) Ave. of serp-talc, ol-serp. rocks (Perseverance) & Hannans Lake serpentinite (Mt Charlotte).
Uspd	Serpentinised Peridotite	0.14	3	38.8	47.8	95	8.3	1.76	CRC: As above. AMC: (3) as above.
Us	Serpentinite	0.13	3	38.8	47.8	95	8.3	1.76	CRC: As above. AMC: (3) as above.
U	Undivided U/mafic Rock	0.12	3	54.6	49.5	98	11.3	1.46	CRC: Ave. of 9 values for talc-chl. & talc-carb. altered rocks from AMC data. AMC: (11).
Uac	Amph.-Chl U/mafic Rock	0.11	3	67.3	49.5	98	11.3	1.46	CRC: Serpentinized (antigorite-bearing) u/mafic rock, Kambalda from AMC data. AMC: (11) Used value for undivided ultramafic rock above.
Shcc	Carbonaceous Shale	0.10	2	21.7	72.5	96	15.4	1.10	CRC: (36) Shale. AMC: (19) Used average for shale.
Sha	Shale (altered)	0.09	2	21.7	72.5	96	15.4	1.10	CRC: (36) Shale. AMC: (19) Used average for shale.
Shl	Shale	0.09	2	21.7	72.5	96	15.4	1.10	CRC: (36) Shale. AMC: (19) Used average for shale.

continued on next page

Table 5.5: *continued*

Rock Code	Rock Type/ Description	Rock Strength		Young's Modulus		UCS ³ (MPa)	UTS (MPa)	Fract. Tough. $\text{Mpa m}^{\frac{1}{2}}$	Comments
		Fuzzy	Class	CRC ¹ (GPa)	AMC ² (GPa)				
Utc	Talc-Chl. U/mafic Rock	0.08	2	47.1	28.5	39	5.7	1.22	CRC: Talc-carb. altered u/mafic rock, Black Swan mine, AMC data. AMC: (3) Omitted extremely strong sample. Frac. toughness value from talc-carb. rock, Long shaft, Kambalda.
Uxa	Ultramafic Autobreccia	0.07	2	22.4	82.0	207	17.1	3.90	CRC: (2) Schist; 2 extreme values were not included in average. AMC: (3) Ave of 3 komatiitic basalts.
Zac	Actinolite Schist	0.06	2	22.4	72.5	96	15.4	1.10	CRC: As above. AMC: (19) Used average for shale.
Zf	Fuchsite Schist	0.05	1	22.4	72.5	96	15.4	1.10	CRC: As above. AMC: (19) Used average for shale.
Zls	Undiff. Felsic Schists	0.04	1	22.4	72.5	96	15.4	1.10	CRC: As above. AMC: (19) Used average for shale.
Zs	Sericite Schist	0.03	1	22.4	72.5	96	15.4	1.10	CRC: As above. AMC: (19) Used average for shale.
Zm	Muscovite Schist	0.02	1	22.4	72.5	96	15.4	1.10	CRC: As above. AMC: (19) Used average for shale.
Zu	Ultramafic Schist	0.01	1	22.4	32.5	49	6.1	1.31	CRC: As above. AMC: (6) Used lower 50 percentile of undivided ultramafic values.
?	Unknown/Unclassified ⁴	-999	6	53.2	66.0	166	15.6	2.33	Average for all rock types used.
X	Mylonite ⁵	-999	6	53.2	66.0	166	15.6	2.33	Average for all rock types used.
Pd	Proterozoic Dykes	-999	-999	-999	-999	-999	-999	-999	Set to ARCVIEW default <i>no data</i> value (-999)
Perm	Permian Sed. Rock	-999	-999	-999	-999	-999	-999	-999	As above
Pmd	Proterozoic Dolerite	-999	-999	-999	-999	-999	-999	-999	As above

¹CRC refers to data obtained from Tables 3-5, Section X, Hatheway & Kiersch (1989).²AMC refers to unpublished data provided by M. Lee, Australian Mining Consultants Pty Ltd, 2000. These data are for rocks from mines in the Yilgarn Block.³UCS = uniaxial compressive strength, UTS = uniaxial tensile strength. The unconfined compressive strength data from AMC are for 50 mm core.⁴All values shown for the "Unknown/Unclassified" represent area weighted average values, except where -999 is used, which is the default *no data* value in ARCVIEW.⁵Rock units formed after gold mineralization (~2.6 Ga) are represented in raster format GIS layers with the value -999, which is the default *no data* value for ARCVIEW.⁶Abbreviations: a/clastic = autoclastic, amphib. = amphibolite, bio = biotite, c.g. = coarse-grained, fels. = felsic, f.g. = fine-grained, hbl = hornblende, int. = intermediate, m.g. = medium-grained, meta- = metamorphosed, p/clastic = pyroclastic, plag. = plagioclase, qtz = quartz, sst = sandstone, sed. = sedimentary, undiff. = undifferentiated, undiv. = undivided, & u/mafic = ultramafic.

5.4.10 Goldfields Pty Ltd Data Sets Not Used in Study

Primary GIS layers described above represent all the available data sets that provide uniform coverage over the complete study area and which are considered to be useful in delineating prospective areas for orogenic gold deposits at a regional scale.

A regolith geochemistry data set, containing point locations for 13,503 auger holes together with the maximum gold concentration in ppb, covers a 23×7 km north-south strip from Broad Arrow to Bardoc, and a percussion drill hole geochemistry data set containing the maximum gold and arsenic concentrations for 112,366 drill hole locations along the Bardoc Tectonic Zone were not included in this study, because they did not cover the entire study area.

In order to include data sets with incomplete coverage, a series of neural networks would have to be constructed so that parts of the study area where ten layers were available could be processed using a network with ten inputs and areas where nine data sets were available would be processed using a network with nine inputs and so on. An alternative would be to devise a method of filling in the missing areas with values that would be neither favourable nor unfavourable. However, a simple average is not suitable because background geochemical values, for example, vary with different lithologies. The problem of how to deal with missing data in a neural network analysis is an important one since most exploration data sets consist of areas of detailed information that do not all overlap. However, this issue requires further research and will most likely involve considerably more software development and is therefore the scope of the present study.

Two other data sets were available but not used in this study. These are a gamma-ray survey and a composite LANDSAT image. Both these data sets provide information about the surface mineralogy and, in the Kalgoorlie area where very little outcrop exists, the data sets are mainly useful for identification of regolith layers.

5.5 Derived GIS Layers

This section describes how the main set of layers that were used as inputs to the neural network analyses were prepared. All the GIS layers that form the inputs to neural networks except the metamorphic grade and deposits layers, are derived by processing the primary GIS layers described above in order to make an exploration criterion or ingredient of the mineral systems model for orogenic gold deposits more explicit. For example, the

structural layer contains a variety of faults and shear zones, although it is known that most deposits in the Kalgoorlie area are associated with crustal-scale NW-trending shear zones. Consequently, rather than present the network with a binary map indicating the presence or absence of faults, faults were separated into separate GIS layers according to scale and orientation and converted so that each cell in a new raster format map represents the proximity to the nearest fault of the specific type displayed in that GIS layer. Raw input parameters that have been modified in this way are referred to as features in the pattern recognition literature. The more effectively the input features presented to a neural network capture the underlying process responsible for the output variable (in this case, the favourability of a cell location for a gold deposit), the more effectively the network can learn the patterns in the data.

5.5.1 Simplified Geology Layers

The legend used by Goldfields Exploration Pty Ltd for the Bardoc Tectonic Zone and Kalgoorlie maps was simplified from 108 to 25 rock types (Table 5.2). Only 22 rock types appear on the legend, however, because lithological units corresponding to three of the rock types do not occur within the Kalgoorlie study area (i.e. as units mapped at 1:100000 scale; chert, iron formation, felsic gneiss and quartzite) and two units are not shown because they post-date gold mineralization (i.e. Proterozoic Dolerite and Permian Sedimentary Rock are represented as *no data* = -999, Table 5.2).

The simplified geology layer was converted to raster format and exported as an ASCII file. The ASCII file was imported into MATLAB (*geol_25.mat*) and used to create other derived layers, i.e. the 1-of-n-coded geology and favourable geology layers, described below. The simplified geology layer comprising 22 rock types is shown in Figure 5.7.

A raster-format, solid-geology map with 55 rock types was also derived from the original 108 rock-type, solid-geology layer (*l1_l_55_nohdr.asc*). This map was used to produce the distance-to-magnetic-anomaly and density-of-lithological-contacts layers described below. It was not used in the neural network experiments described in Chapter 7 directly, because the statistical relationship between deposits and each of the 55 lithologies is less reliable due to the fact that many rock types contain fewer than five known deposits.

5.5.2 Binary Deposit Layer

The primary deposit layer is a point data set in vector format. This was converted to a binary raster layer. As a preliminary step, deposits containing a resource of at least 1000 kg total contained gold were selected and a new attribute to store binary values was added to the database table attached to the vector deposit layer. All records for this field were initially set to one using the *Field Calculator* function. Converting the vector layer to a grid file (using a built-in ARCVIEW function) then resulted in a grid in which all deposits were represented by ones (*l24-d-bin1000*; CD-ROM, vol. 1). However, barren cells all contained a special *No Data* value (-9999) by default. Barren cells were converted to zeros using the ARCVIEW *Map Calculator* function and the following command;

$$([l24_d_bin1000].IsNull.Con(0.AsGrid,[l24_d_bin1000]))$$

5.5.3 Distance to Dolerite, Syenite, & Feldspar Porphyry Layers

Binary GIS layers showing the proximity to the nearest contact for several particularly favourable rock types and a potentially favourable rock type, were created from the solid geology layer. Binary layers were created in ARCVIEW by adding a new attribute field to the solid-geology shape file table, using the built-in field calculator function to select polygons with a simplified rock code = “pf” (Table 5.2) and then creating a grid theme based on the new attribute field. Binary grids contain 1’s to indicate the presence of the favourable rock type and all the remaining cells contain zeros.

Quartz dolerite and leucocratic dolerite were combined into a binary layer (GIS layer *l18-l-mdql* on the attached CD-ROM, vol. 1). These are particularly favourable host rocks as quartz dolerite forms a strongly mineralized unit within the thick Golden Mile Dolerite, which hosts the giant Golden Mile deposit. In addition, quartz dolerite and leucocratic dolerite are relatively competent, brittle units (Table 5.5) and both, particularly the leucocratic dolerite, have high $Fe_{tot} \times Fe / (Fe + Mg + Ca)$ (Phillips, 1986, and Table 5.4).

Feldspar porphyry units (feldspar porphyry, feldspar-quartz-biotite porphyry, feldspar-quartz-hornblende porphyry, feldspar-quartz porphyry, plagioclase $\pm$ hornblende porphyry) were also combined to form a binary layer (GIS layer *l4-l-pf* on the attached CD-ROM, vol. 1). As noted above (in Section 5.2.4) porphyritic intermediate to mafic intrusions are in places associated with gold mineralization and may indicate a connection between ore fluids with the lower crust (S.Halley, pers.comm., 2000). Also, porphyritic intrusions are

quartz-bearing and therefore very brittle (Table 5.5)

A binary layer was also created by combining syenite and syenodiorite units (GIS layer *l19_l_gsy* on the attached CD-ROM, vol. 1). Robert (1997) has noted that, in the Abitibi greenstone belt in Canada, gold ore bodies occur within and along the margins of syenitic stocks, and along faults and lithological contacts away from any intrusions. Orebodies in such positions are interpreted to represent proximal to distal components of large magmatic-hydrothermal systems centred on, and possibly genetically related to, composite syenitic stocks. A similar association has also been suggested by D. Groves (pers. comm., 2000). Syenite and syenodiorite are also relatively competent and brittle rock types (Table 5.5).

The binary rock-type layers were used to create a new set of layers, in which each cell value contains the distance to the nearest lithological contact of one of the selected rock types. The following procedure was used; first the analysis mask was set to an existing raster layer, in which all the *no data* areas are flagged with value -9999. Second, the zero values in the binary grids were converted to nulls (i.e. a special value used by ARCVIEW to signify *no data*, using the following *map calculator* command in the ARCVIEW analysis menu (where the porphyry layer *l4_l_pf* is used as an example);

$$([l4_l_pf_dist] = 0.AsGrid).SetNull([l4_l_pf_dist]).$$

The third step was to convert the binary layer to a layer containing distances using the ARCVIEW analysis function *find distances*. The last step in the procedure was to convert the resultant temporary file to a permanent grid file (i.e. layers *l4_l_pf_dist* shown in Figure 5.16, *l18_mdql_dist*, and *l9_gsy_dist*).

By overlaying the known deposit points over the quartz dolerite and syenite layers, it was possible to determine that, although an association of deposit points and the favourable lithologies appears to exist at a local scale, these rock types have not been mapped in units large enough to appear in more than one or two locations at the regional scale of the solid geology. Consequently, these two binary maps were discarded as possible input layers for neural network analysis.

5.5.4 Distance to Lithological Contacts

Previous prospectivity studies on orogenic gold deposits (Knox-Robinson, 1994; Yun, 2000) have both shown that proximity to lithological boundaries is an important factor control-

ling the location of deposits. Depending on the adjacent rock types, lithological boundaries may be the site of rheological and a chemical contrasts. The GIS layer representing the distance to the nearest lithological contact (*l39_c-dist*) was created from the solid geology layer (i.e. *geology.shp*; a polygon layer in vector format) using the procedure described in Section 5.5.3 (Fig. 5.17).

5.5.5 Distance to Faults and Shear Zones

Separate layers were created from the primary structural layer (*faults.shp*) for each of the fault and shear zone types, shown in Table 5.6.

Table 5.6. Characteristics of fault and shear zone types in primary GIS layer *faults.shp* used to form separate derived GIS layers.

Fault Type	Strike Direction	Definition (Deformation event)	Attribute value in <i>faults.shp</i>
crustal	NNW	≥ 100 km, D ₂ ¹	shear
regional	NNW	≥ 10 km, D ₂	shear
local	NE	≤ 10 km, dextral, D ₃ ²	fault
local	E	≤ 10 km, sinistral ³	fault

Crustal- and regional- scale structures were separated from the other faults on the basis of length, whilst the two classes of faults were separated on the basis of orientation. Crustal-scale faults and shear zones are defined as those greater than or equal to 100 km in length and regional faults as those at least 10 km in length. An additional attribute called *faultclass* was added to a copy of the *faults* layer (*struct.types.shp*). All the line segments corresponding to a particular type of fault/shear zone were then selected individually using the ARCVIEW *select-feature* tool and then a numeric value was assigned to the *faultclass* attribute for the selected features using the *field-edit* function. Later, all the records for each of the fault/shear zone types were selected and converted to raster-format layers (i.e. grid files *l20_s_crust*, *l21_s_shear*, *l22_s_ftt_ne*, *l23_s_ftt_e*). The procedure to convert these

¹D₂ refers to upright folding and high-angle reverse faulting in a structural evolution of the Yilgarn Block, which spans events D_E, D₁-D₄.

²D₃ to D₄ refer to sinistral and/or dextral oblique-slip faulting and reactivation of earlier formed faults.

³The east-west oriented faults appear correspond to the emplacement of Proterozoic dolerite dykes and therefore post-date the main period of gold mineralization. These faults could, however, be associated with the remobilization of earlier deposited gold.

single theme raster grids to distance grids (*l20_f1_dist*, *l21_f2_dist*, *l22_d3_dist*, *l23_d4_dist*) was the same as that for the lithological contacts described above (5.5.3). The layers are shown in Figures 5.18–5.20 below.

5.5.6 Distance to Fold Axes

The position of major anticlinal and synclinal axes were obtained by combining existing maps produced by Swager & Griffin (1990); Swager *et al.* (1990), Yun (2000) and Goldfields Exploration Pty Ltd. The line segments were traced over the existing maps to create a new vector format layer; *folds.shp*. In a second step, the attribute tables were queried to select all the anticlines and synclines in separate steps to create temporary raster grids containing either just anticlines or synclines and then in a third step, distance grids were created using the same procedure described for the lithological contacts above (5.5.3). The name of the grid files containing the distance to anticlinal and synclinal axes are *l46_dist_anti* and *l46_dist_sync*, respectively (Fig. 5.21 and 5.22).

5.5.7 Distance to Intersection of Regional Faults

The procedure to create a layer representing the distance to the nearest intersection of a NNW-trending and NE-trending regional fault 5.4 consists of two parts. The first step was to create a layer showing the intersection of the two fault types using layers *l21_s_f2* and *l22_s_d3* in ARCVIEW. The result of this step is a temporary file (*Map Query*, also save as a permanent grid; *l32_s_f2f3*) which was then used as an input to the ARCVIEW analysis function, *find distance* to produce the distance grid, *l33_s_f23gdst* (Fig. 5.23).

5.5.8 Distance to Magnetic Anomalies

An inspection of the deposit layer superimposed over the total magnetic intensity map (*l5_m_rtp*) in ARCVIEW revealed that there is an association of deposits with magnetic anomalies, but that the deposits are located close to the anomalies and not everywhere within the anomalies. Consequently, proximity to magnetic anomalies appeared to be a more useful predictor of deposit locations.

Since the total magnetic intensity values depend on the average or background values, and these in turn depend on the magnetic susceptibility of the rock, the approach used here was to calculate the z-score for each rock type separately; i.e. the difference between each

Figure 5.4. Procedure used to create a GIS raster layer showing distance to the nearest intersection of regional NNW- & NE-trending faults. The steps refer to ARCVIEW 3.1 commands.

cell value and the average value expressed as numbers of standard deviations. A solid geology layer with 55 rock types was used for this purpose. The z-scores were calculated for each rock type according to the following formula:

$$Z = \frac{x_{rock} - \mu_{rock}}{s_{rock}} \quad (5.1)$$

The procedure to produce the distance-to-magnetic-anomaly maps comprised three steps;

1. calculate z-scores,
2. create a set of binary anomaly maps, and
3. calculate distance grids.

Different thresholds were used in each map to define the anomalies. Figure 5.5 shows the processing steps in detail. Distance-to-magnetic-anomaly maps, *l14-mz-1-dist*, *l14-mz1-dist*, and *l14-mz2-dist*, were created for positive and negative anomalies using z-score threshold values of -1, +1, and +2, respectively.

5.5.9 Aeromagnetic First and Second Vertical Derivatives

Layers showing the first and second vertical derivative of the airborne total-magnetic intensity survey-data were created in the GEOSOFT *Oasis Montaj* software package built-in functions (see layers *l6_m.1vd* and *l7_m.2vd* in the ARCVIEW directory on the attached CD-ROM, vol. 1).

5.5.10 Strike of Faults and Contacts

The fault-strike layers, as well as the contact-strike, rheological and chemical contrast layers, were produced by Stephen Gardoll using ARC/INFO. Fault-strike layers were processed using an AML script written by Dr Carl Knox-Robinson (see Knox-Robinson *et al.*, 1996, p. 5-13). The following steps were required;

1. import faults.shp (ARCVIEW shape file) into ARC/INFO,
2. convert shape file to ARC/INFO polygon coverage (.pat file) using the *shapearc* command,
3. execute ARC/INFO *build* command to establish polygon topology,

1. Calculate Z-scores

2. Create binary anomaly maps using Z-score threshold

3. Create distance grid

Figure 5.5. Procedure used to create a GIS raster layer showing distance to the nearest magnetic anomaly. Magnetic anomalies are defined in terms of z-scores. Note; the *value* field used to create a relational join between the summary statistics and geology tables is a unique identifier for rock type.

4. execute AML to apply the ARCEDIT *spline* command, which inserts vertices into the line segments representing the faults. The *grain* parameter was set to produce vertices at intervals of 100 metres. As a result of the spline command, all the attributes of the original line segment are retained. A new attribute was added to the table to store the strike angles (*additem* command), which are calculated in the next step. The AML reads the arc attribute table (.aat) file associated with the line coverage; for each original fault-line segment, the script reads the coordinates of each pair of vertices defining the 100 metre segments and calculates the orientation of the each segment using the trigonometric identity; $\arctan\theta = \text{opposite}/\text{adjacent}$ and stores the strike value,
5. create distance grid by applying ARC/INFO command, *eucldistance*, “assign by value”. The output of this command is a raster grid. Instead of setting the value of each cell to the distance to the nearest fault as in the standard command, cell values are set to the strike of the nearest 100 metre fault segment, and
6. re-calculate all strikes in the range [180°-360°] to the equivalent angle in the range [0°-170°]. Angles were converted to avoid two identically oriented line segments (i.e. contacts or faults) being described by two different angles (e.g. 0° is equivalent to 180°).

Layers showing the strike of crustal-scale, NNW-trending, NE-trending and E-trending regional-scale faults and lithological contacts (l28_s_f1str, l29_s_f2str, l30_s_f3str, l31_s_f4str, and l39_c_str, respectively) are shown in Figures 5.25–5.27.

5.5.11 Rheological Contrast

Rheological-contrast layers were prepared from the seven rock-strength parameters described in Section 5.4.8 above. These are; subjective estimates (expressed as 10 classes and fuzzy membership values), Young’s modulus, uniaxial compressive strength, uniaxial tensile strength and fracture toughness. Two different data compilations were used for Young’s modulus; those of Hatheway & Kiersch (1989) and M. Lee (unpublished data from Australian Mining Consultants Pty Ltd, 2000). Rheological contrast layers, *l36_Lrh1–6*, are listed in Table 5.7 below. All these layers are derived from the vector-format, solid-geology layer, *geology.shp*, which contains the rock strength properties in an attribute table. Units post-dating the main gold mineralization (2645–2630 Ma; Yeats & McNaughton, 1997), such as Proterozoic Dolerite dykes and Permian sedimentary rocks, are assigned a value used in ARCVIEW and ARC/INFO to signify *no data*, and excluded from rheology

contrast calculations. Rheological-contrast layers were prepared in ARC/INFO using a similar procedure to that described for the contact-type layer above. Raw data used to calculate the rheological contrasts are given in Appendix D.5.

Each cell in the rheological-contrast layers represents the absolute value of the difference between the rock strengths at the nearest lithological boundary. The fuzzy membership values represent the favourability of the rock as a host for gold deposits due to the likelihood the rock will fail in a brittle manner, where surrounding rocks do not, thus resulting in structural permeability and influx of ore-bearing fluids.

The following procedure was used to create the rheological contrast layers;

1. import solid geology shape file (*geology.shp*) from ARCVIEW into ARC/INFO and convert to polygon coverage *geology* using the *shapepoly* command,
2. build new coverage for lines and polygons,
3. add *lrheol*, *rrheol*, & *rh1-7* (rheological contrast) fields to arc attribute table (.aat file),
4. fill the *lrheol* field with the rock-strength parameter values of the rock types on the left-hand side of rock boundaries as follows;
 - a) link the rock strength information in the *geology* polygon attribute table (.pat file) to the arc attribute table, which describes the lines, using the *geology#* field (default polygon identifier in the polygon attribute table) to create a relation join to the *lpoly#* field (containing identifier of left polygon) in the arc attribute table (.aat file). Both the .pat and .aat files refer to the solid geology coverage,
 - b) set the *lrheol* (left-hand rock type) equal to the rheology parameter in the polygon attribute table (e.g. Young's Modulus or fracture toughness etc.),
5. remove relational link,
6. repeat the step above to populate the *rrheol* field with values of the rheology parameter on the right-hand side of the contacts,
7. calculate rheological contrasts (stored in attribute fields *rh1-7*) by finding the difference between rock strength parameter values at contacts, for example as follows;

$$rh1 = | rrheol - lrheol |$$
8. convert polygon coverage to grid using the *rh1-7* attribute fields to supply the values, and

9. create distance grid using ARC/INFO command, *eucldistance*, “*assign by value*”. Instead of setting the value of each cell to the distance to the nearest fault as in the standard command, cell values are set to the rock strength contrast at the nearest lithological contact.

Table 5.7. Rheological contrast layers, which were evaluated as potential input GIS layers for neural network analyses

Layer name	Rock strength or deformational property
l36_lrh1	Subjective estimate, fuzzy membership
l36_lrh2	Subjective estimate, 10 classes
l36_lrh3	Young’s modulus (Hatheway & Kiersch, 1989)
l36_lrh4	Young’s modulus (Lee, 2000) ^a
l36_lrh5	Uniaxial compressive strength (Lee, 2000)
l36_lrh6	Uniaxial tensile strength (Lee, 2000)
l36_lrh7	Fracture toughness (Lee, 2000)

^aM. Lee, unpublished data from Australian Mining Consultants Pty Ltd, 2000

5.5.12 Chemical Contrast

A set of raster layers representing the difference in the chemical reactivity at the nearest lithological contact was prepared using the chemical ratios summarized in Table 5.4 (Section 5.4.7) above. Data for the calculations were obtained from AGSO’s OZCHEM whole-rock geochemical database (Table D.8, Appendix D).

The procedure used to create the chemical contrast layers is the same as that for the rheological contrast layers described above, except that *lrheol*, *rrheol*, and rh1–7 fields are replaced by *lchem*, *rchem*, and ch1–5, respectively. Like the rheological contrast layers, the chemical-contrast calculations were performed using data stored as attributes (*ch1–5*) in the solid geology layer, *geology.shp*. The ratios and the GIS database layer names are shown in Table 5.8 below. The first two ratios are molar ratios. The layers are shown in Figures 5.30, 5.31 and 5.32.

Table 5.8. Chemical contrast layers, which were evaluated as potential input GIS layers for neural network analyses

Layer name	Chemical ratio
l37_l_ch1	$\text{Fe}_{\text{wt}\%} * \text{Fe}_{\text{total}} / (\text{Fe}_{\text{total}} + \text{Mg} + \text{Ca})$
l37_l_ch2	$\text{Fe}_{\text{total}} / (\text{Fe}_{\text{total}} + \text{Mg} + \text{Ca})$
l37_l_ch3	$\text{Fe}_2\text{O}_3 / (\text{Fe}_2\text{O}_3 + \text{FeO})$
l37_l_ch4	$\text{Fe}_2\text{O}_3 / \text{FeO}$
l37_l_ch5	$\text{Fe}^{3+} / \text{Fe}^{2+}$

5.5.13 Favourable Contact Type

The main mechanism of gold deposition for orogenic lode-gold deposits in the Yilgarn is through fluid-wall rock reactions in which the iron-rich minerals in the host rocks react with sulphide complexes, which carry gold in solution, to form Fe-sulphides (Phillips & Groves, 1983; Mikucki, 1998). Consequently, upward migrating hydrothermal fluids may precipitate gold where there is a change in host rock. Further, fluid migration will occur into dilational zones of high fracture-related permeability, which tend to occur where rheological contrasts are high. Thus, the combination of rock types at lithological boundaries may play two roles in the localization of gold deposits.

The favourable contact-type GIS layer is a raster layer in which cell values represent the combination of rock types which occur at the nearest lithological boundary. Since the combinations represent a nominal data type, these rock-type combinations must be converted to a ratio data type. Using a version of the solid geology layer with 25 rock types as a starting point for processing gives a total of 134 rock-type combinations. Assigning a numerical code to each type is not appropriate for a parameter to be used as an input to a neural network, since the network would treat a pair of lithologies with a code of 10 as twice as large as a pair with the code 5. Clearly, if the two contact types are similarly prospective, such a coding scheme is misleading. Due to the large number of combinations, it was not feasible to use 1-of-n coding. This coding scheme was used for the small number of lithologies (12) used in the pilot study in Chapter 4. Instead, the association of known deposits with the different contact rock-type combinations was used as a statistical basis for converting the contact type categories to fuzzy membership values. The fuzzy membership values express the favourability of areas, for which the nearest contact is of a certain type, to host orogenic gold deposits.

The favourable contact-type layer was created in the following three main steps;

1. create the layer showing the nearest contact-type,
2. calculate statistical relationships between known deposits and contact types, and
3. convert to a fuzzy membership layer using statistics.

In the last step, the contact-type names were replaced by fuzzy membership values indicating the degree of favourability of the contact-type.

The nearest-contact-type layer was created using the same procedure as the one used to create the rheological layers described above. The contact-type layer is created by linking the rock name attribute associated with the polygons with the information about left and right neighbours of each polygon that is stored for all arcs in ARC/INFO. A unique name was generated for each contact type using an AML script. Each contact-type name consists of abbreviations for the pair of rock types arranged in alphabetical order. Cell values were then set equal to the concatenated rock codes for the lithologies at the nearest contact. Using a simplified legend with 25 rock types for the solid geology GIS layer results in 134 rock-type combinations. The procedure for ranking layers and for assigning fuzzy membership values for the contact-type layer is the same as that described for the favourable geology layer above.

Since there are some important differences the procedure is listed below. The steps are;

1. import solid geology shape file (*geology.shp*) from ARCVIEW into ARC/INFO and convert to polygon coverage *geology* using the *shapepoly* command,
2. build new coverage for lines and polygons,
3. add *lrocktype*, *rrocktype*, & *contact_type* fields to arc attribute table (.aat file),
4. fill the *lrocktype* field with the names of the rock types on the left-hand side of rock boundaries as follows;
 - a) link the rock name information in the *geology* polygon attribute table (.pat) to the arc attribute table to create a relation join to the *lpoly#* (field containing identifier of left polygon) in the arc attribute table (.aat file). Both the .pat and .aat files refer to the solid geology coverage,
 - b) set the *lrocktype* (left-hand rock type) equal to the value of the rock name field (*rt-25-desc*) in the polygon attribute table,
5. remove relational link,

6. repeat the step above to populate the *rrocktype* field with the name of the rock type on the right-hand side of the contact,
7. populate *contact_type* field by concatenating the *lrocktype* and *rrocktype* fields. This step results in two *contact_type* values for each contact type (e.g. basalt-granite and granite-basalt values are both generated for the same contact type).

The AML script to generate a unique name for each contact type is functionally equivalent to the following code fragment;

```

if (lrocktype < rrocktype) then
    contact_type = concatenate (lrocktype, rrocktype)
else
    contact_type = concatenate (rrocktype, lrocktype)
end

```

where *rrocktype* and *lrocktype* are processed as strings. This step resulted in a set of unique values where the contact types are expressed in alphabetic order of the rock types,

8. convert polygon coverage to grid using the *contact_type* attribute field to supply the values, and
9. create a distance grid using ARC/INFO command, *eucldistance*(assign by value). Cell values are set to the concatenated rock codes of the lithologies at the nearest contact type (e.g. MbGt, where Mb = magnesian basalt and Gt = granite).

Two contact-type maps were prepared; one based on a solid geology rock-type legend comprising 25 rock types (*l35_lrt25*) and second based on a 55 rock-type legend (*l35_lrt55*). The latter map was not used for further calculations because there were too few known deposits associated with the resultant 235 contact types,

The maps of nearest contact-type were converted to a form suitable for input to a neural network by converting the nominal variable (e.g MbGt for a basalt-granitoid contact) to numerical fuzzy membership values. Although subjective judgement was important, the assignment of fuzzy membership values was based on the statistical relationship of known deposits with areas for which the nearest contact lithologies were of a certain type. The following steps were required to convert the GIS contact-type layer to a MATLAB array;

1. Export the ARCVIEW database table for nearest-contact-type layer, *l35_lrt25* as a

DBF file and import into EXCEL. This results in a table (*rt25-value-count-codes.xls*) with numerical codes and concatenated strings representing contact-types (e.g. 6, GtMb for a granitoid-basalt contact).

2. Create a table that contains rock codes together with the rock descriptions in ARCVIEW. Open attribute table for *geology.shp* coverage, and use the *field-summarize* function. Export the table as a DBF file and import into EXCEL.
3. Add rock names to EXCEL table with numerical and textural contact-type codes.
4. Run the MATLAB function, *deps_cont_type*. For each region comprising cells with the same nearest contact type, the following statistics were calculated; the number of cells, deposits, total contained gold (TCG, kg), probability that a cell contains a deposit ($P(D)$), ratio of the percentage of the total deposits to the percentage of the total area (D/A), the ratio of the TCG to area, average TCG per cell, and the product of the probability of a $P(D) \times TCG/cell$. The function only calculates statistics for cells that are located within a user-specified maximum distance from the contacts. This was set to 200 m or 1300 m depending on the layer (see explanation below). Inputs to the *deps_cont_type* function were the geology (l1_l_ass.t25), contact-type (l35_l_rt25), binary deposits (l24_d_all.bin), tonnes-contained-gold (l25_d_tcg2), and distance-to-nearest-lithological-contact (l39_c_dist) layers. Only gold deposits containing a resource of 1000 kg total contained metal were used for these calculations. The function outputs an ASCII file, *deps_cont_type_log* containing a table of the parameters listed above for each contact type. This table was imported and added to the EXCEL spreadsheet containing the contact codes and names.
5. Rank the contact-types in order of decreasing probability of a deposit $P(D)$. A layer was also created based on ranking the layers using the product of probability of a deposit and the total contained gold ($P(D) \times TCG/cell$).
6. Select contact types that are definitely favourable for deposits and assign these a fuzzy membership value of 1.0.

The dolerite-porphyry contact type is arbitrarily chosen as the lowest ranking contact type to be assigned a fuzzy membership value of 1.0 for both the $P(D)$ and $P(D) \times TCG/cell$ ranking criteria. Eight of the top ten ranked contact-types based on $P(D)$ and all of the top ten contact-types based on $P(D) \times TCG/cell$ include at least one of the following rock types; feldspar porphyry, quartz dolerite, dolerite, andesite or carbonaceous shale. These are the lithological units with the highest probability of containing a known deposit (≥ 1000 kg, TCG; Tables D.16 and D.17,

Appendix D). Contact-types that do not contain any known deposits were assigned a fuzzy membership value of 0.1.

The occurrence of orogenic gold deposits in a wide variety of host rocks throughout the Yilgarn Block, (which includes the Kalgoorlie Terrane containing the study area), suggests that none of the host rocks that were present prior to the main phase of gold mineralization should be excluded as potential hosts for gold deposits. Therefore, a minimum fuzzy membership value of 0.1 rather than 0.0 was used (Carranza & Hale, 1999).

A linear interpolation was made between these limits in order to assign fuzzy membership values for all other contact types. The calculations were performed in EXCEL spreadsheets (refer to Tables D.14 and D.15 in Appendix D).

7. The fuzzy membership values determined in the previous step were then used as constants in the MATLAB functions (*favcontact25_pr0110.m*, and *favcontact25_prtcg0110.m*) which created favourable contact-type layers based on $P(D)$ and $P(D) \times (ave.TCG/cell)$, respectively, by reclassifying the contact-type layer, *l35-Lrt25*.

As the distance increases, the effect of the rock types at the nearest lithological boundary on prospectivity must diminish and eventually become irrelevant. In order to model this, fuzzy membership values were set to 0.1 for cells beyond a certain distance to the nearest contact. Distance limits are based on maximum and minimum estimates determined using a variety of statistical tests described in Section 6.3 in Chapter 6. Layers using limits of 200 and 1300 metres were prepared using the MATLAB functions referred to above. These distances correspond to the minimum and maximum estimates obtained for the distance within which proximity to lithological boundaries upgrades the prospectivity for orogenic gold deposits (≥ 1000 kg TCG; Table 6.4 below).

The favourable contact-type layers together with the parameters used to create them, are shown in Table 5.9 below.

5.5.14 Favourable Lithology

Rock types in the solid geology GIS layer, like the contact-types discussed above, represent a nominal data type. Two methods were used to convert the solid geology GIS layer into a numerical form suitable for input to a neural network; 1) conversion to fuzzy membership

Table 5.9. Candidates for favourable contact-type GIS layers and the parameters used to rank them. Cells located beyond maximum distance from the nearest lithological boundary were assigned the minimum fuzzy membership (i.e. 0.1 for 200 m buffer limit; 0.0 for 1300 m buffer limit).

Layer name	Parameter used to rank contacts	Distance limit (m)	M/ship if dist. $\geq$ limit	Matlab function used to create layer
l44_favcont25_pr0110_200	P(deposit)	200	0.1	favcontact25_pr0110_200
l44_favcont25_pxtcg0110_200	P(deposit)* TCG	200	0.1	favcontact25_pxtcg0110_200
l44_favcont25_pr_1300	P(deposit)	1300	0.0	favcontact25_pr0110_1300
l44_favcont25_pxtcg_1300	P(deposit)* TCG	1300	0.0	favcontact25_pxtcg0110_1300

values, and 2) 1-of-n coding. These methods are discussed in the sections below.

Conversion of Solid Geology to Fuzzy Membership Layer

Rock-type codes in the solid geology layer are converted to fuzzy-membership values using the following steps:

1. calculate statistical relationships between known deposits and lithological units
2. rank layers and set definitely favourable rock types to a fuzzy membership to 1.0 and unfavourable rock types to 0.1, and
3. convert to a fuzzy membership layer using statistics;
 - a) calculate fuzzy membership values between 0.1 and 1.0 by linear interpolation, and
 - b) use the fuzzy membership values calculated above to re-classify the solid geology layer.

The first step, in the list above, was performed using the MATLAB function (*deps_litho.m*), which calculates number of cells, deposits, total contained gold (TCG), TCG/cell, probability of deposits ($P(D)$), and $P(D) \times TCG/cell$ for each rock type. The linear interpolations referred to in step 3a were performed in EXCEL spreadsheets (refer to Tables D.16 and D.17 in Appendix D, page 635). The step 3b was performed with the MATLAB function *favgeol25-pr*, which created the favourable lithology layers *l1_favgeol25-pr0110* and *l1_favgeol25-prxtcg*.

Figure 5.6. Conversion of host-rock classes in an input GIS layer to fuzzy member values. Assignment of fuzzy membership values is based on a ranking of rock types in order of the probability of containing a known deposit, ($P(D)$). Definitely favourable and definitely unfavourable rock types are assigned fuzzy membership values of 1.0 and 0.1, respectively. $P(D)$ and fuzzy membership values associated with these groups are then used to construct a triangular fuzzy membership function, which is then used to perform a linear interpolation of the values for the rock types ranked between the end-member groups.

Two fuzzy membership layers are created. The first layer, *l1_favgeol25_pr0110*, is based on ranking rock types according to the probability that the rock type contains a known gold deposit. Definitely favourable and unfavourable host rocks were assigned fuzzy membership values of 1.0 and 0.1, respectively. The second layer is based on a ranking rock types according to $P(D) \times \text{TCG}/\text{cell}$. A minimum value of 0.1 is used for this layer because no rock type is completely unfavourable as a host to gold mineralization (Section 6). Caranza & Hale (1999) have recently used a similar approach in a fuzzy systems estimate of the potential for epithermal gold mineralization in the Philippines. These steps and the triangular fuzzy membership function used in this study are illustrated schematically in Figure 5.6. The procedure is the same as that used for the fuzzy contact-type layer above, except that it was not necessary to process topological information from the vector coverage in ARC/INFO in order to first create a derived layer.

Conversion of Solid Geology to 1-of-n Coding Scheme

In 1-of-n coding, a separate neural network input is assigned to each class in the data; in this case rock types. In order to indicate that the current input corresponds to basalt, the input unit corresponding to basalt is set to one and all the other units are set to zero (Masters, 1993b). Since the simplified version of the Goldfields Pty Ltd lithology legend contained 25 rock types of which 22 occurred in the study area, the 1-of-n coding scheme results in 22 inputs assigned to rock-type. Thus, the first 22 components of the resultant feature vector representing an input pattern belong to the 1-of-n code (Fig. 3.2).

There are two disadvantages to this scheme. First, the number of network inputs is significantly increased, particularly if there are a large number of classes in the data, leading to a consequent increase in the number of interconnections between input neurons and hidden layer neurons. For small training-set sizes, the large number of weights associated with the connections can result in over-learning (i.e. learning the idiosyncrasies rather than the underlying patterns in the data). This reduces the ability of the trained network to generalize to new patterns not presented during training (Masters, 1993b; Singer & Kouda, 1999a). Second, to code the entire solid-geology layer containing 25 rock types effectively results in the creation of 25 new input layers, which requires a very large amount of main computer memory. For example, 512 MB RAM used in this study is not sufficient for layers consisting of 1140×1100 cells.

Simplification of the original mapping legend used by Goldfields Exploration Pty Ltd for the Yilgarn Block from 108 to 25 rock types was a necessary preliminary step in order to apply a 1-of-n coding scheme to the solid geology layer. Although simplification of the legend is not required if fuzzy-membership values are used, a geology layer containing 108 rock types would probably result in less reliable results because many rock types contain less than five known deposits. Due to the large number of classes in the contact-type layer (134 rock-type combinations using a geology legend with 25 rock types), it is not feasible to use a 1-of-n coding scheme for this layer.

Although conversion of the rock-type codes in the solid geology layer to 1-of-n coding was performed at the same time the other layers were combined into feature vectors, merging of cell values from the different input GIS layers to form feature vectors had to be performed in two steps in which each half of the map area was processed separately. These steps were performed in MATLAB as a batch job (*make_train_batch_1ofn*). Processing to code the rock types in 1-of-n format involved the following steps;

1. convert rock type codes to a contiguous sequence using MATLAB function, *geol-*

codes_kal to give the array *geol_22*,

2. combine all layers other than geology to create input patterns (MATLAB script, *merge_cat_10*), and
3. insert 1-of-n codes into feature vectors created in previous step (MATLAB function, *add_geol1ofn*).

5.5.15 Density of Faults

A layer depicting fault density was prepared by calculating the total length of faults in a 5.1×5.1 km moving window and assigning that value to the central cell (*l42_f123den5k* in Figure 5.34). Three vector-format fault layers containing crustal-scale, and NNE-trending and NE-trending regional-scale faults (i.e. *l20_s_crust*, *l21_s_shear* and *l21_s_flt_ne*), were combined using the *Map Calculator* function in ARCVIEW, converted to a binary grid file (faults = 1, other = 0), and exported as an ASCII file. The ASCII file was imported into MATLAB where ARCVIEW header lines were removed using a MATLAB script, *strip_hdr.m* and the function, *fault_density.m* was used to perform a 2D convolution which counted the cells in the processing window, which correspond to faults and assigned the total to the central cell. A 51×51 cell window size allowed for a central cell and 25 cell in each orthogonal direction.

5.5.16 Density of Lithological Contacts

A layer representing a measure of lithological complexity in the area around each cell was created by an integer count of lithological contacts in the neighbourhood of each cell (*l43_lithdiv* in Figure 5.35). A solid geology layer containing a legend comprising 55 rock types (*l11_lass_t55*) was imported into MATLAB using the same procedure as explained above in Section 5.5.15. Within MATLAB, the function, *litho_diversity.m* was used to count the total length of lithological contacts along rows and down columns within a 5.1×5.1 km moving processing window. The algorithm, described by Bonham-Carter (1994), checks if rock types in adjacent cells are different.

5.5.17 Addition of *No Data* Cells to Derived Layers

Areas where data were missing in the geological map supplied by Goldfields Exploration were flagged using a special *No Data* value recognized in ARCVIEW. Since analysis func-

tions used to create the derived layers produced output values for all cells within the boundaries of the study area, the *No Data* values had to be added to the derived layers. This was achieved using the primary solid geology map, in which *No Data* cells were correctly flagged and the ARCVIEW *map calculator* function. The following command was used;

$$([l1_ass_t25].IsNull).SetNull([l46_dist_anti])$$

where the derived layer showing the distance to anticlinal axes has been used as an example.

5.5.18 Fuzzy Membership Layers

A set of fuzzy membership layers, corresponding to the derived layers described above, were prepared using parameter values that define the most favourable regions for deposits. These favourable ranges of parameter values were determined using methods discussed in the next section and are shown in Table 6.4,

Triangular fuzzy membership functions were used to convert the raw data from the GIS layers to values representing the fuzzy membership degree. The processing was performed in the MATLAB environment using the scripts, *layer2fav* and *layer2fav_batch*.

5.6 Summary

The main points discussed in Chapter 5 are listed below.

1. Archaean orogenic gold deposits in the Yilgarn Craton formed over a wide range of crustal depths and, consequently, have correspondingly varied metamorphic grades, structural styles, host rocks and mineralogy.
2. Timing of gold deposition was late within the deformation history of the host terrane. Consequently, the geometry of the structures associated with deposits and rock sequences hosting the deposits that are represented in geological maps are essentially similar to those that existed during gold mineralization. As a result: 1) the locations of gold deposits are related to repeated and predictable structural geometries, and 2) spatial relationships between the structures and known deposits determined from

geological maps can be analyzed in a GIS to predict the location of new gold deposits (Groves *et al.*, 2000).

3. Favourable areas for gold deposits include: 1) large linear greenstone belts with major bounding shear zones, 2) irregularities in strike (and large rheological contrasts) along crustal and regional-scale faults or shear zones, 3) dilational jogs along strike-slip faults, 4) cross faults between first-order faults, 5) changes in strike of first-order faults from a dominant NNW to a NW trend, 6) intersections of two or more faults, 7) anticlinal hinges or domes formed by doubly plunging anticlines, 8) structurally isolated blocks of more competent volcanic rocks surrounded by less competent volcanic or sedimentary rocks, 9) greenschist facies terranes rather than higher-grade metamorphic settings, 10) dykes and small bodies of syenite and porphyritic intermediate to mafic intrusions, particularly those surrounded by magnetite alteration, 11) rheological contrasts across lithological boundaries, and 12) chemically reactive host rocks, that is, mafic rocks and rocks with high Fe and/or high $\text{Fe}/(\text{Fe}+\text{Mg}+\text{Ca})$, such as tholeiitic basalt and banded iron formation (BIF), and some mafic porphyries.
4. The main mechanism of gold deposition in orogenic lode-gold deposits in the Yilgarn Block is fluid-wall rock reactions in which the iron-rich minerals in the host rocks react with sulphide complexes, which carry gold in solution, to form pyrite.
5. Destruction of magnetite (due to reactions involving the replacement of magnetite by pyrite and leucoxene) leads to a magnetically depleted core of some deposits, while some deposits have a magnetic rim due to the precipitation of magnetite by spent ore fluids. Strong positive and negative aeromagnetic anomalies may indicate sites of magnetite production and destruction, respectively.
6. Primary GIS data layers supplied by Goldfields Exploration are; solid geology (108 rock types), faults and shear zones, aeromagnetic and gamma-ray survey data, and Bouguer gravity anomalies. Layers and data derived from other sources are; traces of regional-scale anticlines, deposits and mineral occurrence database, and the OZCHEM whole-rock geochemistry database.
7. Chemical reactivity of host rocks is modelled using two sulphidation ratios; $\text{Fe}/(\text{Fe}+\text{Mg}+\text{Ca})$ and $\text{Fe}_{total}(\text{wt}\%)\times \text{Fe}/(\text{Fe}+\text{Mg}+\text{Ca})$ and three oxidation ratios; $\text{Fe}_2\text{O}_3/(\text{Fe}_2\text{O}_3 + \text{FeO})$, $\text{Fe}_2\text{O}_3/\text{FeO}$, and $\text{Fe}^{3+}/\text{Fe}^{2+}$. These ratios are calculated from the OZCHEM whole-rock geochemistry data. Quantities are weight percentages of metals where oxides are not shown.

8. Competency contrasts across lithological boundaries are an important control on the location of deposits.
9. To determine the best way to model rheological contrast, the following rock strength parameters were tested; two different compilations of Young's Modulus, uniaxial compressive and tensile strength, fracture toughness, and subjective estimates expressed as classes and fuzzy membership values.
10. The effect of using derived rather than primary GIS layers is to emphasize exploration criteria and make the ingredients of the mineral systems model for orogenic gold deposits more explicit. This process of modifying the raw input parameters to emphasize the underlying relationship between the neural network inputs and the outputs is referred to as feature extraction.
11. The original geological legend was simplified from 108 to 25 rock types. This is because the statistical relationship between gold deposits and host rock types cannot be reliably determined from the original legend as many rock types do not host any known gold deposits.
12. The aeromagnetic intensity map was converted to a layer depicting the distance to positive magnetic anomalies. Anomalies were defined as cells with a z-score ≥ 2 , where $z = (x - \mu)/s$, and x = raw value, μ = average total magnetic intensity and s = standard deviation for a single rock type.
13. Rheological-contrast layers represent the absolute values of the difference between rock strengths at the nearest lithological boundary.
14. Rheological contrast values were calculated in ARC/INFO by linking the information about the polygons that are located to the left and right of any line that is stored in the arc (i.e., line) attribute table (i.e., spatial database) together with the rock strength data stored in the polygon attribute table (i.e. non-spatial database). Chemical contrast and nearest-contact-type layers were produced in the same way.
15. The favourable contact-type layer is a raster layer in which cell values represent the favourability of the two adjacent rock types at the nearest lithological boundary to host gold deposits. Favourability is expressed as fuzzy membership values.
16. To model the decreasing effect on prospectivity of the rock types at the nearest lithological boundary as distance increases, fuzzy membership values were set to 0.1 for cells beyond a certain distance to the nearest contact. Distance limits of 200 and 1300 metres are based on minimum and maximum estimates determined using

a variety of statistical tests described in Section 6.3 in Chapter 6.

17. Favourable contact-type and favourable host-rock type layers are objective fuzzy membership layers which are based on the statistical relationships between known deposits and the respective parameters.
18. A subjective fuzzy-membership layer was created to represent rheological contrast. Rocks in the detailed geology legend (108 rock types) were subjectively ranked according to their tendency for brittle or ductile failure based on field observations.
19. The fuzzy membership values for the rheological contrast layer represent the favourability of the rock to host gold deposits due to the likelihood that the rock will fail brittly where surrounding rocks do not, thus resulting in structural permeability and influx of ore-bearing fluids.
20. A 1-of-n coding scheme is used to convert the categorical rock-type data in the geology GIS layer to a form suitable for input to a neural network. Disadvantages of this method are that; 1) the number of network inputs is significantly increased, leading to the possibility of overfitting of the data for small training data sets, and 2) the 1-of-n layers consume a lot of computer memory, especially if there are large numbers of rock types.
21. A layer representing density of lithological contacts is used as a measure of lithological complexity. A 2D convolution was used to determine the number of lithological contacts in a 5×5 km window around each cell. This method was also used to calculate a layer representing the density of regional-scale faults.

Figure 5.7. Simplified solid geology layer *geology* from the Kalgoorlie GIS database. The legend comprises 25 rock types (reduced from 108). The data set was provided by Goldfields Exploration Pty Ltd.

Figure 5.8. Faults and shear zones layer *faults* from the Kalgoorlie GIS database. Structures are separated into NNW-trending crustal-scale, NNW-trending regional, and NE-trending regional faults and shear zones. The data set was provided by Goldfields Exploration Pty Ltd.

Figure 5.9. Layer folds from the Kalgoorlie GIS database showing the ground trace of axial plane of major anticlines and synclines.

Figure 5.10. Airborne total magnetic intensity (reduced to pole) layer *l5.m.rtp* from the Kalgoorlie GIS database. The data set was provided by Goldfields Exploration Pty Ltd.

Figure 5.11. Bouguer gravity anomaly layer *l12_grav* from the Kalgoorlie GIS database. The data set was provided by Goldfields Exploration Pty Ltd.

Figure 5.12. Gold deposit locations from the Kalgoorlie GIS database layer *deps_all*. All gold deposits and mineral occurrences are shown. Data were obtained from MINDEX database, which is compiled by the Geological Survey of Western Australia (Townsend *et al.*, 2000).

Figure 5.13. Gold deposit layer *deps_1000tcs* from the Kalgoorlie GIS database showing only those deposits with a resource of at least 1000 kg total contained gold. Data source: MINDEX database, Geological Survey of Western Australia (Townsend *et al.*, 2000).

Figure 5.14. Map of fracture toughness from the Kalgoorlie GIS database layer *l2.Lrh5*. The map is based on data supplied by M. Lee, unpublished data from Australian Mining Consultants Pty Ltd, 2000.

Figure 5.15. Map of metamorphic grade from the Kalgoorlie GIS database layer *U45_Lmeta*. The map is based on region-scale interpretations by Binns *et al.* (1976) and Witt (1993). Boundaries are approximate only.

Figure 5.16. Layer *U4.Lpf.dist* from the Kalgoorlie GIS database showing the distance to the nearest felsic porphyry intrusion.

Figure 5.17. Layer *l39_c.dist* from the Kalgoorlie GIS database showing the distance to the nearest lithological contact.

Figure 5.18. Layer *l20-f1_dist* from the Kalgoorlie GIS database showing the distance to the nearest crustal-scale fault or shear zone.

Figure 5.19. Layer *l21_f2_dist* from the Kalgoorlie GIS database showing the distance to the nearest NNW-trending regional-scale fault or shear zone.

Figure 5.20. Layer *l22_d3_dist* from the Kalgoorlie GIS database showing the distance to the nearest NE-trending regional-scale fault or shear zone.

Figure 5.21. Layer *l46_dist_anti* from the Kalgoorlie GIS database showing the distance to the nearest trace of a regional-scale anticlinal axis.

Figure 5.22. Layer *U6.dist_sync* from the Kalgoorlie GIS database showing the distance to the nearest trace of a regional-scale synclinal axis.

Figure 5.23. Layer *l34_s.p23gdst* from the Kalgoorlie GIS database showing the distance to the nearest intersection of regional-scale NNW- and NE-trending faults.

Figure 5.24. Layer *l14_mz2.dist* from the Kalgoorlie GIS database showing the distance to the nearest positive magnetic anomaly with a z-score ≥ 2 . Using z-scores allows anomalies to be defined separately for each rock type.

Figure 5.25. Layer *l28_s-11str* from the Kalgoorlie GIS database showing the strike of the nearest crustal-scale fault or shear zone.

Figure 5.26. Layer *l29_s-f2str* from the Kalgoorlie GIS database showing the strike of the nearest NNW-trending regional-scale fault.

Figure 5.27. Layer *l30.s.f3str* from the Kalgoorlie GIS database showing the strike of the nearest NE-trending regional-scale fault.

Figure 5.28. Layer *l38_c_str* from the Kalgoorlie GIS database showing the strike of the nearest lithological contact.

Figure 5.29. Layer *l36_rh1* from the Kalgoorlie GIS database showing rheological contrast at lithological boundaries based on subjective estimates of rock competency, which were converted to fuzzy membership values.

Figure 5.30. Layer *l37_Lch1* from the Kalbarrie GIS database showing chemical contrast at lithological boundaries based on the ratio $\text{Fe}_{\text{wt}\%} \times \text{Fe}_{2\text{ot}} / (\text{Fe}_{2\text{ot}} + \text{Mg} + \text{Ca})$. The data were obtained from AGSO's OZCHEM database Kilgour & Hazell (1998).

Figure 5.31. Layer *l37_Lch3* from the Kalgoorlie GIS database showing chemical contrast at lithological boundaries based on the ratio $\text{Fe}_2\text{O}_3/(\text{Fe}_2\text{O}_3 + \text{FeO})$. The data were obtained from AGSO's OZCHEM database Kilgour & Hazell (1998).

Figure 5.32. Layer *l37.Lch4* from the Kalgoorlie GIS database showing chemical contrast at lithological boundaries based on the ratio $\text{Fe}_2\text{O}_3/\text{FeO}$. The data were obtained from AGSO's OZCHEM database Kilgour & Hazell (1998).

Figure 5.33. Layer *U4favcnt25pr* from the Kalgoorlie GIS database showing the degree of favourability of the nearest contact type for gold deposits as fuzzy membership values. Fuzzy membership values were based on the probability of the occurrence of known deposits, (≥ 1000 kg TCG) within a buffer distance of 200 m of the specific contact. Fuzzy membership values were set to 0.1 for cells beyond a distance of 200 m to the nearest contact.

Figure 5.34. Layer *l42.f123_density* from the Kalgourlie GIS database showing the density of crustal-scale and NNW- and NE-trending regional-scale faults and shear zones calculated in 5.1 x 5.1 km window around each cell.

Figure 5.35. Layer *l43_lith_div* from the Kalgoorlie GIS database showing the density of lithological contacts calculated in 5.1 x 5.1 km window around each cell. The values are used as a measure of lithological complexity.

Chapter 6

Feature Selection: Evaluating the predictive ability of potential input GIS Layers

6.1 Introduction

The purpose of this chapter is to extract and empirically evaluate features in order to select the most useful ones to be used as neural network inputs in Chapter 7. Thus, the task consists of two parts;

1. pre-processing and feature extraction, and
2. feature selection.

Pre-processing and feature extraction can often greatly improve a pattern classification system, particularly if prior knowledge can be incorporated into the inputs (Bishop, 1995). Consequently, much of this chapter is devoted to the preparation of derived GIS layers in order to represent the essential ingredients of the mineral systems in terms of the regional-scale GIS data that are available. For example, rather than present the network with a binary layer indicating the presence or absence of faults, groups of faults which are related to different deformation events are divided into separate layers. Layers are then transformed so that cell values represent the distance to the nearest fault of a specific type. The basic principles are to avoid encrypting the underlying structure of the data and to avoid using irrelevant inputs (Gedeon, 1996).

Feature selection is the problem of choosing a small subset of distinguishing features that are most useful as inputs. It is widely agreed that data encoding and feature selection are of paramount importance for any learning algorithm (Kohavi & Frasca, 1994; Kohavi, 1995; Gedeon, 1996; Piramuthu, 1996). Kohavi & Frasca (1994) have shown that, in practical situations, using a subset of the core features may lead to superior performance.

The approach taken in this study is to apply statistical methods for measuring the spatial association of known deposit points and spatial features in order to assess the predictive value of 60 possible input GIS layers. The methods used are contrast of weights (C_w , Bonham-Carter, 1994), the chi-squared statistic (χ^2), and the Kolmogorov-Smirnov cumulative distribution function (KS). Three new methods are also introduced. These are the cumulative and interval-based calculations of the bivariate J-function and plots of $(O - E)/E$ (where O is the observed and E is expected number of deposits in a buffer; refer to Sections 6.2.6 and 6.2.4). The latter two methods were developed in this study. The best GIS layers selected using these methods were then used as inputs in the neural networks experiments in the following chapters.

One of the problems in modelling mineral systems at a regional scale in order to predict the prospectivity for ore deposits is the choice of potential input layers. There are many different ways to interpret the essential ingredients of a mineral systems model in terms of features that are likely to have been mapped and compiled in a regional-scale GIS database. In addition, each of these ingredients can be represented as GIS layers in different ways. For example, Archaean orogenic gold deposits form selectively where fluids have been focussed into dilatant zones or zones of high structural permeability, which, in turn, are produced by heterogenous stress fields in areas with complex geometries and strong contrasts in rock strength. Such areas could be modelled using layers representing proximity to faults, shear zones, lithological contacts or anticlinal hinges, segments of faults and shear zones with favourable strike orientations, density of lithological contacts, favourability of rock types at the nearest lithological boundary, and chemical or rock-strength contrasts at lithological boundaries. Rheological contrast could be modelled using subjective estimates of rock competency in the form of fuzzy membership values, Young's Modulus, uniaxial compressive strength, uniaxial tensile strength or fracture toughness. The aim is to select only the GIS layers containing the features, which are the best predictors of the known gold deposits in order to ensure that the neural networks correctly learn the underlying patterns in the data.

A sensitivity analysis was not a feasible method in this study as there are 60 potential input GIS layers. In a sensitivity analysis, all the layers are used to predict the known deposits

and then, as each layer is subtracted (and later replaced), it is noted whether the predictive performance of the resultant prospectivity map increases or decreases (e.g. Knox-Robinson *et al.*, 1996). Only those layers that improve the performance are subsequently used as inputs to the analysis.

It has been suggested that principal component analysis could be useful in reducing the number of inputs (P. Wong, pers. comm.). However, Masters (1993b) has warned that it may be that the information required by a network to perform a classification may be contained in the last principle component; i.e. the one that accounts for the smallest percentage of the variance of the data and therefore the most likely to be discarded.

The approach used in this study was to;

1. test each layer separately to determine the layers and ranges of variable values that show a positive relationship with known deposits, using plots of contrast of weights, chi-squared statistic, $(O - E)/E$ (refer to Section 6.2.6), and the bivariate J-function,
2. use the bivariate J-function and the Kolmogorov-Smirnov cumulative distribution function plots to determine if associations are statistically significant,
3. use the favourable ranges of variables (e.g. distance to nearest fault; 0–800 m) to create binary maps,
4. rank binary maps in terms of their ability to predict the 120 known deposits (with a resource of at least 1000 kg TCG), and
5. select a group of 10 or 20 of the best layers.

It is important to note that the binary maps referred to in step 3 above are only used for the purpose of ranking layers and are not used as inputs to neural networks. The methods used to test the layers are summarized Table 6.1 below and are described in separate sections below.

The strong spatial relationship between gold deposits (≥ 1000 kg TCG) and proximity to regional-scale anticlinal axes is used to illustrate the methods described in the following sections. To illustrate the response of each method to a strong negative spatial relationship, a graph showing proximity to synclinal axes is also shown.

Table 6.1. Methods used to evaluate potential neural network input GIS layers.

Statistical Method	Significance Test
Contrast of Weights	no
Kolmogorov-Smirnov Cumulative Distribution Function	yes
Chi-Squared statistic	no
(O - E)/E (Bar graph) ^a	no
Bivariate J-function (Cumulative)	yes
Bivariate J-function (Bar graph)	yes

^aO = observed & E = expected number of deposits.

6.2 Statistical Methods used to Evaluate Layers

6.2.1 Contrast of Weights

Bonham-Carter (1994) used plots of the contrast, C_W , versus cumulative distance or some other variable represented in a predictive input map to determine the optimal threshold values to use in creating binary maps required in the weights-of-evidence method. Contrast is normally expressed as the difference between the positive and negative weights:

$$C_W = W^+ - W^- \quad (6.1)$$

The expression used to calculate the contrast is derived by substituting the right-hand terms in equations 6.2 and 6.3 into equation 6.1. The weights, W^+ and W^- , are defined as;

$$W^+ = \ln O(A|D) - \ln O(A) = \ln \left(\frac{T_{11}T_{2.}}{T_{21}T_{1.}} \right) \quad (6.2)$$

$$W^- = \ln O(A|\bar{D}) - \ln O(A) = \ln \left(\frac{T_{12}T_{2.}}{T_{22}T_{1.}} \right) \quad (6.3)$$

where A represents the event *favourable pattern present*, $\bar{A}$ is *favourable pattern absent*, D is *deposit pattern present*, and T_{ij} stands for areas measured in numbers of cells (Table 6.2). The odds, O , are related to the corresponding probabilities according to the formula, $O = P/(1 - P)$.

Contrast curves were produced together with chi-squared statistic curves (explained in the next section) by exporting GIS layers from ARCVIEW as ASCII files, importing the grid into MATLAB and running the function, *chi_wts3*. The algorithm in function *chi_wts3* generates contrast-cumulative distance curves by determining the areas associated with the cross-tabulation patterns (shown in Table 6.2) within 50 successively increasing buffers. The buffers are gradually increased in size until the entire distance or variable range is covered. Only deposits with a resource of at least 1000 kg TCG are used. It was assumed for the purpose of these calculations that each deposit occupies a single 100 m cell.

Contrast, $C_W = W^+ - W^-$, shows the overall effect resulting from the competing influences of how much being within a zone or range of variable values upgrades the prospectivity for a deposit (expressed in W^+) and how much not being in a particular zone downgrades the prospectivity (expressed in W^-). In cases where proximity to some spatial feature is a strong control on mineralization, the contrast-distance curve contains a peak. The position of this peak is used to determine which areas or variable values of the map are the most prospective. For example, the distance to the nearest trace of an anticlinal axis is shown in Figure 6.1 below. There is a peak at approximately 1400 m, which is interpreted to mean that the effect of being close to an anticlinal axis is greatest within the buffer zone from 0 to 1400 m. For comparison with an example of where there is a negative spatial relationship, the graph of contrast versus cumulative distance to synclinal axes is shown in Figure 6.2.

Although distance is used as the independent variable in the preceding examples, contrast curves and plots for all the other methods used to evaluate layers were generated using the variables in all the potential input GIS layers.

Table 6.2. Area cross-tabulation showing variables used to calculate contrast, C_W where patterns overlap. $T_{.1}$ and $T_{.2}$ = column totals, $T_{1.}$ and $T_{2.}$ = row totals, and $T_{..}$ = grand total.

		Deposit		
		D	$\bar{D}$	
Favourable	A	T_{11}	T_{12}	$T_{1.}$
Evidence	$\bar{A}$	T_{21}	T_{22}	$T_{2.}$
		$T_{.1}$	$T_{.2}$	$T_{..}$

Figure 6.1. Graph of contrast versus cumulative distance to the ground traces of regional-scale anticlinal axes. The peak in the contrast curve for distance to the anticlinal axes at 1400 m is interpreted to indicate that the effect of proximity to an anticlinal axis in upgrading the favourability for gold deposits is at a maximum within a buffer interval of 0–1400 m.

Figure 6.2. Graphs of contrast versus cumulative distance to the ground traces of regional-scale synclinal axes.

6.2.2 Chi-squared Statistic

The chi-squared statistic (χ^2), described in Section 3.3.1 (see equation 3.4), was used to determine if a particular range of variable values (e.g. buffer distance) is favourable for gold deposits. Calculations were based on the numbers of cells corresponding to the overlap conditions shown in Table 6.2 and were performed using the same method as for contrast calculations described above (MATLAB function, *chi_wts2*). The graphs of the chi-squared statistic versus cumulative distance to the nearest anticlinal and synclinal axis are shown in Figures 6.3 and 6.4 below. The peak at approximately 1400 m indicates that locations within a buffer zone from 0 to 1400 m are the most favourable for deposits. A problem with the chi-squared statistic plot is that both positive and negative spatial relationships result in a positive peak (Fig. 6.3). A further difficulty, with both the contrast and the chi-squared statistic plots, is that, for many variables, there are no definite peaks.

6.2.3 Kolmogorov-Smirnov Cumulative Distribution Function

The Kolmogorov-Smirnov (KS) test measures goodness-of-fit between an observed and a theoretical cumulative frequency distribution (Harnett, 1982). In this study, the expected or theoretical distribution, $\hat{F}(x)$, is the cumulative frequency distribution of deposits that would be expected if deposits are randomly distributed and independent of the spatial feature under investigation. The observed distribution, $\hat{G}(x)$, is the distribution of deposits that is associated with ranges of a spatial variable in a GIS grid (e.g. distance from crustal-scale faults). The KS-test is defined by:

H_0 : the data follow the specified distribution

H_a : the data do not follow the specified distribution

The Kolmogorov-Smirnov test statistic, D , is based on the maximum absolute difference between the value of the theoretical and empirical cumulative distribution functions and is given by:

$$D = \max_j \{|G(x_j) - F(x_j)|\} \quad (6.4)$$

The theoretical function is generated by a Monte Carlo simulation in which locations for 1000 “deposit points” are generated according to a uniform random distribution. The test statistic is compared to a critical value from a statistical table (Harnett, 1982). If the

Figure 6.3. Graph of chi-squared statistic versus cumulative distance to the ground traces of regional-scale anticlinal axes. The peak in the chi-squared statistic curve for distance to the anticlinal axes at 1400 m is interpreted to indicate that the effect of proximity to an anticlinal axis in upgrading the favourability for gold deposits is at a maximum within a buffer interval of 0–1400 m.

Figure 6.4. Graph of chi-squared statistic versus cumulative distance to the ground traces of regional-scale synclinal axes.

test statistic is larger than the critical value, it follows that the deposits are not randomly distributed and are therefore associated with the spatial feature in some way. For numbers of data values, $N > 35$, $D_{critical}$ was calculated according to the formula:

$$D = \frac{A}{\sqrt{N}} \quad (6.5)$$

where $A = 1.63$ for a p-value of 0.01 (99%) and N is the number of deposits. A one-tailed test was used since D is always positive. The calculations and plots were performed using the MATLAB function *ks* according to an algorithm described by Thesen (2001).

Graphs showing the KS-test curves for the distance to anticlinal and synclinal axes are shown in Figures 6.5 and 6.6. In Figure 6.5, $D_{test} = 0.39 > D_{critical} = 0.15$ which is strong evidence that there is a significant association between proximity to regional-scale anticlinal axes and gold deposits. It is important to note that this maximum D_{test} value occurs at a distance of approximately 2 km.

6.2.4 Bivariate J-Curve (Cumulative)

This section describes the use of a nonparametric summary statistic called the bivariate J-function for measuring dependence in bivariate processes (X, Y) , where X is a point process and Y is a spatial process of line segments or a more general random set (van Lieshout & Baddeley, 1997; Foxall & Baddeley, 2002).

The association between deposit points and lineaments has been the subject of a number of studies. Berman (1977, 1986) used the Kolmogorov-Smirnov test statistic to evaluate the spatial association between a set of deposit points and a set of lines representing lineaments. The method is a parametric one in which the distance of deposits and the nearest lineament is measured and the resulting *observed* distribution is compared with a distribution that would be expected if the points and lines occurred at random (i.e. the *expected* distribution). This method was applied to uranium deposits and Landsat lineaments in the Pine Creek Geosyncline by Huntington & Green (1978) and Simpson *et al.* (1980). Berman's model assumes that lines are uniformly (Poisson) distributed and independent. However, in practice, this assumption is too restrictive because lines are often clustered. To overcome this problem associated with assuming a Poisson line distribution, Bonham-Carter (1984) obtained an *expected* distribution using a Monte Carlo simulation to generate a large set of uniformly distributed points as well as using the actual lines on the geological map. This method was applied to gold deposits and Landsat lineaments from the Timmins-Kirkland Lake area, Ontario (Bonham-Carter, 1984, 1985) and the Meguma Group, Nova Scotia (Bonham-Carter *et al.*, 1985).

Figure 6.5. Graph of Kolmogorov-Smirnov (KS) cumulative distribution function versus distance to the ground traces of regional-scale anticlinal axes. The maximum difference between the curves representing the empirical (blue) and theoretical (red) distributions at 2100 m is interpreted to indicate that the effect of proximity to an anticlinal axis in upgrading the favourability for gold deposits is at a maximum within a buffer interval of 0–2100 m.

Figure 6.6. Graph of Kolmogorov-Smirnov cumulative distribution function versus distance to the ground traces of regional-scale synclinal axes.

In this study, the bivariate J-function was used to identify positive spatial associations between known orogenic lode-gold deposits and the variables in a range of potential GIS layers in order to select layers to be combined into prospectivity maps. Simulated estimates of the J-function and a Monte Carlo test provide information about the significance of spatial relationships. The cumulative J-curve and a bar graph, based on an interval-based calculation of the J-function, are compared with plots of $(O - E)/E$ (where O is the observed and E is expected number of deposits in a buffer), cumulative contrast of weights, C_W , and the Kolmogorov-Smirnov cumulative distribution function.

As well as dealing with spatial features represented by line segments such as faults and lithological contacts, the method was extended as part of this study to apply to regions within raster GIS layers such as the proximity to magnetic anomalies, or proximity to the intersection of faults (i.e. layers *l14-mz2-dist* & *l33-s-f23gdst*, respectively) and to relationships between deposit points and variables that do not involve distances, such as the density of faults or rheological contrast at the nearest lithological boundary; i.e, layers, *l36-lrh1-6* (Brown *et al.*, 2002c).

The bivariate J-function is defined by Foxall & Baddeley (2002) as:

$$J_{X,Y} = \frac{1 - G_{X,Y}(r)}{1 - F_Y(r)} \quad (6.6)$$

for all $r \geq 0$ such that $F_Y(r) < 1$, where

$$F_Y(r) = P\{d(z, Y) < r\} \quad (6.7)$$

and

$$G_{X,Y}(r) = P\{d(x, Y) < r\} \quad (6.8)$$

where $F_Y(r)$ is the cumulative distribution function of the distance $d(z, Y)$ from any point z to the nearest point of the spatial process Y (e.g. fault pattern) and $G_Y(r)$ is the cumulative distribution function of the distance from a point of X (e.g. gold deposit) to the nearest point of Y (e.g. fault lines). It is assumed that Y is a random set. In a GIS containing deposits and faults, the value of the function F can be regarded as the fraction of the area of the region lying within a distance of r units from the nearest fault and the value of G as the fraction of the deposits located within r units from the nearest fault.

The method involves calculating a cumulative distribution curve defined by the J-function. In the case of a raster GIS layer depicting the distance to the nearest regional fault, Equation 6.9 becomes:

$$J_{X,Y} = \frac{1 - P(\text{cell} \leq \text{distance } r \text{ to fault} \mid \text{deposit})}{1 - P(\text{cell} \leq \text{distance } r \text{ to fault})} \quad (6.9)$$

The numerator represents the probability that no fault occurs within a distance r , given the cell contains a large deposit and the denominator represents the probability that there is no fault within distance r . Values of $J_{X,Y}(r)$ close to 1 suggest independence of X (e.g. deposit points) and the spatial feature Y (e.g. faults), while values less than 1 suggest a positive association or clustering between X and Y and values greater than 1 suggest a negative association. Computations were performed in MATLAB.

The cumulative probability functions in the numerator and denominator in Equation 6.9 above were calculated in MATLAB using the function *j_function_dist* (see attached CD-ROM (vol.1) by counting the deposit cells and all cells within 100 buffer zones. For example, zones of successively increasing distance from faults and shear zones.¹

A Monte Carlo test is applied to determine the significance of a relationship. The procedure is to generate 99 simulations using the same number of randomly located points as there are gold deposits and plot the pointwise maximum and minimum of the simulated J estimates. There are 120 gold deposits in the study area. Only deposits with a resource of at least 1000 kg total contained metal were considered because evidence for smaller deposits is unlikely to have been incorporated in a regional-scale GIS database. At the regional scale of the study area (approximately 100×100 km), deposits can be treated as a point data set. X - and Y -coordinates for the simulations were selected from a uniform random distribution so that these “deposit ” points correspond to the null hypothesis, i.e. that there is no spatial association between the deposit points and faults. At a 100 evenly spaced values of distance, r , the maximum and minimum of the simulated $\hat{J}_{X,Y}(r)$ estimates are plotted, giving a pointwise Monte Carlo test with a p-value of 2%.

Examples of the use of the bivariate J -function to measure the spatial association between gold deposits and anticlinal and synclinal axes are shown in Figures 6.7 and 6.8. The X -axes represent the distance to the trace of the nearest anticlinal and synclinal axis, respectively. In both figures, the blue curves (solid line) represents the estimate of the bivariate J -function for the empirical data $\hat{J}_{X,Y}(r)$, the horizontal dotted line shows the expected value of $J_{X,Y}(r) \equiv 1$ for the case where deposit points and anticlinal axes are independent, and the upper and lower red (dashed) curves represent the pointwise critical envelopes of $J_{X,Y}(r)$ estimated from 99 simulations of the data.

If the empirical curve (blue solid line) lies wholly within the envelopes (red dashed lines), then the null hypothesis (no spatial association) would be accepted. If the observed

¹Separate cumulative and the stepwise versions of the bivariate J -function were written to deal with variables that do not involve distance such as strike angles.

Figure 6.7. Graph of bivariate J-function for distance to the ground traces of regional-scale anticlinal axes. The maximum difference between the lower empirical curve (blue) and the lower critical envelope (dashed red curve) at 2200 m is interpreted to indicate that the effect of proximity to an anticlinal axis in upgrading the favourability for gold deposits is at a maximum within a buffer interval of 0–2200 m.

Figure 6.8. Graph of bivariate J-function for distance to the ground traces of regional-scale synclinal axes.

J-curve (blue solid line) extends well below the envelope created by the lower dashed curve, then this is taken as strong evidence that gold deposits are associated with faults. The bivariate J-curve in Figure 6.7 is an example of a strong positive spatial association. Studies of regional-scale controls on the location of orogenic gold deposits have shown that proximity to major anticlinal axes significantly upgrades prospectivity for mineralization (Groves *et al.*, 2000, 2001).

If the observed J-curve extends well above the upper dashed curve, then some negative or inhibitory relationship exists. Figure 6.8 shows the bivariate J-curve for the proximity to regional-scale synclinal axes. For distances below about 10 km, the empirical (blue solid) curve lies within the envelope of the simulated curves, indicating that no spatial association exists. The positive association at distances greater than 10 km is due to the fact that anticlines are located between the synclines. The curves show an increasing deviation from unity (horizontal line in Fig. 6.7) at high values of r since the variability increases with r .

Edge corrections were not performed. However, recent work by Baddeley *et al.* (2000) on the J-function for univariate point patterns suggests that the bivariate J-function is likely to be relatively insensitive to edge effects. Edge effects arise because the distance to the nearest line segment cannot be correctly estimated for points located close to the borders of the map if the nearest segment lies outside the map boundary.

In addition to spatial associations between deposit points and features represented by line segments (e.g. faults and lithological contacts), the bivariate J-function was also useful for analysing spatial associations between deposit points and regions (e.g. magnetic anomalies) and point data (e.g. intersection of faults). In both cases, layers representing proximity to the features were used as the inputs to the analysis. Figure 6.9 shows plots corresponding to all of the methods described in Section 6.2 for a GIS layer depicting distance to positive magnetic anomalies (layer: *l14_mz2_dist*, attached CD-ROM (vol. 2)).

In general, the methods discussed above are all capable of identifying spatial associations between deposits and layer variables provided the type of the spatial relationship is a simple one involving some inverse or direct proportionality. Examples of this type of relationship are; 1) proximity to linear and point map features (e.g. faults & magnetic anomalies, respectively), where favourability is high at low values and decreases with distance, and 2) density of faults, or sulphidation index, where the maximum variable value is most favourable for deposits. Trends of this type are usually clearly revealed in the cumulative version of the bivariate J-function, chi-squared, contrast, and Kolmogorov-Smirnov tests,

all of which which are based on cumulative curves.²

The cumulative bivariate J-function is not well suited to measuring spatial associations for variables that do not involve distances, such as the density of faults, or rheological contrast at the nearest lithological boundary and strike orientation of regional faults: the latter relationship is shown in Figure 6.12. Cumulative plots (e.g. Kolmogorov-Smirnov cumulative distribution function) generally do not deal very well with spatial relationships where favourable variable values occur in several discrete intervals. Only the $(O - E)/E$ and interval-based bivariate J-function plots, which are calculated at successive discrete intervals, provided useful information for this type of relationship. The association of deposits around segments of regional faults with a particular range of strike angles (possibly due to the existence of dilational zones at the time of mineralization) is a good example of this type of relationship (Fig. 6.12).

6.2.5 Bivariate J-Curve (Incremental)

In order to overcome the problems involving the use of the bivariate J-function for spatial relationships that do not involve distances, or where positive associations exist within discrete ranges of variable values, a procedure for calculating the bivariate J-curve was developed in which the J-function is estimated for successive distance intervals rather than for cumulative distances (Brown *et al.*, 2002c). For example, in the case of proximity to anticlinal axes, the bivariate J-function was calculated for each 349-metre distance interval. This distance interval was chosen so that there are approximately 100 intervals along the X-axis, resulting in a graph that shows detailed trends but is not excessively noisy. Calculations and plots were performed in MATLAB using the function *j_function15_stepwise_dist* (see attached CD-ROM (vol.1)). Examples of the interval-based J-curve are shown in Figures 6.10 and 6.11.

This interval calculation of the J-function was successfully applied to variables other than distance. Figure 6.12 shows the interval-based calculation of the J-function for the strike orientation of crustal-scale faults. As for the cumulative J-curve, the solid line represents the estimate of the bivariate J-function for the empirical data $\hat{J}_{X,Y}(r)$, the horizontal line shows the expected value of $J_{X,Y}(r)$ for the case where deposit points and the spatial variable are independent, and the grey bars show the maximum and minimum values for

²Contrast and chi-squared methods do not have to be plotted as cumulative curves, but experience has shown that non-cumulative plots tend to be very noisy due large fluctuations in the number of deposits in the discrete buffer zones (see examples of the step-wise bivariate J-function curve)

(a) Contrast, C_W

(b) Bivariate J-function (cumulative)

(c) Chi-squared statistic

(d) Bivariate J-function (interval-based)

(e) Kolmogorov-Smirnov test

(f) $(O - E)/E$

Figure 6.9. Plots used to examine the relationship between deposits and the distance to positive magnetic anomalies ($z\text{-score} \geq 2$) based on the GIS layer *l14_mz2_dist*. In b), d) & e), the empirical curve is shown in blue and the theoretical curve is shown in red.

99 simulations of the data at each interval. The interpretation of the stepwise J-function bar graphs is the same as that explained above.

Comparison with Other Graphical Methods

The results obtained using the bivariate J-functions were compared with other methods for measuring spatial relationships. Plots of contrast of weights (Bonham-Carter, 1994), chi-squared, a bar graph of the $(O - E)/E$ (where O = observed number of deposits in a region corresponding to an interval on the X-axis and E = expected number of deposits for a uniform random distribution) and the Kolmogorov-Smirnov (KS) cumulative distribution function for the distance to anticlinal axes are shown in Figures 6.1, 6.3, 6.5, 6.7, 6.10 and 6.13. The KS-curve shows the cumulative fraction of deposits versus distance to anticlinal axes (Fig. 6.5). The upper curve (blue) represents the observed distribution and the lower curve (red) represents a simulated uniform random distribution.

Bonham-Carter (1994) used the position of the peak in cumulative plots of contrast (C_w) to determine which areas of the map are the most prospective. For example, the peak in the contrast plot for anticlinal axes (Fig. 6.1) is interpreted to mean that proximity to the anticlinal axes has a maximum effect in upgrading the prospectivity for deposits within the buffer zone from 0 to 1400 m. In the $(O - E)/E$ plot (Fig. 6.13), the excess in the number of known deposits over those that would be expected if the deposits had a uniform random distribution falls off rapidly between 1200 and 1800 metres. The most favourable zone in this case was estimated to be from 0 to 1800 metres from anticlinal axes. A degree of subjective judgement is required in the estimation of the cut-off distances for the most prospective zones. This approach was applied to the other methods for measuring spatial associations. A comparison of the results for each of the methods is given in Table 6.3 which shows estimates of the most prospective distance to anticlinal axes and strike orientations of crustal-scale faults. Distances have been rounded off to 100 metres, corresponding to the grid cell size, and angles are shown to the nearest 10° , which corresponds to the bar-graph intervals for the $(O - E)/E$ and interval-based bivariate J-function plots.

All of the methods provide evidence for the strong positive nature of the relationship between gold deposits and proximity to anticlinal axes. Although the bivariate J- and KS-plots are not ideally suited to identifying variable ranges in which the spatial association is maximized, the points on the X-axis corresponding to the maximum difference between the observed and simulated curves (Figs 6.5 & 6.7) are interpreted to indicate the distance at which the effect of upgrading the prospectivity for gold deposits is maximized. These

Figure 6.10. Graph of interval-based bivariate J-function for distance to the ground traces of regional-scale anticlinal axes. The distance at which the empirical curve (blue) is located below the lower critical envelope (grey bars below $y = 1$) is 1400 m. This is interpreted to indicate that the effect of proximity to an anticlinal axis in upgrading the favourability for gold deposits is at a maximum within a buffer interval of 0–1400 m.

Figure 6.11. Graph of interval-based bivariate J-function for distance to the ground traces of regional-scale synclinal axes.

(a) Contrast, C_W

(b) Bivariate J-function (cumulative)

(c) Chi-squared

(d) Bivariate J-function (interval-based)

(e) Kolmogorov-Smirnov test

(f) $(O - E)/E$

Figure 6.12. Plots used to examine the relationship between gold deposits and the strike of crustal-scale shear zones. The layer analysed (*l28_s_f1str*) shows the strike angle of the nearest fault reduced to a range 0–179°. In b), d) & e), the empirical curve is shown in blue and the theoretical curve is shown in red.

distances are also shown in Table 6.3. It was not possible to estimate the most favourable strike angles using the Kolmogorov-Smirnov graph. The results agree reasonably well, although estimates for distances to anticlinal axes based on the J- and KS-curves are higher than for the other methods. There is also reasonably good agreement between methods for the strike of regional NNW-trending faults. However, the positive association for strike angles in the range of 10–20°, identified by the contrast of weights, chi-squared, and $(O - E)/E$ methods, was not identified in plots of the cumulative and interval-based J-functions and the Kolmogorov-Smirnov plot. Results for all the GIS layers tested are shown in Table 6.4 below.

Table 6.3. Favourable zones for gold deposits estimated using different statistical methods. Columns show the different statistical methods. Abbreviations: $(O - E)/E$ = bar graph of observed (O) versus expected (E) numbers of known deposits versus distance or strike angle, χ^2 = chi-squared, C_W = contrast of weights, KS = Kolmogorov-Smirnov cumulative distribution function, J-fn (cumul.) = bivariate J-function calculated as a cumulative function, and J-fn (int.) = bivariate J-function calculated for each interval. The first row shows the results for distance to the nearest anticlinal axis. The second row shows the results for a GIS layer in which cell values represent the strike orientation of the nearest crustal-scale fault or shear zone. Angles were converted to unique orientations in the range [0, 179].

GIS layer	C_W	χ^2	KS-test	J-func. cumulative	J-func. interval	$(O-E)/E$
Anticlinal axes (m)	0–1400	0–1400	0–2100	0–2200	0–1400	0–1800
Strike of nearest crustal fault (°)	10, 20 160	10 120, 160	— ^a —	 150–160	 140–160	10–20 120–160

^aIt was not possible to estimate particular intervals corresponding to positive associations using the KS-curve.

Estimates of favourable strike orientations show reasonably good agreement between the interval-based J-function, $(O - E)/E$ and cumulative J-function methods although, as noted above, the latter is not generally useful where favourable variable values occur in discrete ranges.

The bivariate J-function (calculated both as a cumulative curve and over intervals) is a useful method for identifying spatial relationships between deposit point patterns and other spatial features. An advantage of both forms of the J-function over other methods, such as contrast of weights, chi-squared, KS-curves and $(O - E)/E$, is that the Monte Carlo test provides a graphical indication of the statistical significance of the spatial relationships. The interval-based calculation of the J-curve (represented as a bar graph) is useful for

determining the nature of spatial relationships involving variables other than distance and where positive or negative associations occur within discrete ranges of variable values.

6.2.6 Difference Between Observed and Expected Number of Deposits

A graphical method developed in this study to assess the relationship between deposit points and spatial features is to plot a bar graph of the function, $y = (O - E)/E$, where O = observed number of deposits in regions corresponding to an interval on the X-axis and E = expected number of deposits for uniform random distribution. Calculations were made in MATLAB using the function *xchi*. The interval size is user-definable and was chosen to produce a graph that yields detailed trends but is not excessively noisy. An interval size of 200 metres was used for layers involving proximity relationships and approximately 50 intervals for other variables (Figs 6.13 and 6.14).

Variables such as distance to positive magnetic anomalies or density of faults differ from most distance relationships involving faults because deposits are associated with the maximum rather than the minimum value of the variable. For this type of GIS layer, the variable was transformed to give the *difference* between the raw value and maximum value (i.e. most favourable value). This transformation was applied as a pre-processing step in MATLAB using the function *rescale_big_is_fav*. The transformed variable was then used in the contrast, chi-squared, and J-function plots. Layers which were processed in this way are indicated in the right-most column in Table 6.4 (Section 6.3) below.

6.2.7 Average Distance between Spatial Objects

The trends in the plots showing distance on the X-axis cannot always be meaningfully interpreted beyond a certain maximum distance. The reason for this is that, as the distance from a particular linear feature, for example, the ground trace of a particular anticlinal axis increases, the distance to some other favourable feature such as a crustal-scale shear zone or a *different* anticlinal axis increases. Significant trends are those that are apparent at distances that are less than about two or three kilometres. Therefore, the X-axis in some of plots shown in Appendix G have been truncated in order to show the trends at small distances more clearly. The average distance between linear and point features was calculated in MATLAB using the function *median_dist* (Table 6.4).

Figure 6.13. Graph of $(O - E)/E$ versus distance to the ground traces of regional-scale anticlinal axes. The decline in excess of observed deposits over the number of deposits expected for a uniform random distribution of deposits for the anticlinal axes at between 1200 and 1800 m is interpreted to indicate that the effect of proximity to an anticlinal axis in upgrading the favourability for gold deposits is at a maximum within a buffer interval of ~ 0 –1800 m.

Figure 6.14. Graph of $(O - E)/E$ versus distance to the ground traces of regional-scale synclinal axes.

6.3 Results

Fifty-nine potential input GIS layers were created as a result of the work in Chapter 5 (Tables G.1-G.4 in Appendix G). Layers that performed best at predicting the known deposits were selected as inputs for neural networks in the experiments in Chapter 7.

The selection process consisted of two parts. First, the layers were tested using the methods described above to determine: 1) the ranges of variable values that are most favourable for deposits, and 2) the range of variable values over which the positive spatial associations are statistically significant. Plots of contrast (C_W), chi-squared (χ^2), and $(O - E)/E$ were used to identify the positive associations and the Kolmogorov-Smirnov (KS) cumulative distribution function and bivariate J-function were used to determine if the associations are statistically significant.

Second, the thresholds defining the most favourable variable values for gold deposits were used to produce temporary binary layers which were ranked according to the ability to predict known deposits. For the purpose of ranking potential input GIS layers, capture efficiency ratios (see explanation below) are calculated using a temporary binary layer in which the region corresponding to the most favourable classes or range of variable values are set to a value of one and the remaining area to zero. Calculations were performed in MATLAB using the function, *mapstats_binary*. The following four sets of criteria were used to rank the layers;

1. layer from each evidence category with highest D/A value,
2. D/A AND $D \geq \sim 20\%$,
3. $D \times (D/A)$, and
4. $D \times (D/A)$ AND $D \geq \sim 20\%$ AND $D/A \geq \sim 3$,

where D is the percentage of known deposits in the favourable region of the binary layer and A is the percentage of the total map area occurring within the favourable region.

The first method was to select one layer from each evidence category. The best layer within each category is considered to be the one that contains the largest proportion of the known deposits in the smallest proportion of the total area of the map; i.e. the largest value of the *capture efficiency ratio* D/A . A minimal set of 10 layers and a group of 17 layers including all available evidence types was chosen in this way.

In the second method, layers were selected with the highest value of the capture efficiency ratio D/A , where the binary favourable region also contains approximately 20% of all the

known deposits. A problem with this ratio is that the value can be high if just two or three deposits occur in a very small area. In order to account for this, the ratio D/A , is multiplied by the percentage of known deposits that occur in the favourable region of the binary map, giving the statistic $D \times (D/A)$. This was used as the criterion in the third method. A fourth method of ranking the layers was tested, in which a combination of criteria was applied. Layers were ranked according to the $D \times (D/A)$ statistic, but only layers with $D \geq \sim 20\%$ and $D/A \geq \sim 3$ were chosen. Sets of 10 and 17 layers, corresponding to each of the four selection methods, were selected as inputs to neural networks.

Table 6.4 shows the ranges of variable values in which there is a positive association with deposits. For the bivariate J-function, there is also a column showing the variable value corresponding to the maximum difference between the empirical curve and the lower critical envelope created using uniform random data. Although the cumulative bivariate J-function curve is not well suited to determining the zone in which the spatial association is maximized, the points on the X-axis corresponding to the maximum difference between the observed and simulated curves (Fig. 6.7) are shown in Table 6.4. These results agree reasonably well with the other methods, although estimates for distances to anticlinal axes, based on the J- and KS-curves, are higher than for the other methods.

For the Kolmogorov-Smirnov (KS) test, only the D statistic and the critical value of D are shown, since the KS-test was only used to determine whether the variable values for known deposits are different from a uniform random distribution. Blank fields indicate that there is no interval in which there was a clearly a strong positive association. In all cases, except for the strike of the nearest E-trending regional fault (layer, *l31-s-f4str*), the test statistic exceeded the critical value of D ; i.e. $D_{test} > D_{critical}$, indicating that the relationship between the particular variable in the GIS layer and the deposit points are significantly different from a uniform random distribution (p -value = 0.01).

The results shown in Table 6.4 provide quantitative evidence for the importance of structural controls on the location of orogenic gold deposits. In creating the temporary binary layers, the threshold value defining the most favourable region for gold deposits was set to the variable value on the X-axis at which the observed number of deposits falls below the number that would be expected due to a uniform random distribution (i.e. $y = 0$ on the $(O - E)/E$ bar graph). The bivariate J-function plot was used to confirm that the positive association with deposits is statistically significant within the interval from zero to the particular distance (Fig. 6.7).

The following intervals, in which the effect of proximity to a linear or point feature max-

imized, were defined; crustal-scale faults (0-2400 m), NNW-trending regional faults (0-2400 m), NE-trending regional faults (0-800 m), E-trending regional faults (0-800 m), regional-scale anticlinal axes (0-1800 m), lithological contacts (0-200 m), distance to positive magnetic anomalies ($z \geq 2$, 0-1600 m), the intersection of regional-scale NNW- and NE-trending faults (0-1200 m), and felsic porphyritic intrusions (0-1400 m).

Selective mineralization also appears to occur proximal to segments of regional faults and shear zones with particular orientations. The following favourable strike angles were determined from $(O-E)/E$ bar graphs and then modified according to which intervals were statistically significant according to the bivariate J-function plots; crustal-scale faults ($10-20^\circ$ & $130-160^\circ$), NNW-trending regional-scale faults ($30-40^\circ$), NE-trending regional-scale faults ($70-80^\circ$ & $140-170^\circ$), and E-trending regional-scale faults ($80-90^\circ$ & $140-150^\circ$).

The plots also show the importance of high values of rock competency. The following favourable ranges were identified;

1. **rock strength:** Young's Modulus ($\sim 80 \leq x \leq 95$ GPa; Hatheway & Kiersch, 1989 compilation), uniaxial compressive strength (≥ 190 MPa),
2. **sulphidation index:** $Fe_{tot}(wt\%) \times Fe_{tot}/(Fe_{tot} + Mg + Ca)$ ($\geq \sim 4.3$),
3. **rheological contrast:** fuzzy membership (≥ 0.7), subjective classes (≥ 4), Young's Modulus (62.3–69.2 GPa, Hatheway & Kiersch, 1989 compilation), uniaxial compressive strength (148–169, MPa), and fracture toughness (≥ 2.3),
4. **chemical contrast:** $Fe_{tot}/(Fe_{tot} + Mg + Ca)$ (0.20–0.35), $Fe_{tot}(wt\%) \times Fe_{tot}/(Fe_{tot} + Mg + Ca)$ (≥ 4.0), $Fe_2O/(Fe_2O_3 + FeO)$ (0.42–0.60),
5. **regional fault density:** NNW- and NE-trending (300–600 m),
6. **lithological complexity:** (710–1220 m), and
7. **oxidation index:** $Fe_2O/(Fe_2O_3 + FeO)$ (0.11–0.26)

The association of deposits with high values of Young's Modulus and rheological contrast was not as clear using the detailed AMC data set (M. Lee, unpublished data from Australian Mining Consultants Pty Ltd, 2000) as the trend obtained from the compilation of Hatheway & Kiersch (1989). This is despite the fact that the AMC data set was based on samples from mines within the study area. Part of the problem with the AMC data could be due to the high degree of variability in the samples tested due to alteration in the vicinity of the mines.

Table 6.5 shows the sets of 10 and 17 layers selected using each of the four sets of ranking criteria discussed above. The following layers are used in at least one of the sets of inputs: 1) distance to porphyritic felsic intrusions, 2) distance to crustal-scale faults and

shear zones (defined as those exceeding 100 km in length), 3) distance to positive aeromagnetic anomalies, 4) distance to nearest lithological boundary, 5) distance to intersection of NNW- and NNE-trending faults and shear zones, 6) distance to nearest ground trace of a regional-scale anticlinal axis, 7) strike of nearest crustal scale fault or shear zone, 8) strike of nearest NNE-trending regional-scale shear zone, 9) strike of nearest NNW-trending regional-scale shear zone, 10) strike of nearest lithological contact, 11) chemical contrast between rock units at the nearest lithological boundary (sulphidation index based on the ratio, $Fe_{total}wt\% \times Fe/(Fe + Mg + Ca)$), 12) chemical contrast based on the ratio, $Fe_2O_3/(Fe_2O_3 + FeO)$, 13) density of crustal and regional-scale faults and shear zones (calculated using a 5×5 km moving window), and 14) density of lithological contacts (used as a measure of lithological heterogeneity), and 15) favourable geology (subjective fuzzy membership), 16) favourable lithological contact-types (objective fuzzy membership), and 17) favourable rheological contrast (subjective fuzzy membership). A binary deposit layer depicting orogenic lode-gold deposits with a resource of ≥ 1000 kg total contained metal is used to provide the target or desired output values required to train the networks.

These layers were used as inputs in neural networks described in Chapter 7. The details of the rankings of the layers using each of the four methods are shown in Tables G.1, G.2, G.3 and G.4 in Appendix G.

Table 6.4: Favourable ranges of variable values for gold deposits. Bivariate J-functions and the KS-test were used to determine whether spatial relationships are statistically significant.

Layer Type	Layer Name	$(O-E)/E$		χ^2	C_w	J-fn (cumulative)	J-fn (interval)	KS-test	Rescale
		Favourable if value:	Favourable range	X_{peak}	X_{peak}	+ve assoc. in range	Favourable range	D_{obs}	$D_{crit.}$
Rock strength									
Fuzzy membership	l2_lrh1b ¹	high	0.7-0.8, 0.9-1.0	0.18, 0.79, 0.92	0.93	0.17-0.24, 0.69-0.86	0.16-0.20, 0.74-0.80	0.24	0.15
10 classes	l2_lrh2b ¹		7.0-8.0	9.0	7.0	7.0-9.0	7.0-8.0	0.22	0.15
Young's modulus ¹	l2_lrh3	med-high	72.3-98.2	85.8	90.5	36.1-41.0, 73.0-95.8	52.4-66.7, 81.3-98.5	0.20	0.15
Young's modulus ²	l2_lrh4	high	70.0-88.3	63.1	49.4	48.3-74.2	66.1-88.3	0.47	0.15
Compressive Strength ²	l2_lrh5	high	187-250	190	220	140-215	85-95, 174-210	0.49	0.15
Tensile Strength	l2_lrh6	high	16.8-18.5	16.6	11.3	10.8-17.3	16.0-20.8	0.38	0.15
Fracture toughness	l2_lrh7 ¹	med-high	2.3-3.1	1.8	1.7	1.6-3.9	2.24-3.41	0.44	0.15
Chemical ratios									
Fe/(Fe+Mg+Ca)	l3_lch1 ¹			0.40	0.43	0.39-0.44		0.43	0.15
Fe(wt%)*Fe/(Fe+Mg+Ca)	l3_lch2	high	4.3-4.7	4.53	4.75	0.38-0.96, 1.05-4.75	4.6	0.33	0.15
Fe ₂ O ₃ /(Fe ₂ O ₃ +FeO)	l3_lch3	low	0.11-0.26	0.47	0.17	0.25-0.59		0.45	0.15
Fe ₂ O ₃ /FeO	l3_lch4 ¹	low	0.10-0.19	5.56	4.27	0.31-1.42		0.40	0.15
Fe ²⁺ /Fe ³⁺	l3_lch5 ¹	int. ¹	0.13-0.78, 2.00-2.58	4.93	3.84	0.21-1.30		0.40	0.15
Field strength data:									
Magnetic intensity (RTP)	l5_m_rtp	int. ¹	58100-59000	57900		57800-57900	57700	0.18	0.15
Bouguer gravity anomaly	l12_grav	int. ¹	-560- -330	-549	-613			0.33	0.15
Distance to nearest:									
Porphyritic intrusive ⁶	l4_l_pf_dist	low	0-1400			0-15000	3500	0.32	0.15
+ve mag. anomaly ($Z \geq 1$)	l14_mz1_dist	low	0-1200	1200	2200	0-3800	1600	0.30	0.15
+ve mag. anomaly ($Z \geq 2$)	l14_mz2_dist	low	0-1600	1700	2300	0-6400	2900	0.39	0.15
-ve mag. anomaly ($Z \leq -1$)	l14_mz_1_dist	low-med		2300	2300			0.14	0.15

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Table 6.4: *continued*

Layer Type	Layer Name	(O-E)/E		χ_2	C_w	J-fn (cumulative)		J-fn (interval)	KS-test		Rescale
		Favourable if value:	Favourable range			+ve assoc. in range	$ O-E _{\max}$		D_{obs}	$D_{crit.}$	
Crustal-scale shear zone	l20_f1_dist	low	0-2400	1800		0-3500	1800	0-400	0.24	0.15	
Regional NNW fault	l21_f2_dist	low	0-1200	1200		0-1600	1200		0.19	0.15	
Regional NE fault	l22_d3_dist	low	0-800	200		0-4000	900	0-200	0.37	0.15	
Regional E fault	l23_d4_dist	low	0-800	400					0.16	0.15	
Reg. fault intersection	l34_s_f23pdst	low	0-1200	1300		500-3900	1300	200-400, 800-1200	0.25	0.15	
Anticlinal axes	l46_dist_anti	low	0-1800	1400		0-13100	2200	0-1400	0.39	0.15	
Synclinal axes ⁵	l46_dist_sync	low	0-1000	1000		0-2300	1200	0-1000	0.24	0.15	
Lithological contacts	l39_c_dist	low	0-200			0-5700	500	0-200	0.51	0.15	
Strike of nearest:											
Crustal-scale shear zone	l28_s_f1str	int. ⁷	10-20, 120-160	10, 115, 157	8, 18, 157	132-163	150	140-160 ⁴	0.23	0.23	
Regional NW fault	l29_s_f2str	int. ⁷	30-40, 100-120	25, 104, 136, 154	154	10-30 ³	155	30-40, 120-130	0.21	0.19	
Regional NE fault	l30_s_f3str	int. ⁷	70-90, 140-180	67, 108	8, 78, 176		110	70-80, 140-170	0.24	0.19	
Regional E fault	l31_s_f4str	int. ⁷	80-100, 130-150	82, 151, 161	162	150-169		80-90, 140-150 ⁴	0.35	0.38	
Lithological contact	l38_c_str1k	int. ⁷	30-50, 110-120	30, 90, 165				0-10, 170-180	0.11	0.15	
Rheological contrast											
Fuzzy	l36_l_rh1k	high	0.68-0.85	0.77	0.76	0.44-0.71	0.69	0.68 - 0.77	0.22	0.15	yes
10 classes	l36_l_rh2k	high	4-7	5.9	6.0	3-6	5	5-7	0.34	0.15	yes
Young's modulus ¹	l36_l_rh3k	high	62.3-69.2			60.9-69.2	68.7	3.5-6.9, 48.4-51.9	0.15	0.15	yes
Young's modulus ²	l36_l_rh4k	med	32.1-37.5			35.5-47.7	31.5	0.80-10.7, 32.1-34.8	0.19	0.15	yes
Compressive Strength	l36_l_rh5k	med	148-169	148		90-155	151	148-158	0.18	0.15	yes
Tensile Strength	l36_l_rh6k	med	5.9-7.4	6.70, 9.60				5.88-6.62, 8.82-9.56	0.16	0.15	yes

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Table 6.4: *continued*

Layer Type	Layer Name	$(O-E)/E$		χ_2	C_w	J-fn (cumulative)	J-fn (interval)	KS-test		Rescale
		Favourable if value:	Favourable range	X_{peak}	X_{peak}	+ve assoc. in range	Favourable range	D_{obs}	$D_{crit.}$	X -axis
Fracture toughness	l36_Lrh7lk	high	2.24-2.52	0.29, 2.25	2.25	2.56-2.80	0.28-0.42, 2.24-2.38	0.16	0.15	yes
Chemical contrast										
Fe/(Fe+Mg+Ca)	l37_Lch1lk	high	0.20-0.35	0.14, 0.25	0.28	0.03-0.32	0.14-0.15, 0.25-0.27, 0.31-0.33	0.31	0.15	yes
Fe(wt%)*Fe/(Fe+Mg+Ca)	l37_Lch2lk	high	4.00-4.40	2.01, 3.29, 3.96		3.22-4.09	0.23-0.46, 2.0-2.4, 3.3-3.5, 3.9-4.2	0.18	0.15	yes
Fe ₂ O ₃ /(Fe ₂ O ₃ +FeO)	l37_Lch3lk	high	0.42-0.60	0.09, 0.45		0.27-0.58	0.06-0.09, 0.51-0.54, 0.56-0.59	0.16	0.15	yes
Fe ₂ O ₃ /FeO	l37_Lch4lk	med	1.70-2.80	1.65		0.80-2.30	1.7-2.5	0.18	0.15	yes
Fe ²⁺ /Fe ³⁺	l37_Lch5lk	med	1.50-2.50	1.5		0.70-2.03	1.5-2.0	0.18	0.15	yes
Density										
Regional-scale faults	l42_fl23_dens	med-high	300-600	410		250-750	310-420, 490-560	0.39	0.15	yes
Lithological contacts	l43_lith_div	high	710-1220	780	130, 1100	120-1260	710-1230	0.41	0.15	yes
Metamorphic grade	l45_Lmeta	med-high	2-3	2	2	0-3	2-3	0.55	0.1488	yes

¹CRC: data obtained from Tables 3-5, Section X, Hatheway & Kiersch (1989).²AMC: All rheological data, except in first Young's Modulus row, was provided by M. Lee, unpublished data, AMC Pty Ltd, 2000³A negative association (significant at p-value = 2%) exists in range 10–30°.⁴Empirical curve close to, but not outside, critical envelope. Therefore positive association is not significant at the p-value = 2% level.⁵There is a negative association between proximity to regional-scale antinormal axes and deposits (≥ 1000 kg TCG).⁶Porphyritic felsic intrusion.

6.3.1 Discussion

Use of Layer-Evaluation Methods to Test Exploration Criteria

Methods used in this chapter for analysing the spatial relationships between known deposits and variables provide a means of testing whether exploration criteria are generally applicable on a regional scale and provide quantitative information that is useful for applying the criteria in exploration programs. For example, a number of exploration geologists in the Yilgarn have suggested that felsic porphyritic intrusions are favourable for orogenic gold mineralization at a local scale, because these bodies indicate a connection between the faults or shear zones and a deep crustal source and are therefore likely to have also acted as conduits for gold-bearing fluids. However, it has not been previously established if this is a useful exploration criterion on a regional scale. The analysis methods described above show that, at distances less than 400 m (and possibly up to 1400 m), the favourability for gold deposits is significantly increased (see Table 6.4). Clearly, derived layers incorporating empirical exploration criteria are an important means of incorporating geological knowledge into a prospectivity analysis.

Conditional Independence of Input Variables

Kohavi & Frasca (1994) have shown that useful feature subsets are not necessarily maximally independent sets. This is one of the reasons why input layers have not been tested to check if they are conditionally independent with respect to deposits. An additional reason is that the results of Chapter 4 suggest that neural networks are less affected by problems of conditional independence than either the weights-of-evidence or fuzzy systems. Recent work by Singer & Kouda (1999a) who compared the weights-of-evidence method with probabilistic neural networks supports this. Singer & Kouda (1999a) concluded that probabilistic neural networks have no problem in dealing with correlated variables.

Use of Derived GIS Layers to Include Geological Knowledge in a Neural Network Analysis

The use of GIS layers containing fuzzy membership values is another effective method of combining subjective geological knowledge with empirical data in a neural-network approach to mineral prospectivity mapping.

Table 6.5. Layers selected as inputs for neural networks using four different criteria (see text for explanation). A set of 10 and 17 layers (shown in shaded boxes) was selected using each method.

Layer Type	Layer Name	Selection Criteria			
		Evidence category highest D/A AND $D \geq \sim 20\%$	D/A	$D^*(D/A)$	$D^*(D/A)$ AND $D \geq \sim 20\%$ AND $D/A \geq \sim 3\%$
Rock strength					
Compressive Strength ¹	l2_l_rh5			10	
Distance to nearest:					
Porphyritic intrusive ²	l4_l_pf_dist	10	10	10	10
+ve mag. anomaly, $z \geq 2$	l14_mz2_dist	17	17	10	
Crustal-scale shear zone	l20_f1_dist	10	10		17
Regional NE fault	l22_d3_dist	17	17	10	10
Regional E fault	l23_d4_dist				
Reg. fault intersection	l34_s_f23pdst	17	17	17	17
Anticlinal axes	l46_dist_anti	10	17	10	10
Synclinal axes	l46_dist_sync				
Lithological contacts	l39_c_dist	17	17	10	
Strike of nearest:					
Crustal-scale shear zone	l28_s_f1str		17	17	10
Regional NW fault	l29_s_f2str			17	
Regional NE fault	l30_s_f3str	10	10	17	10
Lithological contact	l38_c_str1k	17	10		17
Rheological contrast					
Fuzzy	l36_l_rh11k	10	10	17	10
Chemical contrast					
Fe/(Fe+Mg+Ca)	l37_l_ch11k	10	10	17	17
Fe ₂ O ₃ /(Fe ₂ O ₃ +FeO)	l37_l_ch31k	17			
Fe ₂ O ₃ /FeO	l37_l_ch41k		10		17
Density					
Regional-scale faults	l42_f123_density	10	17	10	10
Lithological contacts	l43_lith_div	10	10	10	10
Metamorphic grade	l45_l_meta	17		10	
Fuzzy membership Layers					
Fav. geology	l1favgeol25pr ¹	10	10	17	10
Fav. contact,P(deposit)	l44favcnt25pr ¹	10	10	10	

¹Data provided by M. Lee, AMC Pty Ltd, unpublished data, 2000

²Porphyritic felsic intrusion.

³Abbreviated name = GIS layer name used in ArcView, text, & CD-ROM: l1favgeol25pr = l1_favgeolt25_pr0110, l44favcnt25pr = l1_favcont25-pr0110_200.

Two types of fuzzy membership layers have been used:

1. objective, and
2. subjective layers.

Objective fuzzy membership layers

In order to create the favourable geology and favourable lithological contact layers, categorical data were converted to fuzzy membership values. This conversion was based on the statistical relationships between known gold deposits and rock types in a solid geology GIS layer, and a layer representing the rock-type combination at the nearest lithological boundary, respectively.

The use of fuzzy membership rather than categorical inputs is useful for MLP networks, particularly if there are a large number of classes in the categorical layer. Categorical data are normally converted to numerical form using 1-of-n coding and this leads to a large number of additional input connections, which, in combination with small training data set sizes, could lead to over-fitting of the training data and poor generalization (see Section 5.5.14).

Subjective Fuzzy Membership Layers

Rheological contrast at lithological boundaries was modelled using a fuzzy membership layer, in which the assignment of fuzzy membership values, although based on geological field observations, was subjective. On a regional scale, most large gold deposits in the Kalgoorlie area are sited in structurally isolated, thick competent units or at contacts between layers of contrasting competency, which are oriented between NNW and NNE. The reason for this is that the more competent units tend to fail selectively in this orientation and hence become sites of increased structural permeability and fluid focusing. Subjective estimates of the relative competency of host rocks are based on the degree of silica content, modal mineralogy, grain size, fabric development, texture, and metamorphic grade. For example, banded iron formation and basalt are ranked as very competent whereas ultramafic schists are ranked as very incompetent. All rock types are assigned a ranking which was used to create a GIS layer containing cell values corresponding to the competency contrast at the nearest lithological boundary.

An additional application for the methods used to evaluate potential input layers described in this chapter is to create objective fuzzy membership layers which are based on statistically measured spatial relationships rather than subjective judgement. The results of evaluating input GIS layers shown in Table 6.4 were used in this way to create the fuzzy

systems and hybrid neural-network fuzzy systems that are compared with neural networks in Chapter 7. The approach used here could potentially be applied to a large range of subjective data (e.g. favourability of tectonic environment, host stratigraphy, or reactivation along major faults) currently used in regional exploration programs, but which would normally not be employed in an empirical neural-network approach.

Figure 6.15. Use of derived GIS layers to include conceptual knowledge in a neural network analysis. The first type of derived layers is the conventional type, which represent exploration criteria that are based on some aspect of a mineral systems model. In the second and third groups of layers, subjective geological knowledge is presented to the neural network as fuzzy membership layers.

6.3.2 Conclusions

The main results are listed below.

1. Methods used to identify spatial associations between deposits and layer variables (contrast of weights, chi-squared, KS-curve, two types of bivariate J-function, and $(O - E)/E$ plots) agree generally very well provided the type of the spatial relationship is a simple one involving some inverse or direct proportionality.

2. Different methods for selecting layers produce very similar results. Although only 3 layers are common to the set of 10 layers selected using the four methods, 13 layers are common to the four 17-layer sets.
3. The ranking of potential input layers shows that the most useful layers for predicting the location of deposits are not composed of raw data, but contain quite explicit representations of essential ingredients of the mineral systems model; e.g. the top ranking layer (according to three different criteria; D/A , $D \times (D/A)$, and $D \times (D/A)$ AND $D/A \geq \sim 3$, AND $D \geq \sim 20\%$) depicts *favourable lithological contacts* expressed as fuzzy membership values. Other examples are the layers representing density of faults and density of lithological contacts (i.e a measure of lithological diversity).
4. $(O - E)/E$ and interval-based bivariate J-function plots are more useful than methods involving cumulative curves in cases where the most favourable variable values for deposits occur over discrete intervals.
5. The bivariate J-function is a useful new non-parametric statistical method for examining spatial relationships that provides information about the existence, nature (positive or negative) and statistical significance of spatial relationships between a point pattern (e.g. deposits) and some other linear or point feature.
6. The cumulative bivariate J-function was modified so that the function is calculated for successive intervals (e.g. distance buffers).
7. Layer-evaluation methods described in this chapter are very useful for quantitatively testing the regional applicability of exploration criteria.
8. Fuzzy membership layers allow geological knowledge to be incorporated into an otherwise data-driven neural network method.
9. Two types of fuzzy membership layers were created; 1) favourable lithology and contact type layers based on the statistics of the spatial relationships between deposits and the variable values, and 2) rock-competency and the rheological contrast layers based on subjective geological judgement.
10. Methods for the evaluation of input layers, particularly the $(O - E)/E$ bar graph, can provide a statistical basis for the preparation of input layers used in fuzzy systems (Chapter 7).

Chapter 7

Case Study: Application of MLP Neural Networks to the Prediction of Orogenic Gold Deposits

7.1 Introduction

The purpose of this chapter is to test a neural-network approach to mineral prospectivity mapping using the Kalgoorlie GIS data set and to investigate the parameters that determine performance of the trained networks and the quality of the resultant prospectivity maps. The Kalgoorlie data set is larger and more complex than the one used in the pilot study in Chapter 4, and is representative of the type of data set used routinely in mineral exploration¹.

The work of this Chapter builds on the results of the previous four chapters; the neural network method for prospectivity mapping developed in Chapter 4 is used together with GIS layers described in Chapter 5 which were analysed and selected using methods developed in Chapter 6. Only those layers which are the best predictors of orogenic gold deposits are used as inputs to the neural networks which form the basis of experiments described in this chapter. Methods used to measure the generalization performance of the trained neural networks² are explained in Section 3.3 of Chapter 3 and Section 4.4.4 of

¹The Tenterfield data set contains 69440 cells in 280 rows $\times$ 248 columns, whereas the Kalgoorlie GIS data set grid contains 1254000 cells in 1140 rows $\times$ 1100 columns and is therefore over 20 times larger.

²Mean square error (MSE), chi-squared statistic, correlation coefficients (ρ & τ), $P(D|map\ class)$, and ROC curves are used as measures of network performance and map quality

Chapter 4.

The approach to the neural network experiments adopted in this chapter was to use a small number of input layers and a simple training algorithm and then progressively attempt to improve the performance of the basic network by altering a single parameter at a time. In a final section, the performance of the Multilayer Perceptron neural networks are compared with a simple fuzzy system and a hybrid fuzzy-neural network.

Parameters examined in this chapter are as follows;

1. effect of random initial weights,
2. effect of random training set selection;
 - a) random split of training patterns into training, training-stop, & test sets,
3. training set size;
 - a) effect of number of deposit patterns used in training set,
4. network parameters;
 - a) network topology; e.g. 5 or 10 hidden layers,
 - b) training algorithms; e.g. use of momentum or adaptive learning rate,
5. augmentation of training sets using random noise;
 - a) network topology for larger noise-augmented training sets,
 - b) optimum maximum percentage of noise to add or subtract,
 - c) uniform random versus normally-distributed random noise,
6. input data;
 - a) choice of input GIS layers,
 - b) number of input GIS layers,
7. input data transformations;
 - a) use of log or inverse of distance instead of raw distance values,
 - b) 1-of-n coded lithology versus favourable lithology as fuzzy membership values,
 - c) limits on distance at which variables that depend on proximity to contacts or faults are considered to have an effect; e.g. chemical contrast of host rocks at a lithological boundary, and
8. input data as fuzzy-membership values.

7.2 Method

The data processing required to combine a set of GIS layers (in ASCII format) into a prospectivity map consist of six main steps;

1. create a feature vector for each grid cell location,
2. create training data sets,
3. train a set of networks,
4. process feature vectors for entire map using a trained network,
5. produce prospectivity maps, and
6. analyse map quality.

These steps and the programs used to perform them in this study are shown in detail in Figure 7.1.

All of the data processing described in this chapter was performed using the MATLAB software package. Matlab provides a range of mathematical, matrix algebra and neural network functions that run in a GUI environment. Built-in neural network functions are provided to perform tasks such as creating a network with a topology, which can be specified by the user, network training and graphing the network error during training.

Other tasks, such as combining layers to produce a set of feature vectors (patterns) for each grid cell on the map and creating the training data sets, had to be written especially for this project. MATLAB includes a scripting language, which closely resembles the C programming language.

The MATLAB functions and scripts, which are referred to in Figure 7.1 and the rest of this chapter are of this type. All functions and scripts written as part of this study are listed and briefly explained in Appendix F and included on the CD-ROM (vol. 1).

7.3 Basic Approach Using an MLP Network

Initially, only ten input layers, selected according to the *category* selection criteria, are used in experiments. Selection criteria are explained in Section 6.3. In later experiments layers sets of 10 and 17 layers, selected using D/A , $D \times (D/A)$ and a combination of criteria ($D \times (D/A)$, $D \geq \sim 20\%$ and $D/A \geq \sim 3$), are used.

The training data sets are created by randomly dividing the 120 patterns, corresponding

Figure 7.1. Data processing required to combine a set of GIS layers (in ASCII format) into a prospectivity map using a neural network.

to deposits containing at least 1000 kg TCG, approximately equally between the training, training-stop and test sets. The training data set is used to adapt the network weights. The training-stop set is used in a cross-validation procedure with early stopping in order to avoid over-fitting the data (Morgan & Bourland, 1990; Wang *et al.*, 1994). The test data set plays no role in training, but is used as a guide to the ability of the trained network to generalize when new data are processed. The random selection of patterns is performed so that the gold deposits from each host rock-type in the solid geology GIS layer are divided approximately equally between the three training sets. Approximately matching numbers of barren patterns are also randomly selected for each rock type. Thus, the deposit and barren patterns are represented in the training sets approximately equally. In cases where there were too few deposit patterns to divide them equally, the patterns are always assigned to the training set, training-stop set, and test set, in that order. Training patterns are split randomly into training, training-stop and test sets. Table 7.1 shows the composition of the training sets.

Table 7.1. Number of patterns in the training data sets

Class	Training set	Stop set	Test set
Deposit	46	39	35
Barren	53	49	46
Total	99	88	81

Most experiments in this chapter involved training a set of ten networks. Since the networks are initialized with random connection weights, which produces some variation in the performance of the trained networks, the *average* results of these 10 networks are shown as the bottom line in each of the tables. In each experiment, the ten networks were initialized with the same set of random weights in order to ensure that variations in performance are due to differences in experimental parameters rather than random initial weights.

The tables in this chapter summarize the experimental results which listed in full in Appendix H and I. Consequently, the rows in the tables in Appendix H generally represent the results for individual neural networks, whereas the rows in the tables in this chapter generally represent the average results for ten networks. It is clearly stated in the following text if a table differs in this respect.

Experimental parameters, such as the criteria used to select the input layers, training algorithm, training set size, and whether rock types are represented by equal numbers

of patterns in the training set or whether the training patterns represent the rock types according to proportion of known deposits hosted in the rock type, are included in the header information for the tables shown in Appendix H. In this chapter, this information is given in the text. Unless otherwise stated, input layers were selected using the *category* selection criteria. The four sets of input layers obtained using each of the selection criteria are shown in Table 6.5.

7.3.1 Measures of Performance and Prospectivity Map Quality

Network performance is measured in two ways using; 1) the percentage of correct classifications for the independent test data set, and 2) measures of the quality of the mineral prospectivity set prepared using the trained network. An arbitrary threshold of 0.5 is used to classify patterns in the test-set. Patterns associated with network output activations greater or equal to 0.5 are classified as deposits and those less than 0.5 are classified as barren cells. The measures of map quality are based on the degree to which the highest prospectivity class (in a nine-class prospectivity map) accounts for the known gold deposits (where $TCG \geq 1000$ kg). The statistics used to measure map quality are: 1) Spearman's correlation coefficient, which indicates the degree of correlation between increasing prospectivity map class and the probability that the region contains a known deposit, 2) the area under a receiver-operating-characteristic (ROC) curve (Fig. 7.2), and 3) the capture efficiency ratios, D/A and $D \times (D/A)$, where D is the percentage of known deposits in highest prospectivity class in a 9-class prospectivity map, in which the output activation values from the neural network are divided into nine classes, and A is the percentage of the total map area corresponding to the highest prospectivity class (see Section 6.3 above).

A ROC curve is generated by plotting the true positive (TP) versus false positive (FP) ratios, over the range of threshold values ($[0, 1]$) used to make the classification (where TP = true positive, TN = true negative, FP = false positive, FN = false negative, TP ratio = $TP/(TP + FN)$ and FP ratio = $FP/(FP + TN)$; Uncini *et al.*, 1990; Zaknich, 1999). The area under the ROC curve is used as a measure of classification performance, and varies from a minimum of 0.5 to a maximum of 1.0. The receiver operating characteristic curve is discussed in Section 3.3.4.

Figure 7.2. Receiver-operating-characteristic (ROC) curve for a neural network prospectivity map. The curve shows how the true- and false positive ratios vary with the threshold value applied to the network output in order to classify cell patterns as either deposits or barren. The area under the curve is an indicator of system performance and varies between 0.5 for a random classifier and 1.0 for perfect discrimination.

7.3.2 Training Pattern Selection

Several aspects of neural network training involve random selection and could potentially affect the performance of the trained network and the quality of the mineral prospectivity map. These are the:

1. random selection of barren patterns for training set from map grid,
2. random split of training data in to training, training-stop, and test sets, and
3. random initial weights assigned to network prior to training.

In order to minimize the influence of the random selection of barren patterns, patterns were randomly selected from locations corresponding to each rock type separately and then grouped together. Deposit patterns were identified and grouped according to the host-rock type and then an approximately equal number of barren patterns from the same rock type were randomly selected. The numbers of barren patterns were only approximately equal, since some host-rocks do not contain any known deposits.

Differences in the data populations represented by the training, stop, and test sets gives rise to differences in the performance of the trained network for the three sets. If the three training sets were statistically identical, then the classification performance of the trained

network on each of the three sets would be the same (Masters, 1993b). The random split of data into the training, stop and test sets is only likely to be important when the amount of training data is small. This is a problem in the application of neural networks to mineral prospectivity mapping due to the limit that the relatively very small number of known deposits (together with the need to represent deposit and barren patterns in approximately equal numbers) places on the size of the training set.

In this study, this problem is dealt with by testing a number of random splits and choosing the split that results in the best network performance. This split was then used for all further experiments. An alternative approach is to use a self-organizing map to classify input feature vectors and then select data from each class according to the quantization errors (i.e. Euclidean distance of feature vectors from the centroid of the class; Wong *et al.*, 1996a).

Table 7.2 shows the result of training ten networks on ten different random splits of the available training data. The same set of random initial weights was used for each split of the training data. Networks with five hidden layer units were used for this initial experiment since these gave the best performance in the Tenterfield pilot study (Chapter 4). The gradient-descent backpropagation training algorithm with an adaptive learning rates and momentum (function *traingdx* in MATLAB) and input layers selected on the basis of the categories criteria (i.e.; layers representing each evidence category with highest D/A value, 6.3) were used.

Statistical similarity of the training data sets should result in similar performance of the trained network for each of the three data sets. Selections 5, 8, and 3 are quite similar in terms of overall pattern classification performance. However, the percentage of deposit patterns correctly identified is similar or worse than that expected due to chance (i.e. 50%). Consequently, set 10 was chosen for use in further experiments because: 1) the classification results for the stop and test sets are reasonably similar (73.9% and 67.9%), and 2) this set gave the best classification performance for deposit patterns.

7.3.3 Network Topology

Single Hidden Layer

Whereas the number of input units are determined by the dimensionality of the input vectors and the number of output units are determined by the problem and are therefore

Table 7.2. Effect of random split of training data into training sets. All networks were trained starting with the same set of initial random weights.

Training set selection	Training Sets		Test Set			Map Quality Statistics			
	Train	Stop	All	Deps	Barren	ρ	D/A	$D^*(D/A)^1$	ROC
1	75.8	80.7	63.0	42.9	78.3	0.93	19.7	262.3	0.81
2	78.8	65.9	60.5	48.6	69.6	0.95	11.6	155.1	0.72
3	72.7	69.3	65.4	42.9	82.6	0.98	19.3	160.6	0.79
4	70.7	59.1	64.2	51.4	73.9	0.44	0.0	0.0	0.70
5	73.7	72.7	75.3	57.1	89.1	0.98	18.5	169.2	0.80
6	63.6	50.0	51.9	71.4	37.0	-0.07	0.0	0.0	0.53
7	68.7	62.5	72.8	48.6	91.3	0.98	15.4	179.1	0.71
8	70.7	67.1	70.4	51.4	84.8	0.98	12.4	31.0	0.75
9	83.8	75.0	74.1	62.9	82.6	0.98	14.7	208.4	0.81
10	84.9	73.9	67.9	65.7	69.6	0.93	8.9	148.8	0.79

^a $D^*(D/A) = D^*(D/A)$ AND $D \geq \sim 20\%$ AND $D/A \geq \sim 3\%$

fixed, the number of hidden units and layers are variable and determine the number of weights (i.e. free parameters) in the network. The network requires a certain minimum number of weights in order to learn the patterns in the data and fit the data well. If the number of weights is too large and the number of patterns available for training is too small, over-fitting of the data may occur. This section shows the results of experiments to determine the optimum number of hidden units and layers.

Ten networks were trained for each topology. The same set of initial weights is used for each experiment, so that any differences in the results are due to changes in the experimental parameters rather than the random starting point in multidimensional weight space. The *average* results for networks with a single hidden layer of neurons are shown in Table 7.3. Networks, which gave the *best* overall test-set classification results, are shown in Table 7.4.

The results in Table 7.3 show that *average* performance varies only slightly with the number of hidden layer units. However, a 10-20-1 topology (20 hidden-layer neurons) gave the highest *overall* test-set performance (percentage correct classification. This applies to both the *average* of 10 networks (Table 7.3) and for a single network (Table 7.3). A 10-15-1 architecture gave the *best* percentage correct test-set performance for *deposit* patterns.

In Table 7.4, which shows the single network with the *best* overall test-set performance,

Table 7.3. Effect of MLP network topology on *average* classification performance & map quality. Each row represents the addition of five hidden neurons. The rows represent averages for ten networks.

Network Topology	Training Sets		Test Set			Map Quality Statistics			
	Train	Stop	All	Deps	Barren	ρ	D/A	D*(D/A)	ROC
10-0-1	77.6	72.3	66.3	72.0	62.0	0.94	23.4	331.3	0.77
10-5-1	80.3	71.3	67.2	66.3	67.8	0.94	13.9	119.0	0.78
10-10-1	83.3	72.1	66.3	68.0	65.0	0.95	8.9	91.7	0.78
10-15-1	84.1	72.7	65.4	72.9	59.8	0.98	8.4	92.0	0.79
10-20-1	84.4	72.7	67.9	68.0	67.8	0.97	8.2	105.3	0.79
10-25-1	89.7	73.2	66.5	70.8	63.3	0.97	6.1	141.7	0.80

Table 7.4. Effect of MLP network topology on the *best* classification performance & map quality. Each row represents the addition of five hidden neurons.

Training set selection	Training Sets		Test Set			Map Quality Statistics			
	Train	Stop	All	Deps	Barren	ρ	D/A	D*(D/A)	ROC
10-0-1	74.8	73.9	69.1	71.4	67.4	0.95	28.1	328.0	0.75
10-5-1	84.9	77.3	72.8	82.9	65.2	1.00	7.8	109.8	0.83
10-10-1	81.8	69.3	71.6	62.9	78.3	0.88	5.2	8.7	0.84
10-15-1	88.9	76.1	72.8	65.7	78.3	0.95	6.6	141.9	0.82
10-20-1	88.9	72.7	76.5	77.1	76.1	0.90	9.6	256.7	0.82
10-25-1	95.0	73.9	70.4	82.9	60.9	0.97	5.1	208.7	0.82

there is a trend of increasing performance with increasing numbers of hidden-layer neurons up to and including 20 hidden neurons. The performance of networks with 25 hidden neurons is slightly lower both for the *average* of 10 networks (Table 7.3) and *best* the single network (Table 7.4) suggesting that the optimal number of hidden-layer neurons is less than 25. Although too many hidden units can lead to over-fitting of the data resulting in poorer generalization, these results clearly show that the optimal number hidden-layer neurons is approximately 20.³ It is interesting to note that the highest values of the map quality statistics D/A , $D \times (D/A)$ were obtained with a network without any hidden-layer neurons. However, this topology resulted in the poorest correct classification rate for a single network (Table 7.4).

Two Hidden Layers

Whereas networks with single hidden layers (i.e. two layers of weights) can generate decision boundaries which partition, for example two-dimensional, input space into a single convex regions, networks with two hidden layers can generate arbitrary, non-convex and disjoint decision regions (Lippmann, 1989; Bishop, 1995). This can be an advantage in solving some problems. Optical character recognition problems are an example of an application area where networks with two or more hidden layers are often used (e.g. Fig. 2.5; Le Cun *et al.*, 1989).

A series of networks with two hidden layers was tested using the same procedure as that described above. The networks have the same total number of hidden units as networks in the previous experiment (see Tables 7.3 and 7.4). The results for the networks with two hidden units are shown in Tables 7.5 and 7.6.

Networks with two hidden layers produced similar results to those with a single hidden layer, except that the *average* values for percentage correct classification of barren patterns was higher and the capture efficiency ratios, D/A and $D \times (D/A)$, were slightly higher. This slight advantage is outweighed by the fact that many networks with two hidden layers had a tendency to generate relatively bimodal prospectivity estimates. In these cases, the bulk of known deposits are located in either low or high prospectivity map classes. This resulted in the lower values of Spearman's correlation coefficient, ρ (i.e. the correlation between the prospectivity map class for a nine class map and the probability of finding a known deposit; see networks with topology 10-3-2-1, 10-10-5-1 and 10-20-5-1 in Table 7.5).

³It is actually the number of adaptable weights (degrees of freedom or effective complexity) in relation to the number of training examples that is significant (Bishop, 1995.).

Table 7.5. Effect of MLP network topology on *average* classification accuracy & map quality for networks with two hidden layers.

Network Topology	Training Sets		Test Set			Map Quality Statistics			
	Train	Stop	All	Deps	Barren	ρ	D/A	D*(D/A)	ROC
10-3-2-1	78.6	72.4	65.6	62.0	68.3	0.79	15.1	229.1	0.75
10-7-3-1	80.5	71.3	68.0	59.4	74.6	0.93	10.5	206.1	0.79
10-10-5-1	81.6	72.1	68.3	64.3	71.3	0.81	11.6	107.4	0.77
10-20-5-1	81.1	70.2	64.6	66.3	63.3	0.87	18.4	159.1	0.76

Table 7.6. Effect of MLP network topology on *best* classification accuracy & map quality for networks with two hidden layers.

Network Topology	Training Sets		Test Set			Map Quality Statistics			
	Train	Stop	All	Deps	Barren	ρ	D/A	D*(D/A)	ROC
10-3-2-1	87.9	79.6	71.6	60.0	80.4	0.83	3.0	181.4	0.79
10-7-3-1	80.8	73.9	72.8	57.1	84.8	0.98	6.0	29.9	0.84
10-10-5-1	74.8	71.6	75.3	62.9	84.8	0.97	16.0	200.1	0.79
10-20-5-1	90.9	72.7	71.6	65.7	76.1	0.97	10.6	354.1	0.85

These results may be explained by the empirical observation that networks with more than one hidden layer are prone to converging to local minima (Masters, 1993b; Duda *et al.*, 2001).

A 10-20-1 topology (i.e. 10 inputs, 20 hidden neurons and 1 output) was selected for use in further experiments as this gives the best generalization performance, as indicated by both the *average* and *best* percentage correct classifications for the independent test set.

7.3.4 Training Algorithms

A range of training algorithms are available within the MATLAB neural network tool-box, which was used for the experiments described in this chapter. Most of the algorithms are designed to improve the speed at which networks reach convergence to a global minimum. Rather than test all the algorithms, the approach adopted here was to use the standard gradient-descent backpropagation algorithm, a gradient-descent algorithm with an adaptive learning rate and momentum (Hagan & Menhaj, 1994), and the Levenberg-

Marquardt training algorithm, which is fastest algorithm available in MATLAB (Hagan & Menhaj, 1994).

All training algorithms described in this study are applied in batch mode; i.e. weights are updated only after the errors for all the patterns in the training data set have been calculated. A 10-20-1 network topology was used for the following experiments.

Although the *average* test-set classification (generalization) results are very similar, the standard and adaptive gradient-descent algorithms produced significantly better values for the capture efficiency statistics, D/A and $D \times (D/A)$ (Table 7.7) than the Levenberg-Marquardt training algorithm. With the exception of the $D \times (D/A)$ value for the *traingdx* algorithm, this also applies to the networks that produced the *best* overall test-set results (Table 7.8).

An average (for ten networks) of 3051, 301, and 11 iterations were required for training using the standard gradient-descent, adaptive gradient-descent and Levenberg-Marquardt algorithms, respectively (refer to Tables H.84, H.85, and H.78 in appendix H). The advantage of the Levenberg-Marquardt algorithm is that it can converge ten to one hundred times faster than the adaptive and standard gradient-descent algorithms, respectively (Hagan & Menhaj, 1994). In addition, a network trained with the Levenberg-Marquardt algorithm gave the *best* overall test-set performance. Consequently, the Levenberg-Marquardt training algorithm was chosen for experiments in the sections that follow.

Table 7.7. Effect of training algorithm on *average* classification accuracy & map quality. Training algorithms: *trainlm* = Levenberg-Marquardt, *traingd* = gradient descent, *traingdx* = gradient descent with adaptive learning rate and momentum. Network topology: 10-20-1, layer selection criteria: categories.

Training Algorithm	Training Sets		Test Set			Map Quality Statistics			
	Train	Stop	All	Deps	Barren	ρ	D/A	$D \times (D/A)$	ROC
trainlm	84.4	72.7	67.9	68.0	67.8	0.97	8.2	105.3	0.79
traingd	82.7	70.6	68.3	70.3	66.7	0.98	20.1	162.5	0.78
traingdx	80.1	69.4	68.0	69.1	67.2	0.96	21.4	152.5	0.78

Table 7.8. Effect of training algorithm on *best* classification accuracy & map quality.

Networks Topology	Training Sets		Test Set			Map Quality Statistics			
	Train	Stop	All	Deps	Barren	ρ	D/A	D*(D/A)	ROC
trainlm	88.9	72.7	76.5	77.1	76.1	0.90	9.6	256.7	0.82
traingd	81.8	75.0	72.8	71.4	73.9	0.98	42.1	315.7	0.81
traingdx	82.8	71.6	72.8	77.1	69.6	1.00	19.9	148.9	0.78

7.4 Input Data

7.4.1 Choice of Input GIS Layers

The purpose of this section is to test different methods for selecting neural network inputs and the effect of using different numbers of inputs on the generalization ability of the trained networks and quality of prospectivity maps. Criteria used to rank the layers are;

1. layer from each evidence category with highest D/A value,
2. D/A AND $D \geq \sim 20\%$,
3. $D \times (D/A)$, and
4. $D \times (D/A)$ AND $D \geq \sim 20\%$ AND $D/A \geq \sim 3$,

where D is the percentage of known deposits in the favourable region of a temporary binary layer and A is the percentage of the total map area occurring within the favourable region. The favourable region was determined by graphing a series of statistics described in Section 6.2. The selection of the input layers is described in 6.3. Sets of 10 and 17 layers, corresponding to each of the four selection methods, were selected as inputs to neural networks (Table 6.5). Details of the rankings of the layers using each of the four methods are shown in Tables G.1, G.2, G.3 and G.4 in Appendix G.

Similar results were obtained for the different sets of 10 inputs, except for the layers selected according to the D/A criterion, which gave significantly poorer *average* and *best* values of the capture efficiency ratios, D/A and $D \times (D/A)$ and a lower *average* percentage of correct classification of deposit patterns (Table 7.10). The lower performance of the D/A layer set may be due to the absence of the *distance-to-anticlinal-axes* and *density-of-faults* layers and the inclusion of two *chemical-ratio* layers i.e. the sulphidation index, $\text{Fe}_{\text{tot}}(\text{wt}\%) \times \text{Fe}_{\text{tot}} / (\text{Fe}_{\text{tot}} + \text{Mg} + \text{Ca})$, and oxidation index, $\text{Fe}_2\text{O}_3/\text{FeO}$.

The similarity of the other results is not surprising considering the high proportion of layers in each selection that are the same (i.e. compared to the categories selection in column 1 of Table 7.9, the input layer sets selected using the D/A , $D \times (D/A)$ and modified $D \times (D/A)$ criteria share 8, 5, and 8 out of 10 layers, respectively). The set of input layers selected using the $D \times (D/A)$ criterion gave slightly better *average* and *best* classification performance for the test set overall, higher values for the area under the ROC curves, and significantly better classification performance for deposit patterns than the other criteria (Tables 7.10 & 7.11).

Table 7.9. Summary of sets of 10 and 17 neural network input layers showing selection criteria.

Number of Layers	Selection Criteria			$D \times (D/A)$	$D \times (D/A)$ AND $D \geq \sim 20\%$ AND $D/A \geq \sim 3$
	Evidence categories with highest D/A value	D/A AND $D \geq \sim 20\%$			
10	favourable geology favourable contacts favourable rheol. contrast dist. to felsic porph. int. ^a dist. to crustal flts dist. to anticlinal axes density of faults ^b density of contacts ^c strike of NE-regional flts chemical contrast (type 1) ^d	favourable geology favourable contacts favourable rheol. contrast dist. to felsic porph. int. dist. to crustal flts density of contacts strike of NE-regional flts strike of contacts chemical contrast (type 1) ^d chemical contrast (type 2) ^e	favourable contacts dist. to felsic porph. int. dist. to +ve mag. anomalies dist. to NE regional flts dist. to contacts dist. to anticlinal axes density of faults density of contacts metamorphic grade rock strength (UCS) ⁱ	favourable geology favourable contacts favourable rheol. contrast dist. to felsic porph. int. dist. to NE reg. flts dist. to anticlinal axes density of faults density of contacts strike of crustal flts strike of NE-regional flts	
17	dist to +ve mag. anomalies ^f dist. to NE regional flts dist. to int. NNW+NW flts ^g dist. to contacts strike of contacts chemical contrast (type 3) ^h metamorphic grade	dist to +ve mag. anomalies dist. to NE-regional flts dist. to int. NNW+NW flts dist. to contacts dist. to anticlinal axes density of faults strike of crustal flts	favourable geology favourable rheol. contrast dist. to int. NNW+NW flts strike of crustal flts strike of NE-regional flts strike of NNW-regional flts chemical contrast (type 1) ^d	dist. to crustal flts dist. to int. NNW+NW flts dist. to contacts strike of contacts chemical contrast (type 1) ^d chemical contrast (type 2) ^e rock strength (UCS)	

^aFelsic porphyritic intrusives.^bCrustal-scale, NNW-, and NE-trending faults.^cCount of lithological contacts in a 5×5 km window used as measure of lithological complexity.^dDifference in Fe_{tot} (wt%)* $Fe_{tot}/(Fe_{tot}+Mg+Ca)$ at lithological contacts (layer: l37_Lch11k).^eDifference in Fe_2O_3/FeO at lithological contacts (layer: l37_Lch41k).^fDistance to nearest positive (RTP) aeromagnetic anomalies, z-score for host lithology ≥ 2 .^gDistance to nearest intersection of faults. Crustal-scale faults & shear zones included as NNW-trending faults.^hDifference in $Fe_2O_3/(Fe_2O_3+FeO)$, (layer: l37_Lch31k).ⁱUniaxial compressive strength.

Different selection criteria for 17 layers also produced similar *average* results (Table 7.12). Compared to the set of layers selected according to the *category* criterion, the D/A , $D \times (D/A)$ and modified $D \times (D/A)$ layer sets (labelled in tables as DDA2) share 15, 14, and 14 out of 17 layers, respectively. The layer set selected with the $D \times (D/A)$ criterion produced slightly better *average* classification performance for the test set overall than the other criteria. The $D \times (D/A)$ criterion also produced significantly higher values for the capture efficiency ratios, D/A and $D \times (D/A)$, than other criteria.

Results for the networks giving the *best* overall test-set performance for 17 inputs are similar for all the layer selection criteria but the other statistics did not show any consistent trends (Table 7.13). The *categories* criteria produced a significantly higher percentage of correct classifications for deposit patterns than the other criteria. Consequently, sets of layers selected using the *categories* and $D \times (D/A)$ criteria were chosen for use in experiments dealing with the augmentation of training data set with noise and fuzzy membership inputs below.

Table 7.10. Effect of criteria used to select 10 input GIS layers on *average* training set performance & map quality. Network topology: 10-20-1, training algorithm: *trainlm*.

Selection criteria	Training Sets		Test Set			Map Quality Statistics			
	Train	Stop	All	Deps	Barren	ρ	D/A	$D \times (D/A)$	ROC
categories	84.4	72.7	67.9	68.0	67.8	0.97	8.2	105.3	0.79
D/A	80.3	70.5	69.1	64.0	73.0	0.94	5.5	54.2	0.77
$D \times (D/A)$	87.9	76.9	72.1	75.1	69.8	0.95	7.4	109.0	0.84
DDA2 ^a	84.9	72.6	69.9	67.1	72.0	0.93	12.1	111.2	0.80

^aDDA2 = $D \times (D/A)$ AND $D \geq \sim 20\%$ AND $D/A \geq \sim 3\%$

Table 7.11. Effect of criteria used to select 10 input GIS layers on *best* training set performance & map quality. Network topology: 10-20-1, training algorithm: *trainlm*.

Selection criteria	Training Sets		Test Set			Map Quality Statistics			
	Train	Stop	All	Deps	Barren	ρ	D/A	$D \times (D/A)$	ROC
categories	88.9	72.7	76.5	77.1	76.1	0.90	9.6	256.7	0.82
D/A	78.8	70.5	72.8	65.7	78.3	0.95	5.7	9.5	0.81
$D \times (D/A)$	92.9	81.8	77.8	82.9	73.9	0.98	5.1	104.5	0.87
DDA2 ^a	81.8	72.7	76.5	77.1	76.1	1.00	11.4	133.5	0.83

^aDDA2 = $D \times (D/A)$ AND $D \geq \sim 20\%$ AND $D/A \geq \sim 3\%$

Table 7.12. Effect of criteria used to select 17 input GIS layers on *average* training set performance & map quality. Network topology: 17-20-1, training algorithm: *trainlm*.

Selection criteria	Training Sets		Test Set			Map Quality Statistics			
	Train	Stop	All	Deps	Barren	ρ	D/A	D*(D/A)	ROC
categories	82.0	70.8	71.0	68.9	72.6	0.88	6.4	49.1	0.78
D/A	87.5	76.1	71.6	72.6	70.9	0.94	4.6	52.9	0.80
D*(D/A)	87.8	77.4	73.1	70.3	75.2	0.95	9.0	117.0	0.83
DDA2 ^a	84.2	75.6	71.6	72.0	71.3	0.95	7.4	93.7	0.81

^aDDA2 = D*(D/A) AND D $\geq$ ~20% AND D/A $\geq$ ~3%

Table 7.13. Effect of criteria used to select 17 input GIS layers on *best* training set performance & map quality. Network topology: 17-20-1, training algorithm: *trainlm*.

Selection criteria	Training Sets		Test Set			Map Quality Statistics			
	Train	Stop	All	Deps	Barren	ρ	D/A	D*(D/A)	ROC
categories	82.8	79.6	76.5	88.6	67.4	1.00	9.7	72.5	0.83
D/A	88.9	72.7	76.5	80.0	73.9	0.97	7.5	111.7	0.79
D*(D/A)	90.9	83.0	75.3	82.9	69.6	0.98	13.2	231.4	0.86
DDA2 ^a	81.8	79.6	79.0	77.1	80.4	1.00	8.0	73.4	0.83

^aDDA2 = D*(D/A) AND D $\geq$ ~20% AND D/A $\geq$ ~3%

7.4.2 Number of Input GIS Layers

In general, networks trained with 17 layers gave slightly better *average* test-set classification results than networks trained with 10 layers (Table 7.14). This is generally true for all layer selection criteria and applies to the classification performance for the test set overall, and deposit and barren patterns separately. Two reasons why such a large increase in the number of input variables leads to only a slight increase in the *average* classification performance (i.e. generalization ability) are: 1) that the sets of 10 inputs may already include all the variables that are truly important for distinguishing deposit and barren classes, and 2) the smaller number of weights, corresponding to a network with 10 inputs, are more likely to be well represented by a very small training data set, such as the one used here, than 17 inputs.

Both explanations relate to the trade-off between adding input features to improve classification and the limiting the dimensionality of the feature space so that the degree to which the training set represents the multidimensional feature space is not too sparse. It is well known that a classification problem may be solved through the addition of appropriate new features (thus creating a hyperplane in a higher dimension). The classic example is the exclusive-OR (XOR) problem which is not solvable in two dimensions but *is* solvable in three dimensions (McClelland & Rumelhart, 1988). However, Bishop (1995) has pointed out that increasing the number of input variables whilst keeping the training-set size fixed means that the higher-dimensional feature space is more sparsely represented—a problem known as the *curse of dimensionality*. This increases the risk that the network may not learn the patterns in the data reliably.

For comparison purposes, a set of 25 layers, which includes all the input variables selected using the four criteria, was also tested. The *average* performance for the 25-input set is between that of the 10- and 17-layer sets. The values of the map quality statistics (ρ , D/A , $D \times (D/A)$, and area under the ROC curve) for the 25-input set were generally slightly poorer than those obtained for 10- and 17-inputs. The map quality statistics produced by the *best* network with 25 inputs were poor compared to the other networks (Table 7.15). This is due to the fact that the highest prospectivity map class (in the 9-class produced by this network) did not contain any of the known deposits.

Comparison of the *best* test-set performance for networks trained with 10 and 17 inputs, selected using the modified $D \times (D/A)$ (labelled in tables as DDA2), and *categories* criteria shows that 17 input layers produce significantly better performance than that obtained by using 10 inputs or 25 (i.e. all available) input variables.

Table 7.14. Effect of number of input GIS layers on *average* training set performance & map quality. Network topology: 10-20-1 or 17-20-1, training algorithm: *trainlm*.

No. of Layers, Selection criteria	Training Sets		Test Set			Map Quality Statistics			
	Train	Stop	All	Deps	Barren	ρ	D/A	D*(D/A)	ROC
10, categories	84.4	72.7	67.9	68.0	67.8	0.97	8.2	105.3	0.79
17, categories	82.0	70.8	71.0	68.9	72.6	0.88	6.4	49.1	0.78
10, D/A	80.3	70.5	69.1	64.0	73.0	0.94	5.5	54.2	0.77
17, D/A	87.5	76.1	71.6	72.6	70.9	0.94	4.6	52.9	0.80
10, D*D/A	87.9	76.9	72.1	75.1	69.8	0.95	7.4	109.0	0.84
17, D*D/A	87.8	77.4	73.1	70.3	75.2	0.95	9.1	117.0	0.83
10, DDA2 ^a	84.9	72.6	69.9	67.1	72.0	0.93	12.1	111.2	0.80
17, DDA2	84.2	75.6	71.6	72.0	71.3	0.95	7.4	93.7	0.81
25, all	89.2	74.2	70.1	71.1	69.4	0.91	6.0	52.5	0.81

^aDDA2 = D*(D/A) AND D $\geq$ ~20% AND D/A $\geq$ ~3%

Table 7.15. Effect of number of input GIS layers on *best* training set performance & map quality. Network topology: 10-20-1 or 17-20-1, training algorithm: *trainlm*.

No. of Layers, Selection criteria	Training Sets		Test Set			Map Quality Statistics			
	Train	Stop	All	Deps	Barren	ρ	D/A	D*(D/A)	ROC
10, categories	88.9	72.7	76.5	77.1	76.1	0.90	9.6	256.7	0.82
17, categories	82.8	79.6	76.5	88.6	67.4	1.00	9.7	72.5	0.83
10, D/A	78.8	70.5	72.8	65.7	78.3	0.95	5.7	9.5	0.81
17, D/A	87.5	76.1	71.6	72.6	70.9	0.94	4.6	52.9	0.80
10, D*D/A	92.9	81.8	77.8	82.9	73.9	0.98	5.0	104.5	0.87
17, D*D/A	90.9	83.0	75.3	82.9	69.6	0.98	13.2	231.4	0.86
10, DDA2 ^a	81.8	72.7	76.5	77.1	76.1	1.00	11.4	133.5	0.83
17, DDA2	81.8	79.6	79.1	77.1	80.4	1.00	8.0	73.4	0.83
25, all	87.9	77.3	74.1	71.4	76.1	0.38	0.0	0.0	0.83

^aDDA2 = D*(D/A) AND D $\geq$ ~20% AND D/A $\geq$ ~3%

7.5 Input Data Transformations

7.5.1 Coding Distance Inputs: Raw Values versus Inverse and Log

Learning in a neural network is facilitated if the relationships between the input and output variables are expressed as explicitly as possible (Masters, 1993b; Zaknich, 1999). For example, the closer a location is to a regional fault and shear zone, the more prospective it is. Thus, if all other parameters are equal, a smaller distance should result in a higher estimate of prospectivity. Consequently, learning may be improved if the inverse of the distance input is used instead of the raw input so that larger distances give larger prospectivity estimates.

The inverse of all input layers depicting proximity relationships was calculated using MATLAB functions, *inv_layer* and *inv_scale_batch_vec2vec* (see attached CD-ROM, vol. 1). Layers that were transformed in this way depict the *distance to the nearest*:

1. felsic porphyritic intrusion,
2. positive aeromagnetic (RTP) anomaly (where z-score for host lithology ≥ 2),
3. crustal-scale fault or shear zone,
4. NE-trending regional-scale fault or shear zone,
5. lithological contact, and
6. trace of anticlinal axis.

Since $\log_{10}(0)$ is undefined, distances of zero were treated as 100 m. The cell size is 100 m, so this corresponds to the uncertainty for distances values. As a final step, the inputs were scaled to the range $[0, 1]$.

Tables 7.16 and 7.17 show the results for the transformed distance inputs together with the results for raw distances (first row). The *average* results for all three inputs are quite similar. However, networks with transformed distance inputs produced slightly poorer test set classification and map quality results compared to the network with the raw inputs. The $1/(x)$ and $\log_{10}(x)$ inputs produce significantly poorer values of the capture efficiency statistic, D/A . For networks that produced the *best* overall test-set classification results (Table 7.17), the transformed inputs also produced significantly poorer correct classification rates for the test set overall and barren cells, and both capture efficiency ratios. Since the results indicate that raw distances produce better results, no transformations were performed in the experiments shown below.

The decrease in network performance for networks trained using transformed-distance inputs may be due to the fact that the transformations actually obscure the relationship between the network input and the output. In ARCVIEW, the calculation of Euclidean distances based a raster grid result in an irregular distribution of distances. This is due to the geometry of the grid, in which only certain discrete inter-cellular distances are possible. Whilst this quantization of distances is less significant at large distances, the results of Chapter 6 (Table 6.4) show that most of the gold deposits are located relatively close to faults, anticlinal axes and contacts. Both the inverse and log-transformations actually emphasize this irregular distribution of small distances. This effect is illustrated in Figures 7.3b & c which show the inverse and log-transformed distances to the nearest NE-trending regional-scale faults and the distance interval 0-800 m which is the most most prospective zone for gold deposits. interval .

Table 7.16. Effect of using inverse and log transformations of distance inputs on *average* results. Network topology: 10-20-1, training algorithm: *trainlm*, layer selection criteria: categories.

Distance input format	Training Sets		Test Set			Map Quality Statistics			
	Train	Stop	All	Deps	Barren	ρ	D/A	D*(D/A)	ROC
x	84.4	72.7	67.9	68.0	67.8	0.97	8.2	105.3	0.79
$1/(x)$	87.8	79.0	67.0	66.5	67.4	0.87	5.4	77.7	0.75
$\log_{10}(x)$	88.7	77.1	67.3	65.7	68.5	0.94	5.3	100.3	0.76

Table 7.17. Effect of using inverse and log transformations of distance inputs on *best* results. Network topology: 10-20-1, training algorithm: *trainlm*, layer selection criteria: categories.

Distance input format	Training Sets		Test Set			Map Quality Statistics			
	Train	Stop	All	Deps	Barren	ρ	D/A	D*(D/A)	ROC
x	88.9	72.7	76.5	77.1	76.1	0.90	9.6	256.7	0.82
$1/(x)$	82.8	72.7	71.6	77.1	67.4	0.90	3.1	26.0	0.76
$\log_{10}(x)$	90.9	77.3	70.4	74.3	67.4	0.98	4.9	77.2	0.82

(a) Neural network: 3 fuzzy membership inputs.

(b) Neural network: 3 fuzzy membership inputs.

(c) Hybrid fuzzy-neural network: 17 fuzzy inputs.

Figure 7.3. Histograms comparing raw and transformed distances to NE-trending faults; a) raw data, b) inverse and c) logarithm of distance. For transformations, zero distances were converted to 100 m (grid cell size). All histograms compiled using 100 bins. The most favourable distance from regional-scale NE-trending faults for gold deposits is approximately 0-800 m (Table 6.4). The fact that the inverse and log transformations emphasize the irregular distribution of data resulting from the grid-based Euclidean distance calculation may explain why better performance was obtained from networks trained with raw data.

7.5.2 Distance Thresholds for Fault Strike Inputs

Experiments in this section address the question of whether network performance could be improved if buffer limits were placed on layers that involve distance to linear features such as faults and lithological contacts. The motivation for this comes from the concept that although, for example, proximity to a fault upgrades the mineral prospectivity for a cell that is close to the fault, there must be a distance beyond which the existence of the fault has no effect on the prospectivity. It should be noted here that the 2D-prospectivity analysis can be applied successfully to the Yilgarn Craton successfully because: 1) regional-scale structural features are the main control on the location of large gold deposits, 2) gold is very late in the sequence of kinematic events, so that geometries revealed in a solid

geology map are similar to those at the time of gold deposition, and 3) major structures associated with gold are generally steeply dipping (Groves *et al.*, 1997, 2000).

In order to model this concept, cell values at a distance exceeding the limit were set to a background value. In the case of proximity layers (listed in Section 7.5.1 above) the cells beyond the buffer limit were set to the maximum distance. For layers representing the strike orientation of the nearest fault or shear zone, i.e. layers showing the strike of:

1. crustal-scale faults and shear zones,
2. NE-trending regional faults and shear zones, and
3. lithological contacts,

the strike was set to the mean for the entire data set.

Buffer limits were estimated by interpreting plots of $(O - E)/E$ (where O = observed number of deposits in a region corresponding to an interval on the X-axis and E = expected number of deposits for a uniform random distribution). The distance threshold was set to the distance on the $(O - E)/E$ bar graph where the $(O - E)/E$ value consistently falls below zero. Bivariate J-function plots (Section 6.2.4) were used to confirm that the positive association with deposits is statistically significant within intervals that appear to be favourable.

Wide and narrow buffer limits were estimated for each of the three types of faults and lithological contacts. The wide buffer limits are based on the values shown in column 4 of Table 6.4. Distances for wide buffer limits are 100 m greater than the values shown in Table 6.4 because Y-intercepts on the $(O - E)/E$ bar graphs were taken as the middle of the bar at which the Y-value falls below zero rather than the start of the interval as quoted in the table. Narrow buffers were based on a partly subjective estimate of the distance at which the value of $(O - E)/E$ starts to decrease significantly. The same limits were used as the inflection points and the $y = 0$ intercepts in the triangular fuzzy membership functions described below.

Cells beyond the distance limits were set to zero in the case of layers depicting proximity and strike angles were set to the mean strike angle for the type of fault and shear zone represented in the layer. Processing was performed in MATLAB using functions *reclass_dist_strike_narrow_buf* and *reclass_dist_strike_wide_buf*. The buffer limits are shown in Table 7.18 below.

Table 7.18. Input GIS layers for which distance transformations were applied. At distances greater than the buffer limit, cell values were set to the maximum distance and mean strike for distance and strike orientation layers, respectively.

Layer type	Layer name in ARCVIEW	Buffer limit (m)	
		Narrow	Wide
Distance Layers			
Felsic porphyry	l4.l_pf_dist	400	1500
+ve magnetic anomalies	l14.mz2_dist	200	1700
Crustal-scale faults	l20.f1_dist	400	2500
NE regional faults	l22.d3_dist	200	900
Lithological contacts	l39.c_dist	200	500
Anticlinal axes	l46_dist_anti	800	2300
Intersection of faults	l34_s.f23pdst	200	1300
Strike Orientation Layers			
Crustal-scale faults	l28_s.f1str	600	1600
NNW regional faults	l29_s.f2str	600	1200
NE regional faults	l30_s.f3str	500	500
Lithological contacts	l38_c_str1k	200	500
Contrast Layers			
Rheological	l36_l.rh11k-71k	200	n.a.
Chemical	l37_l.ch11k-51k	200	n.a.

Narrow and wide buffers cause a significant decrease in the generalization ability of the trained networks. This is indicated by the classification performance for the test-set overall and deposit patterns and applies to both the *average* and *best* results (Tables 7.19 & 7.20). However, the use of narrow buffers does produce a significant increase in the *average* values of the capture efficiency statistics, D/A and $D \times (D/A)$, and the D/A value for the networks that gave the *best* overall test-set classification (Table 7.20). It is possible that the abrupt change in the distance and strike values, in cells located at distances exceeding the buffer limits in the transformed layers, inhibit efficient learning and therefore generalization. The higher capture efficiency values for the narrow buffers may be due to a decrease in the prospectivity estimates cells located beyond the buffer limits. The bulk of these cells would be barren and therefore result in fewer barren cells being falsely identified as deposits (i.e. fewer false positives). This would result in lower areas (A in D/A and $D \times (D/A)$) for

high prospectivity map classes and therefore higher values of D/A and $D \times (D/A)$.

Table 7.19. Effect of applying distance limits in input GIS layers depicting strike and distance on *average* performance. Layers depicting distance were set to the maximum distance and layers depicting strike angle of the nearest fault or shear zone were set to the mean strike for distances $\geq$ *limit*. Network topology: 10-20-1, training algorithm: *trainlm*, layer selection criteria: categories.

Buffer type	Training Sets		Test Set			Map Quality Statistics			
	Train	Stop	All	Deps	Barren	ρ	D/A	D*(D/A)	ROC
no buffers	84.4	72.7	67.9	68.0	67.8	0.97	8.2	105.3	0.79
narrow buffers	84.8	76.6	66.4	59.7	71.5	0.95	10.4	230.5	0.80
wide buffers	88.7	74.1	62.2	59.7	64.1	0.91	5.8	147.4	0.79

Table 7.20. Effect of applying distance limits in input GIS layers depicting strike and distance on *best* performance. Layers depicting distance were set to the maximum distance and layers depicting strike angle of the nearest fault or shear zone were set to the mean strike for distances $\geq$ *limit*. Network topology: 10-20-1, training algorithm: *trainlm*, layer selection criteria: categories.

Buffer type	Training Sets		Test Set			Map Quality Statistics			
	Train	Stop	All	Deps	Barren	ρ	D/A	D*(D/A)	ROC
no buffers	88.9	72.7	76.5	77.1	76.1	0.90	9.6	256.7	0.82
narrow buffers	84.9	76.1	71.6	62.9	78.3	0.93	13.1	229.9	0.82
wide buffers	89.9	83.0	67.9	68.6	67.4	0.92	5.6	74.2	0.82

7.5.3 Distance Limits for Rheological and Chemical Contrast Inputs

Narrow buffer limits were also applied to the rheological and chemical contrast layers used in networks with 10 inputs, where the variables were selected according to the *categories* criterion. The rheological contrast layer is based on subjectively estimated fuzzy membership values (layer l36_lrh11k, described in sections 5.4.8 & 7.8.2) and the chemical contrast layer is based on the ratio, $Fe_{tot}(wt\%)*Fe_{tot}/(Fe_{tot}+Mg+Ca)$ (layer l37_lch11k, described in Section 5.4.7). Contrast was set to zero for cells located outside the buffer limits. Reclassification of the input layers was performed in MATLAB with the function *reclass_dist_contrast_narrow_buf*. The results are shown in Tables 7.21 and 7.22.

In contrast to the distance and strike layers (described above), the *average* results for the contrast layers indicate that the use of narrow buffers has little effect on generalization.

However, for networks with the *best* test-set classification performance, the use of narrow buffers resulted in lower percentage correct classification of the test-set (overall and deposit patterns) but a significant increase in the *average* $D \times (D/A)$ value. The *average* results show a significantly higher value for the capture efficiency ratio, $D \times (D/A)$.

Table 7.21. Effect of applying distance limits in input GIS layers depicting rheological and chemical contrast on *average* performance. Contrast was set to zero for cells where distance to the nearest lithological contact $\geq limit$. Network topology: 10-20-1, training algorithm: *trainlm*, layer selection criteria: categories.

Input layers	Training Sets		Test Set			Map Quality Statistics			
	Train	Stop	All	Deps	Barren	ρ	D/A	D*(D/A)	ROC
no buffers	84.4	72.7	67.9	68.0	67.8	0.97	8.2	105.3	0.79
narrow buffers	87.5	74.3	67.0	66.6	67.4	0.96	9.2	142.9	0.80

Table 7.22. Effect of applying distance limits in input GIS layers depicting rheological and chemical contrast on *best* performance. Contrast was set to zero for cells where distance to the nearest lithological contact $\geq limit$. Network topology: 10-20-1, training algorithm: *trainlm*, layer selection criteria: categories.

Input layers	Training Sets		Test Set			Map Quality Statistics			
	Train	Stop	All	Deps	Barren	ρ	D/A	D*(D/A)	ROC
no buffers	88.9	72.7	76.5	77.1	76.1	0.90	9.6	256.7	0.82
narrow buffers	78.8	65.9	70.4	62.9	76.1	0.95	17.6	117.1	0.80

7.6 Effect of Numbers of Deposit Patterns in Training Set

In Chapter 7, it was noted that one of the main limitations of the weights-of-evidence method for mineral prospectivity mapping is the requirement of a statistically significant number of known deposits. Within the geosciences, neural networks have most frequently been applied to remote-sensing and geophysics problems in which large amounts of data are available. In contrast, the paucity of deposit training patterns compared to the very large number of patterns that correspond to barren cells potentially limits the application of neural networks in mineral prospectivity mapping to well explored areas where many known deposits are available for training. The experiments in this section address the question of how many deposit training examples are required to correctly train a neural

network for this type of application.

In order to ensure that the network correctly learns the patterns in the data, the training data should sample the entire range of variation in the data population and adequately represent feature vectors that are located close to decision boundaries in multidimensional feature space. Both these requirements are difficult to fulfil because there are so few deposit examples relative to barren patterns. An additional problem arising from the gradient-descent backpropagation algorithm (Rumelhart *et al.*, 1986a) used to train multilayer perceptron (MLP) networks is that minimization of the network error function requires that there are approximately equal numbers of training examples from each class (i.e. deposit and barren cells) irrespective of the actual *a priori* probability of occurrence of the classes (Parikh *et al.*, 1999; Zaknich, 1999; Fig. 7.4). In most cases, the solution to this problem is to collect more data. However, this is expensive and time consuming in the case of ore deposits and, even in areas very well endowed with mineral resources, map grid cells containing deposits are very rare compared to barren cells. Thus, the overall size of the training data sets is limited by the small number of known deposits.

Figure 7.4. Schematic illustration of the relationship between numbers of map grid, deposit and training set patterns. The paucity of patterns representing known deposits limits the size of training sets for a neural network method in which supervised training and a training algorithm based on the minimization of an error function over all the training patterns is used.

Method

A series of training data sets were prepared using 5, 10 20 40 80 and 100 deposit patterns in order to test the way in which the limited number of deposit patterns available for training affects the performance of the trained network. For each of these numbers of deposit patterns, ten training data sets are created by randomly allocating deposits to each of the three training sets. Only the 120 known deposits with a total resource of at least 1000 kg gold are used to train the networks. Where possible, the training and training-stop data were allocated the same number of deposit patterns. If this was not possible, the training-stop and test data sets were allocated equal numbers of deposits. For each experiment, the total number of deposit and barren patterns used to train the networks were the same. The composition of the training sets is shown in Table 7.23.

Table 7.23. Composition of training data sets used to test effect of the number of deposit patterns in the training set on network generalization performance and prospectivity map quality. Patterns represent cells containing orogenic gold deposits and barren cells from raster GIS data for the Kalgoorlie Terrane.

Number of deposits	Training set		Stop set		Test set	
	Deposits	Barren	Deposits	Barren	Deposits	Barren
5	5	5	5	5	110	110
10	10	10	10	10	100	100
20	20	20	20	20	80	80
40	40	40	40	40	40	40
80	80	80	20	20	20	20
100	100	100	10	10	10	10

Results and Discussion

The results are shown in Figures 7.5, which show the percentage correct classification for the test set overall, deposit patterns in the test set, and $D \times (D/A)$ and area under the ROC curve as measures of the quality of the prospectivity map, respectively. Each point on the plots represents the average of ten networks for each of the ten training data sets; i.e. 100 networks.

All of the plots show; 1) a trend of significantly increasing generalization ability of the networks and map quality with increasing numbers of deposit patterns and training data set size, and 2) that the rate at which performance increases levels off above 40 deposit patterns. In the case of the test-set patterns, the percentage correct classification rate

levels off at 80 deposit patterns and for test-set deposit patterns, the percentage correct classification rate levels off at about 20 deposit patterns (see Figs 7.5a & b). Parikh *et al.* (1999) obtained similar results for experiments using unequal class sizes for patterns corresponding to normal and fault conditions. In their data, the rate of network performance improvement decreases as a 1:1 ratio is approached between the numbers of patterns corresponding to the two classes. It should be noted that in these experiments, training sets contained equal numbers of deposit and barren patterns.

The slight drop in performance for 100 deposit patterns indicated in Figures 7.5a and c may be due to the fact that there are only 20 patterns in the training-stop and test data sets. Due to decreasing size of the test data sets, the reliability of the results decreases with increasing numbers of deposit patterns.

The observation that above approximately 40 deposit patterns, the effect of increasing deposit patterns decreases as deposit patterns are added is important because it suggests that 40 deposit patterns is approximately the minimum number of deposit patterns required for training. Clearly, this number is dependent on the characteristics of the data set and the degree to which the input variables are predictive of the deposits but it provides a rough guide to the number of deposit patterns required to reliably train a neural network for this sort of problem. The standard (not noise-augmented) training data set used in this chapter contains 46 deposit patterns. In contrast, the training data set in the Tenterfield pilot study contained only 21 deposit patterns.

7.7 Increasing Training Set Size Using Random Noise

It is clear from the foregoing section the prediction of mineral prospectivity represents a difficult problem to solve using neural networks due to the lack of abundant deposit training data. This problem potentially excludes or limits the application of neural networks to new exploration areas where there are few known deposits. A possible solution might be to include the the abundant smaller deposits in the training data set (1327 orogenic lode gold deposits and occurrences exist within areas for which solid geology data are available). However, there are good geological and GIS-related reasons for training networks on larger deposits (i.e. those with ≥ 1000 kg total contained gold). First, ore systems responsible for minor deposits and occurrences are smaller and therefore less likely to be associated with geological features that would be captured in a regional-scale GIS database than those associated with large deposits. Second, if the large deposits represent the type of targets that any useful neural network system would be expected to identify then training target

(a) Test-set classification: overall

(b) Test-set classification: deposits

(c) Map quality statistic D/A.

(d) Map quality statistic, $D \times D/A$.

(e) Correlation of map class & P(Deposit)

(f) Area under ROC curve.

Figure 7.5. Graphs of test set performance and map quality indices versus the number of deposit patterns in the training data set. Figures a) & b) refer to classification of the independent test-set patterns by the trained network. Figures c)–f) are measures of the quality of the prospectivity map. Figures c) & d) refer to the highest prospectivity class in the prospectivity maps, where D = % of total known deposits and A = % of total map area. Figures e) & f) are calculated using all areas in the map. All graphs show that the performance of the network increases with the number of deposit patterns.

data should consist of these deposits.

This and the following section (Section 7.8) present two very different approaches to compensating for the paucity of deposit examples. The approach, described in this section involves a technique for increasing the number of deposit patterns available for training. The other approach is to add knowledge to an otherwise data-driven neural network method in the form of fuzzy-membership input layers.

7.7.1 Previous Work

A number of studies show that adding noise to the input data, outputs, weight connections, and weight changes can improve the generalization ability of trained networks (Sietsma & Dow, 1991; Holmstrom & Koistinen, 1992; Matsuoka, 1992; Clay & Sequin, 1992; Krogh & Hertz, 1992). An (1996) demonstrated that input noise is effective in improving the generalization performance for both regression (function approximation) and classification problems. Cho *et al.* (1998) described a method for generating “virtual training samples” and reported a 10% improvement in prediction performance for networks trained using a combination of virtual and real samples. Bishop (1995) shows that the addition of noise is equivalent to error regularization, and Reed *et al.* (1992, 1995) compare the effects of adding noise on the generalization performance to error regularization, sigmoid gain scaling (i.e. reducing the slope of the sigmoid function), and target smoothing. More recently, Wang & Principe (1999) investigated the effect of injecting noise into the target output on learning speed and the ability to avoid local minima. Most papers concentrate on the effect of noise on the generalization ability.

Comparatively little work has been done on the composition of the training sets and how to deal with problems where the number of training examples representing different classes is significantly different. Parikh *et al.* (1999) studied the performance of a MLP classifier in a condition monitoring and fault diagnosis application, in which data representing normal operation are readily available compared to fault data. Such data are often difficult or very expensive to obtain. They showed that the highest overall network performance is obtained if roughly equal numbers of samples from the normal and fault classes are used for training.

7.7.2 Training Data Sets

All input variables are scaled to the range $[0, 1]$. As noted above, the requirement to have approximately equal numbers of training patterns from both deposit and barren classes means that training set size is limited by the number of known deposits. Since the GIS data are captured at a regional scale, only the 120 deposits with a total contained gold resource >1000 kg, together with an approximately equal number of barren patterns can be used to train and test the neural networks. The original training data (i.e. those without added noise) are created by randomly splitting the deposit patterns into three approximately equal groups; that is, training, training-stop and test sets. Deposits from each rock-type in the solid geology GIS layer are divided approximately equally between the three training sets. A number of barren patterns approximately equal to the deposit patterns is also randomly selected for each rock type. There are slightly more barren than deposit patterns because some rock types do not contain any known deposits. The composition of the training sets is shown in Table 7.24. Training was performed with cross validation and early stopping to avoid over-fitting the data.

Table 7.24. Number of patterns in the training sets in which the training set was expanded by adding random noise to the original training data patterns.

Pattern type	Original set			Noise (train set)			Noise (train + stop sets)		
	Training	Stop	Test	Training	Stop	Test	Training	Stop	Test
Deposit	46	39	35	1058	39	35	1058	897	35
Barren	53	49	46	1053	49	46	1053	895	46
Total	99	88	81	2111	88	81	2111	1792	81

7.7.3 Augmentation of Training Data set with Noise

In order to augment the original training data sets, random noise is added to each component of the original deposit feature vectors in the training data set to create 22 new patterns from each original pattern. Random vectors, with a dimensionality equal to the number of inputs, are added repeatedly to each original feature vector in the training set (Fig. 7.6). This ratio of new to original patterns results in 1058 deposit patterns compared with 46 in the original training set. Matching numbers of new barren patterns were randomly selected from the map grid so that the numbers of deposit and barren patterns are approximately equal. Equal numbers of barren patterns are selected from each host-rock type (Table 7.24).

Figure 7.6. Schematic diagram of data processing steps used to augment the training data set through the addition of random noise to deposit patterns to create multiple new patterns. Twenty-two new deposit patterns were created from each original pattern to increase the number of patterns in the training set from 46 to 1058.

Training data sets were created with the MATLAB function *add_noise_equal.m* (see CD-ROM, Vol. 1). For experiments to determine the optimum amount and type of noise, the training-stop and test data sets are not changed. In a final experiment, the training-stop data set is also expanded using additive noise.

7.7.4 Network Topology for Noise-Augmented Training Sets

This section shows the results of experiments to determine the optimum number of hidden layer units for networks trained with the noise-augmented training set. Since the noise-augmented training data set is approximately twenty times greater than in the original training set, it is important to check if more hidden units are required to learn the patterns in the data set.

Tables 7.25 and 7.26 show that a 10-20-1 topology gave the highest correct-classification rates for the noise-augmented test set overall (2111 patterns) and for *deposit* patterns in the test set. This applies to both the *average* performance for 10 networks and to the single networks that gave the *best* overall test-set performance. Consequently, a 10-20-1 topology was used for all further noise experiments. The same number of hidden-layer units was found to give the *best* performance for the standard training data-set (99 patterns) in

Section 7.3.3. The fact that the network topologies means that differences in performance are due to the different training-set sizes.

Table 7.25. Effect of MLP network topology on *average* classification accuracy & map quality for large noise-augmented data sets. Noise: $\pm 10\%$ uniform, training algorithm: *trainlm*, 10 input layers, layer selection criteria: categories.

Network Topology	Training Sets		Test Set			Map Quality Statistics			
	Train	Stop	All	Deps	Barren	ρ	D/A	D*(D/A)	ROC
10-0-1	74.3	66.5	69.9	67.1	72.0	0.98	9.0	83.4	0.75
10-10-1	81.2	75.1	71.9	64.3	77.6	0.98	13.5	142.8	0.85
10-15-1	81.8	74.8	71.6	70.6	72.4	0.97	15.4	175.4	0.84
10-20-1	83.1	72.7	72.2	72.3	72.2	0.97	13.7	160.5	0.85
10-25-1	83.1	73.0	70.1	65.7	73.5	0.98	18.5	152.3	0.85
10-50-1	84.5	71.4	70.6	66.0	74.1	0.97	13.4	165.7	0.84

Table 7.26. Effect of MLP network topology on *best* classification accuracy & map quality for large noise-augmented data sets. Noise: $\pm 10\%$ uniform, training algorithm: *trainlm*, 10 input layers, layer selection criteria: categories.

Network Topology	Training Sets		Test Set			Map Quality Statistics			
	Train	Stop	All	Deps	Barren	ρ	D/A	D*(D/A)	ROC
10-0-1	74.0	77.3	71.6	68.6	73.9	0.98	14.7	441.2	0.80
10-10-1	85.2	76.1	76.5	57.1	91.3	0.98	9.7	48.7	0.84
10-15-1	85.5	73.9	75.3	68.6	80.4	0.95	6.1	20.2	0.86
10-20-1	84.0	75.0	76.5	80.0	73.9	0.98	9.7	96.6	0.86
10-25-1	86.6	70.5	75.3	74.3	76.1	0.98	20.5	68.3	0.86
10-50-1	92.0	72.7	77.8	74.3	80.4	0.92	7.2	29.8	0.87

7.7.5 Optimum Amount of Noise

Experiments were performed using ± 5 , ± 10 , ± 20 , ± 40 and $\pm 80\%$ noise in an attempt to determine the optimal amount of noise. Two different types of noise, uniform random and normally-distributed or Gaussian random noise, were also tested. In the case of uniform random noise, the percentages represent the maximum amount added or subtracted. For normally-distributed noise, the standard deviation was set to a fraction of the variable

value represented by the percentage. The mean was set to the value of the component in the original feature vector.

Tables 7.27 and 7.28 show the results of experiments using various amounts of uniform random noise. The same network topology (10-20-1) and set of initial weights was used for each of the 10 networks trained for each noise level. Each row in Table 7.27 shows the *average* results for 10 networks, whereas Table 7.28 shows the network which gives the *best* overall test-set performance. In both tables, the results for the original training set without added noise is shown in the first row.

The *average* results (Table 7.27) show that the increased training data-set size, due to the addition of noise, results in a significant improvement in generalization and most measures of map quality. The percentage classification of the test set, both capture efficiency ratios, D/A , $D \times (D/A)$ and the area under the ROC, are significantly increased. The *average* values of D/A and $D \times (D/A)$ are approximately doubled. The results for 40% noise represent a very significant improvement in the percentage correct classification for deposit patterns (i.e. from 68.0% to 77.1%), although, for most other noise levels, there is only a slight improvement.

The *best* test-set results (Table 7.28) vary considerably with different amounts of added noise. In many cases, the classification performance for barren cells and the $D \times (D/A)$ statistic are poorer than for the network trained without added noise (top row in Table 7.28). However, the results for ρ , D/A and the area under the ROC are significantly improved and the correct classification of test-set deposit patterns for the 40% noise level show a similarly large improvement as displayed in the *average* results (i.e. from 77.1% to 85.7%). A notable feature of the *average* results is that there appears to be a weak inverse relationship between correct classification performance for deposit and barren patterns in the test set (see for example the results for $\pm 20\%$ and $\pm 40\%$ in Table 7.27).

Examples of mineral prospectivity maps for part of the Kalgoorlie Terrane, Western Australia, showing the potential for orogenic lode-gold deposits, are given in Figures 7.7-7.8. The maps were created using a 10-20-1 MLP neural network, which was trained with a training data set expanded from 46 to 1058 deposit patterns through the addition of $\pm 40\%$ and $\pm 80\%$ uniform random noise. The effect of training the network with patterns created with $\pm 80\%$, rather than $\pm 40\%$, noise is to reduce the size of areas estimated to have high prospectivity. A similar difference exists between maps which were produced using $\pm 5\%$ and $\pm 10\%$ normally-distributed noise (Figs 7.9 & 7.10, respectively). For comparison, the neural network with 10 inputs (layer selection criteria: categories), which

was trained without noise and which gave the *best* overall test-set performance, is shown in Figure 7.15.

Table 7.27. Effect of the amount of uniform random noise used to augment the training data set on *average* performance. Network topology: 10-20-1, training algorithm: *trainlm*, layer selection criteria: categories.

Noise max.(%)	Training Sets		Test Set			Map Quality Statistics			
	Train	Stop	All	Deps	Barren	ρ	D/A	D*(D/A)	ROC
± 0	84.4	72.7	67.9	68.0	67.8	0.97	8.2	105.3	0.79
± 5	83.3	74.1	74.1	70.3	77.0	0.98	17.3	202.2	0.86
± 10	83.4	74.1	72.4	71.4	73.0	0.97	15.3	178.8	0.85
± 20	85.2	74.6	71.6	66.6	75.4	0.97	18.9	237.5	0.85
± 40	82.5	73.2	72.8	77.1	69.6	0.99	17.9	226.4	0.87
± 80	86.5	73.9	71.5	68.9	73.5	0.98	14.6	188.2	0.84

Table 7.28. Effect of the amount of uniform random noise used to augment the training data set on *best* performance. Network topology: 10-20-1, training algorithm: *trainlm*, layer selection criteria: categories.

Noise max.(%)	Training Sets		Test Set			Map Quality Statistics			
	Train	Stop	All	Deps	Barren	ρ	D/A	D*(D/A)	ROC
± 0	88.9	72.7	76.5	77.1	76.1	0.90	9.6	256.7	0.82
± 5	81.3	80.7	79.0	74.3	82.6	0.98	13.2	164.8	0.89
± 10	84.0	75.0	76.5	80.0	73.9	0.98	9.7	96.6	0.86
± 20	82.7	75.0	76.5	80.0	73.9	0.95	16.7	152.7	0.82
± 40	82.9	75.0	76.5	85.7	69.6	1.00	14.4	216.0	0.90
± 80	92.9	79.6	80.3	74.3	84.8	0.97	11.0	247.3	0.86

Table 7.29. Effect of the amount of normally-distributed random noise used to augment the training data set on *average* performance. Network topology: 10-20-1, training algorithm: *trainlm*, layer selection criteria: categories.

Noise max.(%)	Training Sets		Test Set			Map Quality Statistics			
	Train	Stop	All	Deps	Barren	ρ	D/A	D*(D/A)	ROC
± 0	84.4	72.7	67.9	68.0	67.8	0.97	8.2	105.3	0.79
± 5	83.1	72.8	72.8	71.4	73.9	0.94	12.9	143.0	0.84
± 10	83.4	73.6	73.8	66.9	79.1	0.92	13.7	131.2	0.86
± 20	84.3	75.0	73.1	69.7	75.7	0.93	17.9	321.5	0.87
± 40	84.2	77.1	71.2	68.6	73.3	0.93	13.1	149.8	0.84
± 80	84.8	67.4	64.7	47.7	77.6	0.86	19.1	109.9	0.76

Table 7.30. Effect of the amount of normally-distributed random noise used to augment the training data set on *best* performance. Network topology: 10-20-1, training algorithm: *trainlm*, layer selection criteria: categories.

Noise max.(%)	Training Sets		Test Set			Map Quality Statistics			
	Train	Stop	All	Deps	Barren	ρ	D/A	D*(D/A)	ROC
± 0	88.9	72.7	76.5	77.1	76.1	0.90	9.6	256.7	0.82
± 5	83.9	77.3	79.0	85.7	73.9	0.97	19.0	269.0	0.87
± 10	87.5	71.6	80.3	80.0	80.4	0.98	12.0	130.4	0.85
± 20	88.4	78.4	77.8	82.9	73.9	1.00	13.2	439.7	0.90
± 40	85.7	78.4	77.8	82.9	73.9	0.98	8.9	110.8	0.87
± 80	86.8	68.2	69.1	62.9	73.9	0.97	16.3	81.6	0.76

Figure 7.7. Detail of a mineral prospectivity map of part of the Kalgoorlie Terrane, Western Australia, showing the potential for orogenic lode-gold deposits. The map was created using a 10-20-1 MLP neural network, which was trained with a training data set expanded from 46 to 1058 deposit patterns through the addition of $\pm 40\%$ uniform random noise. The ten input layers are selected according to the evidence-categories criterion. Yellow circles indicate the location of deposits containing a resource of ≥ 1000 kg TCG.

Figure 7.8. Detail of a mineral prospectivity map of part of the Kalgoorlie Terrane, Western Australia, showing the potential for orogenic lode-gold deposits. The map was created using a 10-20-1 MLP neural network, which was trained with a training data set expanded from 46 to 1058 deposit patterns through the addition of $\pm 80\%$ uniform random noise. The effect of training the network patterns created with $\pm 80\%$, rather than $\pm 40\%$, noise is to reduce the size of areas estimated to have high prospectivity. The ten input layers are selected according to the evidence-categories criterion. Yellow circles indicate the location of deposits containing a resource of ≥ 1000 kg TCG.

Figure 7.9. Detail of a mineral prospectivity map of part of the Kalgoorlie Terrane, Western Australia, showing the potential for orogenic lode-gold deposits. The map was created using a 10-20-1 MLP neural network, which was trained with a training data set expanded from 46 to 1058 deposit patterns through the addition of $\pm 5\%$ normally-distributed random noise. The ten input layers are selected according to the evidence-categories criterion. Yellow circles indicate the location of deposits containing a resource of ≥ 1000 kg TCG.

Figure 7.10. Detail of a mineral prospectivity map of part of the Kalgoorlie Terrane, Western Australia, showing the potential for orogenic lode-gold deposits. The map was created using a 10-20-1 MLP neural network, which was trained with a training data set expanded from 46 to 1058 deposit patterns through the addition of $\pm 10\%$ normally-distributed random noise. The effect of training the network patterns created with $\pm 10\%$ rather than $\pm 5\%$ noise is to reduce the size of areas estimated to have high prospectivity. A similar effect was noted in Figures 7.7 and 7.8. The ten input layers are selected according to the evidence-categories criterion. Yellow circles indicate the location of deposits containing a resource of ≥ 1000 kg TCG.

7.7.6 Uniform and Normally-Distributed Random Noise

The experiments described above are repeated to check the effect of using normally-distributed rather than uniform random noise (Tables 7.31 & 7.32). The addition of normally-distributed noise improves the *average* overall test-set performance as well as measures of map quality, D/A , $D \times (D/A)$, and the area under the ROC curve. However, the percentage correct classification for test-set deposit patterns, and the correlation between probability of a deposit and increasing prospectivity map class (Spearman's ρ), are generally poorer than the results obtained without using noise (Table 7.31). An exception is for $\pm 5\%$ noise, where the correct classification rate for deposit patterns increases from 68.0% to 71.4%.

To allow a comparison between uniform and normally-distributed noise, results from the previous Tables, 7.27, 7.28, and 7.29 and 7.30, have been combined into Tables 7.31 and 7.32, respectively.

Despite the fact that the *average* results for normally-distributed noise are generally poorer than those for uniform random noise, the results for the networks with the *best* test-set classification performance using $\pm 5\%$, $\pm 10\%$ and $\pm 20\%$ normally-distributed noise are slightly better than those for uniform noise. The network with $\pm 10\%$ normally-distributed noise gave the best combination of overall test-set and test-set deposit pattern classification performance of all the networks shown in Tables 7.27-7.30.

7.7.7 Use of Noise-Augmented Training and Training-Stop Sets

Although the patterns in the training data set must provide the network with a representative sample of the variation in the data population that the trained network will be required to process, the training-stop data set also determines the generalization ability of the trained network. In this last experiment, the same procedure used to augment the number of deposit patterns is applied to the training-stop data set, so that the size of both the training and training-stop sets are increased. Training data sets were created with the MATLAB function *add_noise_equal_bigVV.m* (see CD-ROM, Vol.1). The composition of the training-data sets is shown in Table 7.24.

The noise levels giving the *best* test-set performance for using uniform and normally-distributed random noise are repeated with both noise-augmented training and training-stop data sets. Ten networks are trained using $\pm 40\%$ uniform random noise and $\pm 10\%$ normally-distributed noise. The results are shown in Tables 7.33 and 7.34. For $\pm 40\%$

Table 7.31. Comparison of uniform and normally-distributed random noise showing the *average* test-data-set performance. Network topology: 10-20-1, training algorithm: *trainlm*, layer selection criteria: categories.

Noise max.(%)	Training Sets		Test Set			Map Quality Statistics			
	Train	Stop	All	Deps	Barren	ρ	D/A	D*(D/A)	ROC
± 5 uni.	83.3	74.1	74.1	70.3	77.0	0.98	17.3	202.2	0.86
± 5 norm.	83.1	72.8	72.8	71.4	73.9	0.94	12.9	143.0	0.84
± 10 uni.	83.4	74.1	72.4	71.4	73.0	0.97	15.3	178.8	0.85
± 10 norm.	83.4	73.6	73.8	66.9	79.1	0.92	13.7	131.2	0.86
± 20 uni.	85.2	74.6	71.6	66.6	75.4	0.97	18.9	237.5	0.85
± 20 norm.	84.3	75.0	73.1	69.7	75.7	0.93	17.9	321.5	0.87
± 40 uni.	82.5	73.2	72.8	77.1	69.6	0.99	17.9	226.4	0.87
± 40 norm.	84.2	77.1	71.2	68.6	73.3	0.93	13.1	149.8	0.84
± 80 uni.	86.5	73.9	71.5	68.9	73.5	0.98	14.6	188.2	0.84
± 80 norm.	84.8	67.4	64.7	47.7	77.6	0.86	19.1	109.9	0.76

Table 7.32. Comparison of uniform and normally-distributed random noise showing the results for the networks with the *best* test-data-set performance. Network topology: 10-20-1, training algorithm: *trainlm*, layer selection criteria: categories.

Noise max.(%)	Training Sets		Test Set			Map Quality Statistics			
	Train	Stop	All	Deps	Barren	ρ	D/A	D*(D/A)	ROC
± 5 uni.	81.3	80.7	79.0	74.3	82.6	0.98	13.2	164.8	0.89
± 5 norm.	83.9	77.3	79.0	85.7	73.9	0.97	19.0	269.0	0.87
± 10 uni.	84.0	75.0	76.5	80.0	73.9	0.98	9.7	96.6	0.86
± 10 norm.	87.5	71.6	80.3	80.0	80.4	0.98	12.0	130.4	0.85
± 20 uni.	82.7	75.0	76.5	80.0	73.9	0.95	16.7	152.7	0.82
± 20 norm.	88.4	78.4	77.8	82.9	73.9	1.00	13.2	439.7	0.90
± 40 uni.	82.9	75.0	76.5	85.7	69.6	1.00	14.4	216.0	0.90
± 40 norm.	85.7	78.4	77.8	82.9	73.9	0.98	8.9	110.8	0.87
± 80 uni.	92.9	79.6	80.3	74.3	84.8	0.97	11.0	247.3	0.86
± 80 norm.	86.8	68.2	69.1	62.9	73.9	0.97	16.3	81.6	0.76

uniform noise, there is a small improvement in the percentage of correct classifications for the test-set (overall, deposit and barren patterns) and in the capture-efficiency statistic, $D \times (D/A)$. In the case of the normally-distributed noise, there is a small increase in the overall test-set performance and correlation coefficient (ρ), and a large increase in the classification performance for deposit patterns and both capture-efficiency statistics D/A and $D \times (D/A)$. There is no increase in the *best* test-set results for either uniform or normally-distributed noise

Table 7.33. Effect of expanding the stop data set in addition to the training set using random noise: *average* results. Network topology: 10-20-1, training algorithm: *trainlm*, layer selection criteria: categories.

Network Topology	Training Sets		Test Set			Map Quality Statistics			
	Train	Stop	All	Deps	Barren	ρ	D/A	D*(D/A)	ROC
± 40 ,uniform	82.5	73.2	72.8	77.1	69.6	0.99	17.9	226.4	0.87
± 40 ,uni.,lge stop	85.9	77.8	73.5	77.4	70.4	0.98	14.7	296.2	0.87
± 10 ,normal	83.4	73.6	73.8	66.9	79.1	0.92	13.7	131.2	0.86
± 10 ,nml.,lge stop	86.2	76.4	74.1	76.6	72.2	0.98	15.0	245.6	0.87

Table 7.34. Effect of expanding the stop data set in addition to the training set using random noise: *best* results. Network topology: 10-20-1, training algorithm: *trainlm*, layer selection criteria: categories.

Network Topology	Training Sets		Test Set			Map Quality Statistics			
	Train	Stop	All	Deps	Barren	ρ	D/A	D*(D/A)	ROC
± 40 ,uniform	82.9	75.0	76.5	85.7	69.6	1.00	14.4	216.0	0.90
± 40 ,uni.,lge stop	82.9	79.8	76.5	85.7	69.6	1.00	14.4	216.0	0.90
± 10 ,normal	87.5	71.6	80.3	80.0	80.4	0.98	12.0	130.4	0.85
± 10 ,nml.,lge stop	87.5	76.7	80.3	80.0	80.4	0.98	12.0	130.4	0.85

7.7.8 Conclusions: Augmentation of Training Data with Random Noise

The use of random noise to create additional synthetic deposit-patterns helps overcome the lack of deposit patterns that limits the training set sizes for neural networks trained using a backpropagation training algorithm. In particular, the following results are obtained:

1. Training with the larger noise-augmented data sets results in significantly increased classification accuracy for the test set (overall) and test-set deposit patterns, area under the ROC curve and capture efficiency (D/A and $D \times (D/A)$) statistics.
2. The best results are obtained using an MLP network with a 10-20-1 topology and $\pm 40\%$ noise.
3. Uniform random noise generally gives better *average* results than normally-distributed noise.
4. Networks with *best* overall test-set and test-set deposit classification performance are ± 5 , ± 10 & ± 20 .
5. Increasing the amount of uniform random noise from $\pm 40\%$ to $\pm 80\%$ reduces the size of areas estimated to have high prospectivity.
6. Increasing the size of the training-stop data set yields a small increase in *average* overall test-set and test-set deposit-pattern classification performance.

The method described here could be applied to increase the number of patterns available for training in other applications in which training data are rare, difficult or expensive to obtain.

7.8 Input Data as Fuzzy-Membership Values

Different approaches to mineral prospectivity are needed depending on the type of exploration area and the availability and reliability of data compared to geological knowledge available. In well-explored areas where there are large amounts of data, statistical methods like weights of evidence and neural networks are appropriate (Fig. 7.11). In poorly-explored areas, containing few known deposits and where little reliable data are available, a purely subjective method like fuzzy systems is appropriate (An *et al.*, 1991; Bonham-Carter, 1994; Eddy *et al.*, 1995; Wyborn *et al.*, 1995b). Ideally, lessons learned from mature exploration areas should be applied to new areas and, conversely, new conceptual models or exploration criteria need to be applied to well-explored areas. Woodall (1994) notes that exploration success depends on the correct blend of empiricism and conceptual thinking. Fuzzy weights of evidence and hybrid fuzzy-neural networks are examples of systems which combine elements from both conceptual and empirical approaches (Fig. 7.11). The fuzzy-neural system represents a hybrid architecture that combines the ability of fuzzy systems to deal with imprecise or error-prone inputs with the pattern recognition

capability of neural networks. This enables conceptual and empirical approaches to be combined by incorporating subjective geological knowledge into an otherwise data-driven neural network method.

Figure 7.11. Relationship of hybrid fuzzy-neural-network systems and fuzzy weights-of-evidence approach to main empirical and conceptual methods for mineral prospectivity mapping. Both weights-of-evidence and neural network methods require large amounts of data, commonly available in well-explored areas, whereas fuzzy systems, which incorporate geological knowledge, are more suited to new areas where few data are available.

Since the early 1990's, there has been considerable interest in methods of combining neural network and fuzzy-logic approaches. Much of the research has been directed towards solving complex non-linear control problems in engineering (Jang & Sun, 1995; Kasabov, 1996). The reason for combining the two methods is that they appear to complement one another. Whilst both methods can deal with uncertain and imprecise inputs, neural networks represent a data-driven approach whereas fuzzy systems represent a conceptual approach. Neural networks can detect very complex patterns in data, but fuzzy systems are able to incorporate expert knowledge, which neural networks cannot do directly. The benefits of combining the two approaches have been demonstrated in a number of studies. Wong *et al.* (1998) used a subjective geological layer as an input to a neural network to interpolate porosity data obtained from well-sites over the area of a fluvial sandstone oil reservoir. They showed that the addition of the subjective geological knowledge significantly improved the quality of porosity estimates. Huang *et al.* (1996) used a fuzzy neural network to estimate permeability in a petroleum reservoir and showed that the fuzzy neural network resulted in faster convergence, and a lower test-set error, than an MLP network which was trained using the backpropagation algorithm. Three main ways of com-

binning neural networks and fuzzy systems are described in the literature (Gupta & Rao, 1994; Jang & Sun, 1995; Kasabov, 1996). These are 1) fuzzy neurons, 2) multi-modular hybrid neural network-fuzzy systems, and 3) adaptive network-based fuzzy inference systems (ANFIS). This study demonstrates a very simple form of hybrid fuzzy-neural-network system of the second type.

Using GIS layers, in which the cell values represent fuzzy membership values, is one method of combining subjective geological knowledge with empirical data in a neural-network approach to mineral prospectivity mapping. In this section, this approach to forming a simple hybrid fuzzy-neural networks system is investigated and compared with the results for an MLP neural network. The hybrid systems are used to combine up to 17 GIS layers to predict the potential for orogenic gold deposits.

Two types of fuzzy membership layers are used in this study. In the first type of layer, *statistical* relationships between known gold deposits and the variable in the GIS thematic layer are used to determine the fuzzy membership values. For example, GIS layers depicting solid geology and rock-type combination at the nearest type of lithological boundary for each cell (i.e. categorical data) are converted to fuzzy membership layers representing favourable lithologies and favourable lithological boundaries. In the second type of fuzzy membership layer, the assignment of fuzzy membership values, although based on geological field data, is *subjective*. The most effective layer representing rheological contrast at the nearest lithological boundary is modelled in this way. In each of the layers, the fuzzy membership values represent the degree to which the raw variable values belong to the fuzzy set *favourable for orogenic lode gold deposits*.

7.8.1 Objective Fuzzy-Membership Layers

The solid geology and contact-type layers are examples of objective fuzzy membership layers because they are converted to fuzzy membership values using the statistical association between the classes and known deposits (containing ≥ 1000 kg TCG).

Two fuzzy membership layers are created; one where fuzzy membership values are based on ranking rock types according to the probability of at least one deposit per cell and a second layer based on ranking rock types according to $P(D) \times TCG/cell$.

The two favourable host-rock layers are compared using capture efficiency ratios, D/A and $D \times (D/A)$, where D refers to the percentage of known deposits in the area corresponding to the favourable region, and A refers to the percentage of the total map area represented

by the region. The second ratio is used because the ratio D/A may be high if the most favourable region contains just a few deposits and the area of the region happens to be small. The ratios are measures of the degree to which the most favourable region in the map accounts for the known deposits.

In order to compare the two different methods used to create the favourable contact layers, the favourable region is arbitrarily defined as the upper quartile of membership values (i.e. 0.75-1.0). In the favourable geology layer based on ranking rock types according to the probability of deposits, the favourable region contains 19% of the deposits in 3% of the area. This compares to 29% of the deposits in approximately 10% of the area for the layer based on $(P(D) \times TCG)/cell$ (Table 7.35). Values of D/A and $D \times (D/A)$ for the layer based on the probability of deposits, $P(D)$ and $P(D) \times TCG/cell$ are 6.0 and 116 versus 3.0 and 86, respectively (Table 7.35). The layer based on the probability of deposits was therefore selected as the input to the neural networks.

7.8.2 Subjective Fuzzy-Membership Layers

A variety of statistical methods, described in Chapter 6, were used to test the strength and statistical significance of associations between the seven GIS layers representing rheological-contrast and known gold deposits. Methods used comprise plots of cumulative and interval-based bivariate J-curves, contrast of weights (Bonham-Carter, 1994), chi-squared, $(O - E)/E$ (where O = observed number of deposits in a region corresponding to an interval on the X-axis and E = expected number of deposits for a uniform random distribution) and the Kolmogorov-Smirnov (KS) cumulative distribution function.

The subjective fuzzy rheological-contrast layer shows the strongest association with known deposits and was therefore selected as the layer to use as a neural network input. A plot of $(O - E)/E$ (where O = observed number of deposits in a region corresponding to an interval on the X-axis and E = expected number of deposits for a uniform random distribution) versus favourable rheological contrast, represented using the fuzzy-membership values, is shown in Figure 7.12.

The reason for the weak association between known deposits and estimates of rheological contrast based on the quantitative data may be due to the fact that rock strength properties for many rock types in the study area are not available and are therefore approximated by using data for similar rocks. In addition, tabulated data from Hatheway & Kiersch (1989) mainly refers to unaltered, massive specimens, whereas rocks in the Kalgoorlie Terrane are altered and deformed to varying degrees. Although the compilation from M.Lee

Table 7.35. Comparison of the ability of alternative rock-type, contact-type and rheological contrast layers to predict known orogenic gold deposits in the Kalgoorlie Terrane of Western Australia

Layer Type or variable	Deposits (%)	Area (%)	D/A	$D*(D/A)$
Favourable geology				
P(D)	19.2	3.2	6.0	116
$P(D) \times \text{TCG/cell}$	29.2	9.8	3.0	86
Favourable contact-type				
P(D) 0–200 m ^a	15.8	0.6	25.2	398
$P(D) \times \text{TCG/cell}$ 0–200 m	18.3	1.0	18.0	330
P(D) 0–1300 m ^b	17.5	1.2	14.3	251
$P(D) \times \text{TCG/cell}$ 0–1300 m	21.7	1.9	11.3	246
Rheological Contrast				
Subjective fuzzy membership	20.0	3.7	5.5	110
Subjective 10 classes	37.5	14.9	2.5	94
Young's modulus ^c	2.5	0.2	11.9	30
Young's modulus ^d	12.5	1.9	6.8	85
Uniaxial compressive strength	4.2	0.2	20.3	85
Uniaxial tensile strength	12.5	4.6	2.7	34
Fracture toughness	10.0	2.2	4.5	45

^aFuzzy membership values set to 0.1 at distance >200 m in order to model the decreasing effect of proximity to a lithological boundary with distance. Limit is based on the minimum estimate obtained using a variety of statistical tests used to measure the spatial association of known deposits with proximity to lithological contacts. Refer to Table 6.4.

^bFuzzy membership values set to 0.1 at distance >1300 m. See footnote above.

^cCRC: data obtained from Hatheway & Kiersch (1989). See Section D.5.1 in Appendix D.

^dAMC: data provided by M.Lee (unpublished data from Australian Mining Consultants Pty Ltd, 2000). See Section D.5.1 in Appendix D.

(unpublished data from Australian Mining Consultants, 2000) is obtained from mine sites in the Yilgarn Craton, the data refer only to a small number of locations.

7.8.3 Comparison of Fuzzy Membership with Other Methods for Representing Lithology Input

Different methods of representing host-rock lithology as inputs to a neural network are compared in Table 7.36. Host-rock lithology is represented using: 1) 1-of-n coding, 2)

Figure 7.12. Plot of $(O - E)/E$ versus subjective fuzzy membership values for rheological contrast, where O = observed number of deposits in a region corresponding to an interval on the X-axis and E = expected number of deposits for a uniform random distribution of deposits. The rheological contrast layer containing subjectively estimated fuzzy membership values shows the strongest association with known deposits of all the rheological contrast layers and is therefore selected as the layer to use as a neural network input. Other rock strength variables tested were Young's modulus (two different data compilations), uniaxial tensile and compressive strength, and fracture toughness.

three rock strength layers (Young's modulus⁴, uniaxial compressive strength & fracture toughness, and layers for the sulphidation index, $Fe_{(total\ wt\% \ oxides)} \times Fe/(Fe + Mg + Ca)$, and the oxidation ratio, $Fe_2O_3/(Fe_2O_3 + FeO)$, and 3) fuzzy membership values.

Networks with 1-of-n coded and fuzzy host-rock inputs have 10 inputs, whereas the networks, in which rock-strength and chemical-ratio inputs are used to represent the rock type have 14 inputs. In both cases, the other 9 inputs are the same and include the favourable contact-type and favourable rheological contrast input layers, described above. For this experiment, GIS layers which have the highest value of the capture efficiency ratio, D/A , for each evidence-category were selected as inputs to the neural network. These input-layer selection criteria are abbreviated in the table captions below as *categories*.

⁴data from M. Lee, Australian Mining Consultants Pty Ltd (AMC), 2000

Although the network performance statistics are generally similar for both methods, 1-of-n coding produced slightly better *average* classification performance for test-set, and map quality statistics, and approximately 40% higher values for the capture efficiency statistic, $D \times (D/A)$. In contrast, the best test-set results (see second last line of Table 7.36) are obtained using fuzzy membership values. In addition, the $D \times (D/A)$ value is much higher for the network with the fuzzy membership inputs compared to the one with 1-of-n coded geology inputs. As noted above, 1-of-n coding is more difficult to use for problems involving a large number of classes (if patterns are stored as arrays in memory during processing) due to the large amount of main computer memory required. The similarity of results suggests that fuzzy membership values are a viable alternative for categorical data inputs to a neural network in this domain.

Table 7.36. Effect of using 1-of-n coding, 5 rock strength and chemical ratio layers, and fuzzy membership values to represent host-rock lithology for input to a neural network on the test-set performance. The following rock strength and chemical ratios were used to represent lithology; Young's Modulus, uniaxial compressive strength, fracture toughness, sulphidation index, $\text{Fe}_{\text{totalwt}}\% \times \text{Fe}/(\text{Fe}_{\text{total}} + \text{Mg} + \text{Ca})$, & oxidation ratio, $\text{Fe}_2\text{O}_3/(\text{Fe}_2\text{O}_3 + \text{FeO})$. Each row represents the *average* of 10 networks. Values for training and test set performance represent the percentages of correctly classified patterns. Network topology: 10-20-1, training algorithm: *trainlm*, layer selection criteria: GIS layers which have the highest value of the capture efficiency ratio, D/A , for each evidence-category. These criteria are abbreviated in subsequent tables as *categories*.

Lithology input type	Training Sets		Test Set			Map Quality Statistics			
	Train	Stop	All	Deps	Barren	ρ	D/A	$D \times (D/A)$	ROC
Average performance									
Fuzzy m/ship ^a	84.4	72.7	67.9	68.0	67.8	0.97	8.2	105.3	0.79
Rheol.+ Chem. ^b	86.6	72.9	69.4	69.1	69.6	0.90	9.1	148.7	0.79
1-of-n coding ^c	87.9	78.2	68.5	71.5	66.3	0.98	9.0	147.4	0.81
Best performance									
Fuzzy m/ship	88.9	72.7	76.5	77.1	76.1	0.90	9.6	256.7	0.82
Rheol.+ Chem.	86.9	69.3	71.6	77.1	67.4	0.95	10.3	197.1	0.81
1-of-n coding	93.9	79.3	72.5	76.5	69.6	0.97	8.0	200.0	0.82

^aFuzzy membership values. Network topology: 10-20-1

^bRheology and chemical ratio layers. Network topology: 14-20-1

^cNetwork topology: 33-20-1

7.8.4 Fuzzification Of All Neural Network Inputs

An extension of the concept of using fuzzy membership values in order to represent categorical data types as inputs is to use fuzzy membership values for all the network inputs. Such a system effectively represents a simple form of hybrid fuzzy-neural network system (Fig. 7.13). A series of networks were tested in which all 10 or 17 inputs are converted to fuzzy membership values. Triangular fuzzy membership functions were used to convert the scaled raw data to membership values (refer to Fig. 5.6). The thresholds above which all raw data values are mapped to a fuzzy membership value of 1.0, or below which the raw data values are mapped to 0.1, are determined using plots of $(O - E)/E$, such as that shown in Figure 7.12. Reclassification of the original raster GIS layers is performed in MATLAB using the functions *layer2fav* and *layer2fav_batch*. Since all neural network inputs are scaled to the range $[0, 1]$, the fuzzy membership inputs require no special pre-processing.

Results for neural networks with 10 inputs, in which 1, 3 and 10 inputs are represented as fuzzy membership values, are shown in Table 7.37. Systems for which all 10 inputs are presented as fuzzy membership values represent a form of hybrid fuzzy-neural network. Each row represents the *average* for ten networks. The top half of each table shows the results for inputs selected using the evidence-category criteria and the lower half of each table shows the results for inputs selected using the $D \times (D/A)$ criteria. Table 7.38 shows the results for the neural network, hybrid fuzzy-neural network and fuzzy system with the *best* percentage of correct classifications for the independent test data. Although networks and fuzzy systems, which are grouped according to the layer selection criteria, have different numbers of fuzzy and standard scaled inputs, each system uses the same total number of inputs and the input variables correspond to the same set of GIS layers. Tables 7.39 and 7.40 are similar, but show the *average* and *best* results for networks using 17 inputs.

Networks with 1, 3, and 10 fuzzy inputs produce similar results for the percentage correct classification of the test-set data. However, those with 1 and 3 fuzzy inputs generally performed slightly better than the equivalent networks with 10 fuzzy inputs (i.e. those with the same number of inputs and selection criteria). An exception is for 10 input layers selected according to the evidence categories criteria, where the *average* test-set classification percentage is 67.9% and 70.5% for three and ten fuzzy inputs, respectively (top of Table 7.37).

Figure 7.13. Schematic diagram of a hybrid, fuzzy-neural network system. Some or all of the network inputs may be fuzzy membership values.

In addition, the highest overall test-set classification accuracies were obtained with networks using only fuzzy inputs (i.e. 79.0% for the *best* 10 input network with layers selected with the category criterion, Table 7.38), and 79.0% for the *best* 17 input network with layers selected using the $D \times (D/A)$ criterion, (bottom of Table 7.40).

The fuzzy-neural networks with both 10 and 17 inputs generally gave better results (i.e. *average* and *best*) for the two capture efficiency ratios and the area under the ROC curves. For example, the values of these statistics for the *average* of 10 networks with 10 inputs (selection criteria: $D \times (D/A)$) are 7.4, 109.0, and 0.84 for 3 fuzzy inputs compared with 14.4, 264.3 and 0.86 for ten fuzzy inputs (see lower half of Table 7.37).

Table 7.37. Comparison of neural networks with 3 and 10 fuzzy-membership inputs (i.e. latter is a hybrid fuzzy-neural network): *average* results. Network topology: 10-20-1, training algorithm: *trainlm*.

Number of fuzzy inputs	Training Sets		Test Set			Map Quality Statistics			
	Train	Stop	All	Deps	Barren	ρ	D/A	$D \times (D/A)$	ROC
Layer selection criteria: categories									
3	84.4	72.7	67.9	68.0	67.8	0.97	8.2	105.3	0.79
10	84.3	75.2	70.5	66.9	73.3	0.94	9.7	133.4	0.83
Layer selection criteria: $D \times (D/A)$									
3	87.9	76.9	72.1	75.1	69.8	0.95	7.4	109.0	0.84
10	87.2	78.4	69.1	71.4	67.4	0.97	14.4	264.3	0.86

Table 7.38. Comparison of neural networks with 3 and 10 fuzzy-membership inputs (i.e. latter is a hybrid fuzzy-neural network), and a fuzzy system with 10 inputs: *best* results. Network topology: 10-20-1, training algorithm: *trainlm*.

Number of fuzzy inputs	Training Sets		Test Set			Map Quality Statistics			
	Train	Stop	All	Deps	Barren	ρ	D/A	D*(D/A)	ROC
Layer selection criteria: categories									
3	88.9	72.7	76.5	77.1	76.1	0.90	9.6	256.7	0.82
10	86.9	80.7	79.0	71.4	84.8	0.90	10.3	120.6	0.86
10 fuzzy ($\gamma=0.96$)	69.7	73.9	67.9	65.7	69.6	1.00	160.6	267.7	0.87
Layer selection criteria: $D \times (D/A)$									
3	92.9	81.8	77.8	82.9	73.9	0.98	5.0	104.5	0.87
10	82.8	84.1	74.1	85.7	65.2	0.98	19.5	519.0	0.89
10 fuzzy ($\gamma=0.94$)	67.7	72.7	70.4	62.9	76.1	1.00	68.2	397.7	0.89

Table 7.39. Comparison of neural networks with 3 and 17 fuzzy-membership inputs (i.e. latter is a hybrid fuzzy-neural network): *average* results. Network topology: 10-20-1, training algorithm: *trainlm*.

Number of fuzzy inputs	Training Sets		Test Set			Map Quality Statistics			
	Train	Stop	All	Deps	Barren	ρ	D/A	D*(D/A)	ROC
Layer selection criteria: categories									
3	82.0	70.8	71.0	68.9	72.6	0.88	6.4	49.1	0.78
17	82.7	72.8	64.8	57.4	70.4	0.95	7.8	96.7	0.82
Layer selection criteria: $D \times (D/A)$									
3	87.8	77.4	73.1	70.3	75.2	0.95	9.0	117.0	0.83
17	90.1	77.4	70.0	62.6	75.7	0.96	8.7	133.7	0.86

Table 7.40. Comparison of neural networks with 3 and 17 fuzzy-membership inputs (i.e. latter is a hybrid fuzzy-neural network), and a fuzzy system with 17 inputs: *best* results. Network topology: 10-20-1, training algorithm: *trainlm*.

Input type	Training Sets		Test Set			Map Quality Statistics			
	Train	Stop	All	Deps	Barren	ρ	D/A	D*(D/A)	ROC
Layer selection criteria: categories									
3	82.8	79.6	76.5	88.6	67.4	1.00	9.7	72.5	0.83
17	91.9	76.1	70.4	68.6	71.7	1.00	21.6	541.0	0.88
17 fuzzy ($\gamma=0.97$)	71.7	76.1	70.4	51.4	84.8	0.98	266.4	887.8	0.89
Layer selection criteria: $D \times (D/A)$									
3	90.9	83.0	75.3	82.9	69.6	0.98	13.2	231.4	0.86
17	93.9	80.7	79.0	71.4	84.8	0.97	15.6	349.9	0.88
17 fuzzy ($\gamma=0.97$)	70.7	73.9	71.6	54.3	84.8	0.98	199.8	665.9	0.89

Increasing the number of inputs from 10 to 17 does not result in a significant improvement in performance nor map quality (Tables 7.37 & 7.38 versus 7.39 & 7.40). Better recognition of the deposit patterns in the test data set is achieved with networks using layers selected according to the $D \times (D/A)$ criterion than with the categories criterion. Networks using the $D \times (D/A)$ set of layers also generally give significantly higher values for the measures of prospectivity map quality (i.e. Spearman's correlation coefficient, D/A , $D \times (D/A)$, and area under the ROC curve).

For comparison purposes, maps are prepared using simple fuzzy systems, in which the same input layers were combined using the gamma function (Zimmermann, 1984). Maps are created and tested for values of the gamma parameter in the range $[0.0, 1.0]$ in 0.01 increments. Results for gamma values in the range $[0.9, 1.0]$ are shown in Table 7.41 below. The results corresponding to the *best* test-set classification performance are shown in Tables 7.38 and 7.40.

The generalization performance of the fuzzy systems is significantly poorer than the neural networks and the hybrid fuzzy-neural networks. For example, the systems with 10 inputs give *average* results of 76.5%, 79.0%, and 67.9% correct classification of the test set and 77.1%, 71.4%, and 65.7% correct classification of the deposit patterns in the test set, respectively (Table 7.37). The fuzzy system does yield some extremely high values of the capture efficiency ratios, D/A , $D \times (D/A)$ (e.g. 266.4 and 887.8, respectively, for 17 inputs, category selection criterion; see Table 7.40).

Table 7.41. Performance of fuzzy systems using the gamma function for a range of gamma values: 10 and 17 input layers, layer selection criteria: categories.

Gamma value (γ)	Training Sets		Test Set			Map Quality Statistics			
	Train	Stop	All	Deps	Barren	ρ	D/A	D*(D/A)	ROC
10 layers, cat. ^a									
0.94	62.6	71.6	65.4	22.9	97.8	0.95	348.5	580.9	0.87
0.95	65.7	76.1	61.7	28.6	87.0	0.98	292.5	487.5	0.87
0.96	69.7	73.9	67.9	65.7	69.6	1.00	160.6	267.7	0.87
0.97	58.6	60.2	56.8	94.3	28.3	0.98	95.8	159.7	0.87
0.98	56.6	48.9	48.2	97.1	10.9	0.98	51.1	127.7	0.87
10 layers, D*(D/A)									
0.94	67.7	72.7	70.4	62.9	76.1	1.00	68.2	397.7	0.89
0.95	72.7	73.9	65.4	80.0	54.4	0.98	88.5	811.3	0.89
0.96	58.6	56.8	63.0	100.0	34.8	0.96	87.4	1019.6	0.89
0.97	49.5	48.9	48.2	100.0	8.7	0.92	65.6	928.7	0.89
0.98	48.5	46.6	44.4	100.0	2.2	0.85	29.8	546.7	0.89
17 layers, cat.									
0.94	54.6	56.8	59.3	5.7	100.0	1.00	744.6	620.5	0.89
0.95	55.6	61.4	60.5	8.6	100.0	1.00	744.6	1241.0	0.89
0.96	58.6	65.9	64.2	20.0	97.8	1.00	321.2	535.3	0.89
0.97	71.7	76.1	70.4	51.4	84.8	0.98	266.4	887.8	0.89
0.98	51.5	53.4	53.1	100.0	17.4	0.92	109.5	547.2	0.89
17 layers, D*(D/A)									
0.94	55.6	61.4	60.5	8.6	100.0	0.47	0.0	0.0	0.89
0.95	57.6	64.8	61.7	11.4	100.0	0.53	0.0	0.0	0.89
0.96	61.6	67.1	63.0	22.9	93.5	0.53	0.0	0.0	0.89
0.97	70.7	73.9	71.6	54.3	84.8	0.98	199.8	665.9	0.89
0.98	50.5	52.3	50.6	100.0	13.0	0.96	117.2	781.4	0.89

^acat. = categories. Input layers selected using category criteria.

This highlights the limitation of using summary statistics like capture efficiency ratios. The very high values of D/A , and $D \times (D/A)$ are due to the fact that the region corresponding to the highest prospectivity map class contains a small number of deposits in a very small proportion of the map (i.e. 4 deposits in 123 grid cells for the 17 *categories* input fuzzy system shown in the top part of Table 7.40). However, the bulk of the deposits occur in the region corresponding to classes 5-7 (i.e. 104 deposits in 482464 cells). By comparison, the hybrid fuzzy-neural network with the same inputs (Table 7.40), generates a map with

the largest number of deposits (30) in the area corresponding to class 9 (11355 cells), the highest prospectivity area. In this prospectivity map, in which the prospectivity values are divided into 9 classes, the bulk of deposits are located in the area corresponding to classes 7-9 (i.e. 73 deposits in 82,258 cells). Details of the statistics for each neural network and fuzzy system are given in the file *mapstats* on the attached CD-ROM (vol.1).

7.8.5 Discussion: Use of Fuzzy Inputs in Neural Networks

The better map quality statistics, but poorer test-set classification performance, for fuzzy systems and hybrid fuzzy-neural networks with 10 and 17 fuzzy inputs compared to neural networks with 1 and 3 fuzzy inputs may be due to the way in which the two types of tests differ⁵. Good performance in terms of the map quality statistics, D/A , $D \times (D/A)$ and area under the ROC curve, depends on capturing a high proportion of the known deposits in a small proportion of the total map area.

In maps produced with fuzzy systems and, to a lesser degree, hybrid fuzzy-neural network systems, high relative prospectivity values are assigned to a much smaller proportion of the area than in maps produced with neural networks. This is evident in Figure 7.14, which shows histograms of the output values produced by a neural network, a hybrid fuzzy-neural and fuzzy systems for the maps covering the entire study area. For fuzzy systems, this may be due to the high values of the gamma parameter (0.94-0.97) used in the gamma function which is used to combine input layers.

The gamma function is a combination of two functions; the fuzzy algebraic product and fuzzy algebraic sum. At very high values of the gamma parameter, the gamma function is dominated by the fuzzy algebraic sum component of the function and is therefore additive in character; that is, favourable input values result in an output that is larger than any of the inputs. Bonham-Carter (1994) notes that the gamma value, at which the gamma function behaves in an increasing or decreasing way, is data dependent.

The following evidence suggests that the fuzzy systems which produced the *best* overall test-set performance (Tables 7.38 & 7.40) combined the inputs in an increasing way; 1) very large increases in the percentage correct classification for deposit patterns occur for 10- and 17-input fuzzy systems at gamma values above 0.92 and 0.96, respectively (see statistics for individual prospectivity maps on attached CD-ROM (vol.1). Gamma values

⁵Similar results were obtained using narrow buffers applied to layers depicting distance and contrast (Tables 7.19-7.22).

in the systems quoted in Tables 7.38 & 7.40 range from 0.94-0.97, and 2) the 10-input fuzzy systems (layer selection: categories, $\gamma = 0.96$ and layer selection: $D \times (D/A)$, $\gamma = 0.94$) and 17-input systems (layer selection: categories, $\gamma = 0.97$ and layer selection: $D \times (D/A)$, $\gamma = 0.97$) produced minimum output values of 0.26, 0.17, 0.26, and 0.26, respectively (see histograms in Figure 7.14). However, locations where there is a conjunction of high input values are very rare. Consequently, cells that are assigned very high prospectivity values are also very rare.

The percentage correct classification results for the independent test-set is a measure of the ability of the trained neural network system to generalize from the patterns learnt during training to new patterns. For the fuzzy systems, it is a guide as to how well the system can distinguish between deposit and barren cells on the basis of the deposit model implicit in the definitions of the fuzzy membership functions.

The poorer generalization performance of the fuzzy, and to a lesser extent, the fuzzy hybrid systems may be due to the way in which the fuzzy membership functions, which define the favourable variables, simplify and smooth out spatial relationships. Compared to a neural network, in which no information is provided about how the inputs must be interpreted in order to produce the target output, the membership functions in fuzzy systems narrow the definition of what constitutes a highly favourable location for gold deposits.

Since a certain proportion of the known deposits conform to the model represented by the fuzzy membership functions, this, combined with the small number of cell locations which are assigned high output values, leads to good performance in terms of the capture efficiency ratios. However, deposits which do not fit this simpler model, may not be recognized and therefore contribute to the poorer test-set classification (i.e. generalization) performance for systems in which the inputs consist of fuzzy membership layers compared to neural networks.

The strength of the neural network method is that it is predictive. Although the neural-network approach is effective in highlighting areas of known mineralization, new prospective areas are also identified. For example, some very high prospectivity areas within a narrow folded lithological unit in the south of the Kalgoorlie study area (Fig. 7.25; 366700 E, 6561360 N) and in scattered patches north of Kalgoorlie in the middle of the study area (Fig. 7.25; 351040 E, 6607100 N). The predictive nature of the neural-network map is due to the ability of the network to generalize from patterns contained in the training data.

Mineral prospectivity maps, produced using a neural network with three fuzzy inputs, a

(a) Neural network: 3 fuzzy membership inputs.

(b) Neural network: 3 fuzzy membership inputs.

(c) Hybrid fuzzy-neural network: 17 fuzzy inputs.

(d) Hybrid fuzzy-neural network: 17 fuzzy inputs.

(e) Fuzzy system: 17 inputs, $\gamma = 0.97$. (f) Fuzzy system: 17 inputs, $\gamma = 0.97$.

Figure 7.14. Histograms comparing outputs of the a) neural network, 2) hybrid fuzzy-neural network, and 3) fuzzy system ($\gamma = 0.97$) that produced the *best* overall test-set classification performance (see Table 7.40). The left and right columns show results for systems in which the input layers were selected using the *categories* and $D \times (D/A)$ criteria, respectively.

hybrid fuzzy-neural network and a fuzzy system using the gamma function, are shown in Figures 7.15–7.17. Only a small portion of the study area is shown as the data for this study were provided by Goldfields Exploration Pty Ltd and exploration is still being conducted in other areas. All maps account reasonably well for the known gold deposits. Those containing at least 1000 kg TCG are shown as yellow circles.

The three maps show a trend of decreasing detail from the neural network to the hybrid fuzzy-neural network and fuzzy system. The fuzzy systems map (Fig. 7.17) shows only a small range of variation in the estimated prospectivity compared to the other two maps. There is little evidence of geological features, such as faults, lithological units or boundaries, reflected in the map. The most geological information appears in the neural-network map (Fig. 7.15), although some of the detail represents artifacts resulting from the way in which some of the input layers are prepared. For example, layers representing the strike orientation of the nearest fault or rheological contrast at the nearest lithological boundary contain triangular zones corresponding to a single value. These zones widen away from the linear feature from which the cell values are derived. The use of fuzzy membership values smooths these abrupt transitions, thus simplifying the map and making it appear more geological.

Inputs affecting the prospectivity estimate are most clearly represented in the hybrid fuzzy-neural-network map (Fig. 7.16). The elongate shapes in the north-west represent NNE-trending faults and shear zones, and lines corresponding to lithological boundaries are evident along the eastern margin of the map. This map appears to be the best trade-off of the three maps in terms of sensitivity to the detail in the input GIS layers while displaying overall trends in the data without a lot of noise or loss of information.

7.8.6 Conclusions: Use of Fuzzy Membership Layers as Inputs

The use of both objective (i.e. statistically based) and subjectively derived fuzzy-membership layers is a useful means of incorporating geological knowledge in an otherwise data-driven neural network method of combining geoscience data sets to produce mineral prospectivity maps.

Objective fuzzy-membership layers, in which the fuzzy-membership values are based on the statistical relationships have been used to represent solid geology and rock-type at the nearest lithological boundary. This type of fuzzy-membership input represents a useful alternative to the 1-of-n coding, that is normally used to encode categorical data as neural network inputs, particularly if there are a large number of classes in the data (e.g. 134

rock-type combinations in the contact-type layer).

It is shown that, in some cases (e.g. rheological contrast), subjectively estimated inputs may be superior to objective data if those data are inconsistent or not extensive enough to be representative at a regional scale. The use of fuzzy membership values for some or all of the inputs to a neural network results in similar performance to conventional data.

Presenting all inputs to the network as fuzzy membership values results in slightly decreased generalization performance, as indicated by the test-set classification performance, but significantly increased values of statistics used to measure the quality of the resultant mineral prospectivity map.

Figure 7.15. Detail of a mineral prospectivity map produced with a neural network, showing the potential for orogenic lode-gold deposits in part of the Kalgoorlie Terrane, Western Australia. The map was created using the 10-20-1 MLP neural network that gave the best overall test-set classification performance without added noise. The ten input layers are selected according to the evidence-categories criterion. Three of the ten inputs are in the form of fuzzy membership values; i.e. favourability of host rock, combination of rock types at nearest lithological boundary, and rheological contrast at the nearest lithological boundary. Yellow circles indicate the location of deposits containing a resource of ≥ 1000 kg TCG.

Figure 7.16. Detail of a mineral prospectivity map produced with a hybrid fuzzy-neural- network, showing the potential for orogenic lode-gold deposits in part of the Kalgoorlie Terrane, Western Australia. The map is created using a 10-20-1 MLP neural network in which all ten inputs are converted to fuzzy membership values before being processed by the network. The ten input layers are selected using the $D \times (D/A)$ criterion. Yellow circles indicate the location of deposits containing a resource of ≥ 1000 kg TCG.

Figure 7.17. Detail of a mineral prospectivity map produced with a fuzzy system showing the potential for orogenic lode-gold deposits in part of the Kalgoorlie Terrane, Western Australia. The fuzzy system uses 10 inputs (selected with the categorise criterion), which are combined using the gamma function. A gamma value of 0.96 is used. Yellow circles indicate the location of deposits containing a resource of ≥ 1000 kg TCG.

Prospectivity maps produced using hybrid fuzzy-neural networks clearly reflect the geology and structure in the input GIS maps, but, at the same time, appear to smooth some of the noise in the input maps without the loss of information that is apparent in maps produced using the fuzzy systems.

The methods used here could potentially be applied to a large range of subjective data (e.g. favourability of tectonic environment, host stratigraphy, or reactivation along major faults) currently used in regional exploration programs, but which would not normally be included as inputs in an empirical neural-network approach.

7.9 Prospectivity Maps

This section contains graphs used to assess map quality together with the corresponding prospectivity maps for neural networks, hybrid fuzzy-neural networks, and fuzzy systems referred to in the text above.

The following plots are shown:

1. Percentage correct classification for deposit and barren patterns versus classification threshold,
2. Percentage of deposit cells correctly classified versus percentage of total cells classified as mineralized,
3. ROC curve: true positive versus false positive ratio for classification thresholds in the range $[0,1]$,
4. True positive and false positive probability for deposit and barren cells, respectively versus threshold, and
5. Histogram of neural network and fuzzy system outputs for all map patterns.

The first two plots have been used by Harris & Pan (1999) to measure model and exploration performance, respectively. Detailed descriptions are given in Section 3.3.5. The plots are useful for comparing the *relative* performance of different prospectivity models. In the first type of plot, the threshold that maximizes the correct classification of deposit *and* barren patterns corresponds to the intersection of the two curves (Fig. 7.18a). The greater the area under the curves, the better the performance of the model. Such a curve would resemble the inverted letter “J”, and have an inflection point that is close to one of

the top corners of the plot. An example of a model with very good generalization and map quality statistics is shown in Figure 7.24. The corresponding network results are shown in Table 7.28 above.

The second plot represents the measure of exploration performance used by Harris & Pan (1999) and shows the percentage of deposit versus total cells captured for classification thresholds in the range $[0,1]$. An example is shown in Figure 7.18b. It represents a scenario in which all the map cells, where a network output (or the output fuzzy membership values in a fuzzy system) exceeds a threshold, are classified as deposits and are retained for further exploration. Depending on the threshold, different proportions of deposits and barren cells are incorrectly classified. A very effective model would allow a very high proportion of deposits to be retained in a very small area. Such a model would result in a J-shaped curve similar to the one in Figure 7.24. Again, the greater the area under the curve, the better the model. This plot represents the way the capture efficiency statistic, D/A varies according to the threshold used for classification. Although it appears to be identical to the ROC curve, it is derived from a different formula. The equivalence is discussed in Section 3.3.5.

The third type of plot is the ROC curve (e.g. Fig. 7.18c). The area under the ROC curve is also a measure of the classification performance of the system. ROC curves are explained in detail in Section 3.3.4.

In the fourth type of plot represents TP and FP probability versus classification threshold. The red curve is the same as that in the first type of plot and represents the fraction of deposits which are correctly identified (e.g. Fig. 7.18d). For any given threshold, the larger the fraction of deposits correctly identified as deposits (and the smaller the percentage of barren cells falsely identified as deposits), the better the model. In general, the greater the area under the TP curve (red), the smaller the area under the FP curve, and the greater the space between the two curves, the better the model.

Histogram plots illustrate why some models can produce good generalization performance but average or poor results for the capture efficiency statistics, D/A , and $D \times (D/A)$ (e.g. Fig. 7.18e). Networks or systems with good generalization generally produce high capture efficiency ratios if the histogram is strongly skewed towards the low end of the output range (X -axis). In this case the frequency of high prospectivity cells is very low. This corresponds to an intuitive notion of prospectivity; that is, that cells representing the conjunction of a high number of favourable variable values must be very rare compared to cells where only one or two variables are favourable. The interpretation of the histograms is discussed in Section 7.8.5.

7.10 Summary

The main points discussed in Chapter 7 are listed below.

1. The approach to the neural network experiments was to use a simple training algorithm and then progressively attempt to improve the performance of the basic network by altering a single parameter at a time.
2. Ten input layers, selected according to the *category* selection criterion, were used in initial experiments.
3. Training sets were created by randomly dividing 120 patterns, corresponding to gold deposits containing at least 1000 kg TCG, approximately equally between training, training-stop and test sets. Gold deposits from each host rock-type in the solid geology GIS layer are divided approximately equally between the three training sets. Approximately matching numbers of barren patterns were also randomly selected for each rock type. Deposit and barren patterns are represented in the training sets approximately equally.
4. The average results for ten networks are reported in order to account for the variation in the performance of the trained networks due to random initial connection-weights.
5. In each experiment, ten networks were initialized with the same set of random weights in order to ensure that the variation in performance is due to differences in the patterns allocated to the training, stop and test sets.
6. Performance of trained networks are measured using the percentage of correct classifications for the independent test data set (i.e. overall, deposit and barren patterns separately).
7. The quality of mineral prospectivity maps is measured using; 1) Spearman's correlation coefficient, which indicates the degree of correlation between increasing prospectivity map class and the probability that the region contains a known deposit, 2) the area under a receiver-operating-characteristic (ROC) curve, and 3) the capture efficiency ratios, D/A and $D \times (D/A)$, where D = % of known deposits in highest prospectivity class in a 9-class prospectivity map and A = % of total map area for the highest class.
8. Compared with networks with a single hidden layer, networks with two hidden layers produce slightly higher average percentage-correct classification values for test-set patterns (overall) and barren test-set patterns, and significantly higher values for capture efficiency ratios, D/A and $D \times (D/A)$. Values for Spearman's correlation

coefficient (indicating the correlation between increasing prospectivity map class and the probability of a deposit) are lower for networks with two hidden layers than for one hidden layer.

9. Networks with two hidden layers commonly produce relatively bimodal prospectivity estimates. In this case, the bulk of known deposits are located in either low or high prospectivity map-classes.
10. A 10-20-1 topology (i.e. 10 inputs, 20 hidden neurons and 1 output) was selected for use in further experiments because this gives the best generalization performance, as indicated by both the average and best percentage correct classifications for the independent test set.
11. The standard and adaptive gradient-descent algorithms produce significantly better values for the capture efficiency statistics, D/A and $D \times (D/A)$, than the Levenberg-Marquardt training algorithm. All algorithms produce similar average test-set classification (generalization) results.
12. The Levenberg-Marquardt algorithm converges approximately ten to one hundred times faster than the adaptive and standard gradient-descent algorithms, respectively.
13. The Levenberg-Marquardt algorithm also gives the best overall test-set performance. Consequently, this algorithm was chosen for subsequent experiments.
14. Sets of 10 and 17 input layers were tested as neural network inputs. The following criteria were used to rank and select the inputs; 1) layer from each evidence category with highest D/A value, 2) D/A and $D \geq \sim 20\%$, 3) $D \times (D/A)$, and 4) $D \times (D/A)$ and $D \geq \sim 20\%$ and $D/A \geq \sim 3$, where D = % of known deposits in the favourable region of the binary layer and A = % of the total map area occurring within the favourable region.
15. Similar generalization and map quality results were obtained for the sets of 10 inputs selected using the *category*, $D \times (D/A)$, and modified $D \times (D/A)$ criteria. Layers selected according to the D/A criterion produce significantly poorer results.
16. The set of 10 input layers selected using the $D \times (D/A)$ criterion result in slightly better average and best classification performance for the test set overall, higher values for the area under the ROC curves, and significantly better classification performance for deposit patterns, than the evidence-category, D/A , and modified $D \times (D/A)$ criteria.

17. The set of 17 inputs selected with the $D \times (D/A)$ criterion produce the highest average test-set (overall) classification performance and significantly higher average values for the capture efficiency ratios, D/A and $D \times (D/A)$, than other criteria.
18. In general, networks trained with 17 layers give slightly better *average* test-set classification results than networks trained with 10 layers.
19. Layers selected using the category and $D \times (D/A)$ criteria were used for experiments with random noise and fuzzy inputs.
20. Networks trained with $1/(x)$ and $\log_{10}(x)$ transformed distance inputs produce poorer results compared to those without any transformation.
21. Buffer limits were placed on layers that involve distance to linear features, such as faults and lithological contacts, to model the concept that the existence of a fault or contact can have no effect on the prospectivity beyond a certain distance limit. Cell values at distances exceeding the limit were set to the maximum distance, and, in strike orientation layers, the strike angle was set to the mean for the entire map grid.
22. Buffer limits were estimated by interpreting plots of $(O - E)/E$ (where O = observed number of deposits in a region and E = expected number of deposits for a uniform random distribution).
23. The use of both narrow and wide buffers causes a significant decrease in the generalization ability of the trained networks.
24. The use of narrow buffers produces a significant increase in the average values of the capture efficiency statistics, D/A and $D \times (D/A)$.
25. Narrow buffer limits were also applied to the rheological and chemical contrast layers but have little effect on generalization. Contrast was set to zero for cells located outside the buffer limits.
26. The overall size of the training data sets is limited by the small number of known gold deposits.
27. Plots of the percentage correct classification, for the test set overall, deposit patterns in the test set, and $D \times (D/A)$ and area under the ROC curve, show a trend of significantly increasing generalization-ability and map quality with increasing numbers of deposit patterns and training data set size.
28. The addition of random noise to augment the number of deposit patterns available for training (from approximately 50 to 1000) significantly improves the classification

performance of trained networks and the quality of the resultant prospectivity maps. The average values of D/A and $D \times (D/A)$ are approximately doubled.

29. The results for $\pm 40\%$ noise represent a very significant improvement in the percentage correct classification for deposit patterns (i.e. from 68.0% to 77.1%).
30. The effect of training the network with patterns created with $\pm 80\%$, rather than $\pm 40\%$, noise is to reduce the size of areas estimated to have high prospectivity. There is a similar difference between maps produced using $\pm 5\%$ and $\pm 10\%$ normally-distributed noise.
31. Average results for normally-distributed noise are generally poorer than those for uniform random noise. However, networks trained using $\pm 5\%$, $\pm 10\%$ and $\pm 20\%$ normally-distributed noise result in slightly better, best test-set classification results than those trained with uniform noise.
32. The network with $\pm 10\%$ normally-distributed noise, that gives the best overall test-set performance, also produces the best test-set deposit pattern classification-performance of all the networks tested, that is, 80.3%, 80.0%, and 80.4% for the overall, deposit, and barren test-set patterns, respectively.
33. Increasing the size of the training-stop data set results in a further small increase in classification performance and map quality statistics compared to increasing the size of the training set only.
34. The subjective fuzzy rheological-contrast layer shows the strongest association with known deposits and was therefore selected as the layer to use as a neural network input.
35. Fuzzy membership values and 1-of-n coding of host-rock geology produce similar network performance statistics. However, the best test-set results are obtained using fuzzy membership values. The $D \times (D/A)$ value (measure of map quality) is much higher for the network with the fuzzy membership than 1-of-n coded geology input.
36. The results above suggest that fuzzy membership values are a viable alternative to 1-of-n coding for categorical data inputs to a neural network in this domain.
37. An extension of the concept of using fuzzy membership values, in order to represent categorical data types as inputs, is to use fuzzy membership values for all the network inputs. Such a system effectively represents a simple form of hybrid fuzzy-neural network system.
38. Networks with 1, 3, and 10 fuzzy inputs produce similar results for the percentage

correct classification of the test-set data.

39. The highest overall test-set classification accuracies are obtained with networks using only fuzzy inputs; that is, 79.0% for the best 10 input network with layers selected with the category criteria, and 79.0% for the best 17 input network with layers selected using the $D \times (D/A)$ criterion.
40. Better recognition of the deposit patterns in the test data set is achieved with networks using layers selected according to the $D \times (D/A)$ criterion than with the categories criterion. This applies to both average and best test-set classification performance, and 10 and 17 inputs.
41. Networks using the $D \times (D/A)$ set of layers also generally give significantly higher values for the measures of prospectivity map quality (i.e. Spearman's correlation coefficient, D/A , $D \times (D/A)$, and area under the ROC curve).
42. The generalization performance of the fuzzy systems is significantly poorer than for neural networks and hybrid fuzzy-neural networks.
43. The poorer generalization performance of the fuzzy and, to a lesser extent, the fuzzy-neural network, systems may be due the way that fuzzy membership functions in fuzzy systems narrow the definition of what constitutes highly favourable locations for a gold deposit. This excludes many deposits which do not fit this simpler model.
44. Fuzzy systems and hybrid fuzzy-neural networks produce better map quality statistics than neural networks with the same inputs.
45. Very high values of map quality statistics, D/A , and $D \times (D/A)$, for maps produced using fuzzy systems are due to the fact that the region corresponding to the highest prospectivity map class contains a small number of deposits in a very small proportion of the map area. However, for a 9-class prospectivity map, the bulk of the deposits are located in prospectivity classes 5-7. In contrast, a hybrid fuzzy-neural network system, with the same 10 inputs, generates a map in which the bulk of the deposits are located in map classes 7-9.
46. Histograms of the system output values suggest that the higher capture efficiency ratios, D/A , and $D \times (D/A)$, produced by fuzzy and, to a lesser degree, hybrid fuzzy-neural network systems, are due to the fact that high prospectivity values are assigned to a much smaller proportion of the map than in maps produced with neural networks.

47. A comparison of prospectivity maps produced with neural network, fuzzy and hybrid fuzzy-neural network systems shows that the hybrid system produces the best trade-off in terms of sensitivity to the detail in the input GIS layers, while displaying overall trends in the data without significant noise nor loss of information.

a) Classification accuracy versus threshold.

b) Percentage of deposit versus total cells captured for classification thresholds in the range $[0,1]$.

c) ROC curve showing threshold values.

d) Proportion of correct and false deposit classification vs classification threshold.

(e) Histogram of output activations of trained networks.

Figure 7.18. Classification performance of the 10-0-1 neural network with the *best* test-set classification accuracy. Input layer selection: categories. Learning algorithm: *trainlm*.

Figure 7.19. Prospectivity map obtained using the 10-0-1 network with the best test-set classification. (Network: *lm_cat.10-0-1-r6*, Input layers: 10, layer selection: categories, training algorithm: *trainlm*).

a) Classification accuracy versus threshold.

b) Percentage of deposit versus total cells captured for classification thresholds in the range $[0,1]$.

c) ROC curve showing threshold values.

d) Proportion of correct and false deposit classification vs classification threshold.

(e) Histogram of output activations of trained networks.

Figure 7.20. Classification performance of the 10-20-1 neural network with the *best* test-set classification accuracy. Input layer selection: categories. Learning algorithm: *trainlm*.

Figure 7.21. Prospectivity map obtained using the 10-20-1 network with the best test-set classification. (Network: *lm_cat_10_20_1.r1*, Input layers: 10, layer selection: categories, training algorithm: *trainlm*).

a) Classification accuracy versus threshold.

b) Percentage of deposit versus total cells captured for classification thresholds in the range $[0,1]$.

c) ROC curve showing threshold values.

d) Proportion of correct and false deposit classification vs classification threshold.

(e) Histogram of output activations of trained networks.

Figure 7.22. Classification performance of the 10-20-1 neural network with the *best* test-set classification accuracy. Input layer selection: categories. Learning algorithm: gradient descent with adaptive learning rate and momentum (*traingdx*).

Figure 7.23. Prospectivity map obtained using the 10-20-1 network with the *best* test-set classification. (Network: *gdx_cat_10_20_1.r7*, Input layers: 10, layer selection: categories, training algorithm: *trainingdx*).

a) Classification accuracy versus threshold.

b) Percentage of deposit versus total cells captured for classification thresholds in the range $[0,1]$.

c) ROC curve showing threshold values.

d) Proportion of correct and false deposit classification vs classification threshold.

(e) Histogram of output activations of trained networks.

Figure 7.24. Classification performance of the 10-20-1 neural network with the *best* test-set *deposit* classification accuracy. The training data set was expanded using $\pm 40\%$ uniform random noise. Input layer selection: categories. Learning algorithm: *trainlm*.

Figure 7.25. Prospectivity map obtained using the 10-20-1 network with the best test-set *deposit* classification. (Network: *lm_cat.10_20.1_uni40pent.r5*, Input layers: 10, layer selection: categories, training algorithm: *trainlm*, noise: $\pm 40\%$ uniform).

a) Classification accuracy versus threshold.

b) Percentage of deposit versus total cells captured for classification thresholds in the range $[0,1]$.

c) ROC curve showing threshold values.

d) Proportion of correct and false deposit classification vs classification threshold.

(e) Histogram of output activations of trained networks.

Figure 7.26. Classification performance of the 10-20-1 neural network with the *best* test-set classification accuracy. The training data set was expanded using $\pm 80\%$ uniform random noise. Input layer selection: categories. Learning algorithm: *trainlm*.

Figure 7.27. Prospectivity map obtained using the 10-20-1 network with the best test-set classification. (Network: *lm_cat.10.20.1.uni80pcnt.r9*, Input layers: 10, layer selection: categories, training algorithm: *traininglm*, noise: $\pm 80\%$ uniform).

a) Classification accuracy versus threshold.

b) Percentage of deposit versus total cells captured for classification thresholds in the range $[0,1]$.

c) ROC curve showing threshold values.

d) Proportion of correct and false deposit classification vs classification threshold.

(e) Histogram of output activations of trained networks.

Figure 7.28. Classification performance of the 10-20-1 neural network with the *best* test-set *deposit* classification accuracy. The training data set was expanded using $\pm 5\%$ normally-distributed random noise. Input layer selection: categories. Learning algorithm: *trainlm*.

Figure 7.29. Prospectivity map obtained using the 10-20-1 network with the *best* deposit test-set classification. (Network: *lm_cat_10.20.1_normal15pct_r1*, Input layers: 10, layer selection: categories, training algorithm: *trainlm*, noise: $\pm 5\%$ Gaussian).

a) Classification accuracy versus threshold.

b) Percentage of deposit versus total cells captured for classification thresholds in the range $[0,1]$.

c) ROC curve showing threshold values.

d) Proportion of correct and false deposit classification vs classification threshold.

(e) Histogram of output activations of trained networks.

Figure 7.30. Classification performance of the 10-20-1 neural network with the *best* test-set classification accuracy. The training data set was expanded using $\pm 10\%$ normally-distributed random noise. Input layer selection: categories. Learning algorithm: *trainlm*.

Figure 7.31. Prospectivity map obtained using the 10-20-1 network with the best test-set classification. (Network: *ln-cat-10-20-1-normal10pct-r4*, Input layers: 10, layer selection: categories, training algorithm: *trainingdx*, noise: $\pm 10\%$ Gaussian).

a) Classification accuracy versus threshold.

b) Percentage of deposit versus total cells captured for classification thresholds in the range $[0,1]$.

c) ROC curve showing threshold values.

d) Proportion of correct and false deposit classification vs classification threshold.

(e) Histogram of output activations of trained networks.

Figure 7.32. Classification performance of the 10-20-1 neural network with the *best* test-set classification accuracy. Learning algorithm: *trainlm*. Input layer selection criteria: D/A.

Figure 7.33. Prospectivity map obtained using the 10-20-1 network with the best test-set classification. (Network: *lm-da-10-20-1-r3*, Input layers: 10, layer selection: D/A, training algorithm: *trainlm*).

a) Classification accuracy versus threshold.

b) Percentage of deposit versus total cells captured for classification thresholds in the range $[0,1]$.

c) ROC curve showing threshold values.

d) Proportion of correct and false deposit classification vs classification threshold.

(e) Histogram of output activations of trained networks.

Figure 7.34. Classification performance of the 10-20-1 neural network with the *best* test-set classification accuracy. Learning algorithm: *trainlm*. Input layer selection criteria: $D^*(D/A)$.

Figure 7.35. Prospectivity map obtained using the 10-20-1 network with the best test-set classification. (Network: *lm-dda-10-20-1-r7*, Input layers: 10, layer selection: $D*(D/A)$, training algorithm: *trainlm*).

a) Classification accuracy versus threshold.

b) Percentage of deposit versus total cells captured for classification thresholds in the range $[0,1]$.

c) ROC curve showing threshold values.

d) Proportion of correct and false deposit classification vs classification threshold.

(e) Histogram of output activations of trained networks.

Figure 7.36. Classification performance of the 10-20-1 neural network with the best test-set classification accuracy. Learning algorithm: *trainlm*. Input layer selection criteria: $D \cdot (D/A)$ AND $D \geq \sim 20\%$ AND $D/A \geq \sim 3\%$.

Figure 7.37. Prospectivity map obtained using the 10-20-1 network with the best test-set classification. (Network: *lm-dda2-10-20-1-r5*, Input layers: 10, layer selection: $D \cdot (D/A)$ AND $D \geq 20\%$ AND $D/A \geq 3\%$, training algorithm: *trainlm*).

a) Classification accuracy versus threshold.

b) Percentage of deposit versus total cells captured for classification thresholds in the range $[0,1]$.

c) ROC curve showing threshold values.

d) Proportion of correct and false deposit classification vs classification threshold.

(e) Histogram of output activations of trained networks.

Figure 7.38. Classification performance of the 17-20-1 neural network with the *best* test-set classification accuracy. Input layer selection: categories. Learning algorithm: *trainlm*.

Figure 7.39. Prospectivity map obtained using the 17-20-1 network with the best test-set classification. (Network: *lm-cat-17-20-1-r7*, Input layers: 17, layer selection: categories, training algorithm: *trainlm*).

a) Classification accuracy versus threshold.

b) Percentage of deposit versus total cells captured for classification thresholds in the range $[0,1]$.

c) ROC curve showing threshold values.

d) Proportion of correct and false deposit classification vs classification threshold.

(e) Histogram of output activations of trained networks.

Figure 7.40. Classification performance of the 17-20-1 neural network with the *best* test-set classification accuracy. Input layer selection: D/A. Learning algorithm: *trainlm*.

Figure 7.41. Prospectivity map obtained using the 17-20-1 network with the best test-set classification. (Network: *lm-da-17-20-1-τ4*, Input layers: 17, layer selection: D/A, training algorithm: *trainlm*).

a) Classification accuracy versus threshold.

b) Percentage of deposit versus total cells captured for classification thresholds in the range $[0,1]$.

c) ROC curve showing threshold values.

d) Proportion of correct and false deposit classification vs classification threshold.

(e) Histogram of output activations of trained networks.

Figure 7.42. Classification performance of the 17-20-1 neural network with the *best* test-set classification accuracy. Input layer selection: $D*(D/A)$. Learning algorithm: *trainlm*.

Figure 7.43. Prospectivity map obtained using the 17-20-1 network with the best test-set classification. (Network: *lm-dda-17-20-1-r2*, Input layers: 17, layer selection: $D*(D/A)$, training algorithm: *trainlm*).

a) Classification accuracy versus threshold.

b) Percentage of deposit versus total cells captured for classification thresholds in the range $[0,1]$.

c) ROC curve showing threshold values.

d) Proportion of correct and false deposit classification vs classification threshold.

(e) Histogram of output activations of trained networks.

Figure 7.44. Classification performance of the 17-20-1 neural network with the *best* test-set classification accuracy. Input layer selection: $D \ast (D/A)$ AND $D \geq \sim 20\%$ AND $D/A \geq \sim 3\%$. Learning algorithm: *trainlm*.

Figure 7.45. Prospectivity map obtained using the 17-20-1 network with the best test-set classification. (Network: *lm-dda2-17-20-1-r5*, Input layers: 17, layer selection: $D*(D/A)$ AND $D \geq 20\%$ AND $D/A \geq 3\%$, training algorithm: *trainlm*).

a) Classification accuracy versus threshold.

b) Percentage of deposit versus total cells captured for classification thresholds in the range $[0,1]$.

c) ROC curve showing threshold values.

d) Proportion of correct and false deposit classification vs classification threshold.

(e) Histogram of output activations of trained networks.

Figure 7.46. Classification performance of the 25-20-1 neural network with the *best* test-set classification accuracy. Input layer selection: all layers used. Learning algorithm: *trainlm*.

Figure 7.47. Prospectivity map obtained using the 25-20-1 network with the *best* test-set classification. (Network: *lm-all-25-20-1-r5*, Input layers: 25, layer selection: all layers used, training algorithm: *trainlm*).

a) Classification accuracy versus threshold.

b) Percentage of deposit versus total cells captured for classification thresholds in the range $[0,1]$.

c) ROC curve showing threshold values.

d) Proportion of correct and false deposit classification vs classification threshold.

(e) Histogram of output activations of trained networks.

Figure 7.48. Classification performance of the 10-20-1 hybrid fuzzy-membership-input network with the *best* test-set classification accuracy. All 10 inputs are fuzzy membership values. Input layer selection: categories. Learning algorithm: *trainlm*.

Figure 7.49. Prospectivity map obtained using the 10-20-1 hybrid fuzzy-membership-input network with the best test-set classification. (Network: *lm-fuzzy-cat-10-20-1-r6*, Input layers: 10, layer selection: categories, training algorithm: *trainlm*).

a) Classification accuracy versus threshold.

b) Percentage of deposit versus total cells captured for classification thresholds in the range $[0,1]$.

c) ROC curve showing threshold values.

d) Proportion of correct and false deposit classification vs classification threshold.

(e) Histogram of output activations of trained networks.

Figure 7.50. Classification performance of the 10-20-1 hybrid fuzzy-membership-input network with the *best* test-set classification accuracy. All 10 inputs are fuzzy membership values. Input layer selection: $D^*(D/A)$. Learning algorithm: *trainlm*.

Figure 7.51. Prospectivity map obtained using the 10-20-1 hybrid fuzzy-membership-input network with the *best* test-set classification. (Network: *lm-fuzzy-dda-10-20-1-r8*, Input layers: 10, layer selection: $D*(D/A)$, training algorithm: *trainlm*).

a) Classification accuracy versus threshold.

b) Percentage of deposit versus total cells captured for classification thresholds in the range $[0,1]$.

c) ROC curve showing threshold values.

d) Proportion of correct and false deposit classification vs classification threshold.

(e) Histogram of output activations of trained networks.

Figure 7.52. Classification performance of the 17-20-1 hybrid fuzzy-membership-input network with the *best* test-set classification accuracy. All 17 inputs are fuzzy membership values. Input layer selection: categories. Learning algorithm: *trainlm*.

Figure 7.53. Prospectivity map obtained using the 17-20-1 hybrid fuzzy-membership-input network with the best test-set classification. (Network: *lm-fuzzy-cat-17-20-1-r5*, Input layers: 10, layer selection: categories, training algorithm: *trainlm*).

a) Classification accuracy versus threshold.

b) Percentage of deposit versus total cells captured for classification thresholds in the range $[0,1]$.

c) ROC curve showing threshold values.

d) Proportion of correct and false deposit classification vs classification threshold.

(e) Histogram of output activations of trained networks.

Figure 7.54. Classification performance of the 17-20-1 hybrid fuzzy-membership-input network with the *best* test-set classification accuracy. All 17 inputs are fuzzy membership values. Input layer selection: $D^*(D/A)$. Learning algorithm: *trainlm*.

Figure 7.55. Prospectivity map obtained using the 17-20-1 hybrid fuzzy-membership-input network with the best test-set classification. (Network: *lm-fuzzy-dda-17-20-1-r7*, Input layers: *D*(D/A)*, training algorithm: *trainlm*).

a) Classification accuracy versus threshold.

b) Percentage of deposit versus total cells captured for classification thresholds in the range $[0,1]$.

c) ROC curve showing threshold values.

d) Proportion of correct and false deposit classification vs classification threshold.

(e) Histogram of output activations of trained networks.

Figure 7.56. Classification performance of the 10-input fuzzy system with the *best* test-set classification accuracy. Layers were combined using the gamma function ($\gamma = 0.96$). Layer selection: categories.

Figure 7.57. Prospectivity map obtained using the 10-input fuzzy system with the best test-set classification. (Fuzzy system: fuzzy-cat-10-fgamma-96, input layers: 10, $\gamma = 0.96$, layer selection: categories).

a) Classification accuracy versus threshold.

b) Percentage of deposit versus total cells captured for classification thresholds in the range $[0,1]$

c) ROC curve showing threshold values.

d) Proportion of correct and false deposit classification vs classification threshold.

e) Histogram of output activations of trained networks.

Figure 7.58. Classification performance of the 10-input fuzzy system with the *best* test-set classification accuracy. Layers were combined using the gamma function ($\gamma = 0.94$). Layer selection: $D^*(D/A)$.

Figure 7.59. Prospectivity map obtained using a 10-input fuzzy system with the *best* test-set classification. (Fuzzy system: fuzzy-dda-10-fgamma-94, input layers: 10, $\gamma = 0.94$, layer selection: $D*(D/A)$).

a) Classification accuracy versus threshold.

b) Percentage of deposit versus total cells captured for classification thresholds in the range $[0,1]$.

c) ROC curve showing threshold values.

d) Proportion of correct and false deposit classification vs classification threshold.

(e) Histogram of output activations of trained networks.

Figure 7.60. Classification performance of the 17-input fuzzy system with the *best* test-set classification accuracy. Layers were combined using the gamma function ($\gamma = 0.97$). Layer selection: categories.

Figure 7.61. Prospectivity map obtained using a 17-input fuzzy system with the best test-set classification. (Fuzzy system: fuzzy-cat-17-fgamma-97, input layers: 17, $\gamma = 0.97$, layer selection: categories).

a) Classification accuracy versus threshold.

b) Percentage of deposit versus total cells captured for classification thresholds in the range $[0,1]$.

c) ROC curve showing threshold values.

d) Proportion of correct and false deposit classification vs classification threshold.

(e) Histogram of output activations of trained networks.

Figure 7.62. Classification performance of the 17 input fuzzy system with the *best* test-set classification accuracy. Layers were combined using the gamma function ($\gamma = 0.97$). Layer selection: $D*(D/A)$.

Figure 7.63. Prospectivity map obtained using a 17-input fuzzy system with the best test-set classification. (Fuzzy system: fuzzy-cat-17-fgamma-97, input layers: 17, $\gamma = 0.97$, layer selection: $D*(D/A)$).

Chapter 8

Summary and Conclusions

8.1 Contribution Demonstrated in this Thesis

8.1.1 Developed Neural Network Mineral Prospectivity Method

The initial concept of this thesis was that neural networks have characteristics which make them well suited to the integration of mineral exploration data. These include their ability to learn the underlying patterns in large mixed data sets which: 1) are noisy or contain outliers, 2) involve non-linear relationships, 3) have high dimensionality, and 4) contain multiple and interacting variables. This leads to the hypothesis that digital geological, geophysical and geochemical maps can be superimposed in a GIS system to produce a set of feature vectors from which the signatures of ore deposits can be extracted and that neural networks can be trained to recognize these signatures, and hence predict the location of new deposits of similar type.

At the time this study commenced (1997), it was not clear that neural networks could be used to produce mineral prospectivity maps, in which favourability could be expressed as a continuous variable. Although a large body of literature describes the application of neural networks to pattern recognition and classification of remotely sensed data, only a few studies described the use of neural networks for mapping applications. Two studies described the use of neural networks to produce multiclass maps in which bedrock geology (Schau *et al.*, 1994) and hydrothermal alteration type (An *et al.*, 1994) were depicted as categorical variables. Bonham-Carter (1994) mentioned neural networks as a possible data-driven method for mineral potential mapping. However, only two studies existed in the literature that referred to the use of neural networks to produce prospectivity maps

(Clare *et al.*, 1997; Singer & Kouda, 1996). The first of these described a proprietary system for which few details were available and, in the other study, the output was simply in the form of the distance to the nearest deposit.

Most of the early work in which neural networks were combined with GIS focused on automated pattern recognition and the classification of remotely sensed imagery. A neural network, used as a classifier in a mineral prospectivity problem, would produce a binary map since there are only two output classes. On the other hand, it seemed likely that a neural network trained using binary target variables (i.e. 1 = deposit & 0 = barren cells) might also produce outputs that closely approximate binary values, as do networks that learn Boolean functions.

Consequently, the first and most important problem in this study was to test the feasibility of the method using a simple GIS. A pilot study was a necessary step, since a fuller investigation of the use of neural networks for prospectivity mapping could only be justified if the networks performed reasonably well compared to the two main existing methods of prospectivity mapping, weights of evidence and fuzzy systems. Therefore, a second aspect of the pilot study was to establish methods suitable for comparing the quality of the prospectivity maps. As well as being used to assess the effectiveness of the neural network method, the empirical weights-of-evidence and the conceptual fuzzy-logic methods mineral prospectivity maps provide a means of validating the neural-network maps.

The main contribution of this study is that it demonstrates that neural networks can produce prospectivity maps that are at least as predictive as those produced using the weights-of-evidence and fuzzy-logic methods, but also offer many significant advantages compared to existing methods.

8.1.2 Developed Methods for Quantitatively Comparing Prospectivity Maps

Chapter 3 introduces three new methods for comparing the quality of prospectivity maps. A further two measures are introduced in Chapter 7. These are the use of:

1. Spearman's and Kendall's rank correlation coefficients, which show the degree to which the conditional probability of occurrence of known deposits $P(D/C_k)$, increases with increasing prospectivity map class C_k ,
2. $P(D/C_k)$, the posterior conditional probability of a deposit given that a cell occurs in map class C_k , where $P(D/C_k)$ values are listed for each prospectivity map class,

3. $P(D/C_k)/P(D)$, the ratio of posterior conditional probability to the prior probability of a deposit,
4. $D \times (D/A)$, and
5. area under a receiver operating characteristic (ROC) curve.

The third measure of map quality, $P(D/C_k)/P(D)$, shows how much being located in the area corresponding to map class C_k upgrades or downgrades the probability of finding a known deposit relative to selecting a grid cell at random. The ratio is equivalent to D/A where $D = \% \text{ total known deposits}$ and $A = \% \text{ of total map area}$. The map class quoted is always the highest prospectivity class where the network or fuzzy system output is divided into nine classes.

A problem with the D/A ratio is that the value can be high (e.g. >300) when only a few deposits are located in the highest prospectivity class, provided the area is very small. In order to account for this, a second ratio is quoted, in which D/A is multiplied by the percentage of known deposits that occur in the favourable region of the binary map, giving the statistic, $D \times (D/A)$.

Although the fourth measure is a standard one for showing how classification performance varies with the value of the decision threshold, an examination of the literature indicates that it has not previously been used in mineral prospectivity studies.

8.1.3 Demonstrated Effectiveness of Neural-Network Approach

The pilot study, based on primary and secondary intrusion-related granite-hosted disseminated gold deposits in the Tenterfield area of New South Wales, (Chapter 4), shows that neural networks produce mineral prospectivity maps similar to those produced using the fuzzy systems and weights-of-evidence methods (Brown *et al.*, 1999, 2000b,a). This similarity validates the neural network results in two ways. First, the similarity of neural-network maps to those produced with the conceptually-based, fuzzy-systems method indicates that the neural network result conforms to a current understanding of geological factors important for gold mineralization in the Tenterfield area. Second, the broad similarity between the neural network and empirically-derived weights-of-evidence maps indicates that the neural-network result accounts for observed spatial relationships between known mineral deposits and the variables of the GIS database.

Statistical measures of map quality indicate that the neural network method performs as

well as, or better than, existing methods. Values of Spearman's correlation coefficient ρ , $P(D)$, and $P(D/C_k)/P(D)$ are all higher for the the neural-network maps than for maps produced with the other methods. The value of χ^2 statistic indicates greater differences between the observed numbers of deposits and the numbers expected due to chance.

The network output is interpreted to represent an approximation to the posterior probability that the input vector $\mathbf{x}$ belongs to the class of deposits $C_{deposit}$; i.e. $P(C_{deposit}|\mathbf{x})$, (White, 1989; Richard & Lippmann, 1991; Bishop, 1995; Duda *et al.*, 2001). This value can also be interpreted as a measure of how similar the input vector is to the deposit patterns in the training set. This interpretation of the network output fits with the intuitive notion that a prospective area has characteristics that closely resemble areas known to contain mineral deposits.

8.1.4 Compared Performance with Weights-of-Evidence and Fuzzy Systems

An interpretation of the differences between the prospectivity estimates generated by the neural network, fuzzy-systems, and weights-of-evidence methods indicates that the neural network method has several advantages over existing methods. These include the ability to:

1. respond to critical combinations of variables, rather than automatically increasing the prospectivity due to all favourable variables,
2. combine data sets without the loss of information inherent in existing methods, and
3. produce results that are relatively unaffected by redundant data, spurious data and data containing multiple populations.

The Kalgoorlie case study is based on a large database used in an active exploration program for Archaean orogenic lode-gold deposits and therefore provides a more realistic test of the neural-network approach to prospectivity mapping than in the pilot study. Gold deposits in the Kalgoorlie Terrane formed at a wide range of crustal depths, resulting in a range of metamorphic grades, structural styles, host rocks and mineral assemblage. As a result, there are wide variations in the attributes that characterize deposits, making this a difficult pattern recognition problem.

8.1.5 Developed Novel GIS Layers

Pre-processing and feature extraction can often greatly improve a pattern classification system, particularly if prior knowledge can be incorporated into the inputs (Kohavi & Frasca, 1994; Bishop, 1995). Consequently, much work in Chapter 5 is devoted to the preparation of derived GIS layers in order to represent the essential ingredients of the mineral systems in terms of the regional-scale GIS data that were available. A regional approach rather than one focusing on ore deposit models was adopted, since mineral systems present a much larger target than deposits themselves, and because this is more appropriate to the scale at which the data were captured and compiled in a regional GIS (Wyborn *et al.*, 1994c, 1995b). An important contribution of this work is the development of novel layers that help predict the location of Archaean orogenic gold mineralization, such as;

1. distance to felsic porphyritic intrusions,
2. distance to nearest magnetic anomaly (defined for each lithology using z-score thresholds),
3. rheological contrast at lithological boundaries (using both subjective fuzzy membership layers and a range of rock strength properties),
4. chemical contrast at lithological boundaries (sulphidation and oxidation ratios),
5. lithological diversity based on a fault density convolution,
6. strike of nearest fault (for specific types),
7. favourability of host rock (fuzzy membership values), and
8. favourability of nearest lithological contact (fuzzy membership values).

8.1.6 Developed and Tested New Methods for Measuring Spatial Associations

The selection of layers to be used as inputs for neural networks is the central theme of Chapter 5. Sixty potential input GIS layers were generated as a result of the work described in Chapter 6. In order to select the most useful layers for predicting deposits, a variety of statistical methods to identify positive spatial associations between known deposit points and spatial features were applied. Besides contrast of weights (Bonham-Carter, 1994, C_w), chi-squared (χ^2), and Kolmogorov-Smirnov cumulative distribution function, three new methods are also introduced. These are;

1. cumulative bivariate J-function,

2. interval-based bivariate J-function, and
3. plots of $(O - E)/E$ (where O is the observed and E is expected number of deposits in a buffer).

The latter two methods were developed in this study.

The advantage of the J-function methods is that a Monte Carlo test involving simulated J-estimates provide information about the significance of spatial relationships. Although Foxall & Baddeley (2002) developed the bivariate J-function as a non-parametric measure of association between a point process, X , and any random set, Y , they restricted their tests to a comparison with Berman's analysis of a data set involving deposit points and lineaments (Berman, 1986). In this study, the bivariate J-function is compared to other statistical methods (listed above) and applied to a variety of types of spatial associations. As well as confirming the usefulness of the bivariate J-function for measuring spatial associations between deposit points and features represented by line segments (e.g. faults and lithological contacts), this work also shows that the bivariate J-function:

1. produces results on the identification of positive and negative associations which agree with the other methods,
2. is also useful for analysing spatial associations between deposit points and regions (e.g. magnetic anomalies) and point data (e.g. intersection of faults; Brown *et al.* 2002c), and
3. can be used to estimate the variable ranges in which the spatial association is maximized by determining the x -value corresponding to the maximum difference between the observed and simulated curves (e.g. Fig. 6.5).

The cumulative bivariate J-function is not well suited to measuring spatial associations for variables that do not involve distances (e.g. density of faults) or where positive or negative associations occur within discrete ranges of variable values (e.g. strike orientation of faults). It should be noted that none of the cumulative plots (contrast of weights, chi-squared, and the Kolmogorov-Smirnov cumulative distribution function) handle this latter type of spatial relationships well. In order to overcome this problem, a procedure for calculating the bivariate J-curve was developed in which the J-function is estimated for successive distance intervals rather than for cumulative distances. This interval-based J-function, represented as a bar graph, overcomes the problems referred to above.

8.1.7 Quantitatively Assessed Exploration Criteria

An important result of the development of derived GIS layers and statistical methods to measure the spatial associations is that local empirical exploration criteria were quantitatively tested to determine:

1. the most favourable ranges of the variable values, and
2. whether the observed spatial associations are statistically significant.

Methods for measuring the spatial association between deposit points and GIS-layer variables have helped to confirm that proximity to felsic porphyritic intrusions (≥ 400 m and possibly up to 1400 m) is a useful exploration criterion on a regional scale. Proximity to anticlinal axes, although well-established as an important control on the location of turbidite-hosted gold deposits (e.g. Meguma and Bendigo), has not been widely recognized as a control in the Archaean Yilgarn Block. This work provides evidence for their significance in the Kalgoorlie Terrane. Estimates of the favourable ranges of variables are useful for further exploration and contribute to our understanding of the regional metallogeny of the Yilgarn. The Yilgarn is one of Australia's most richly endowed areas, and improvements in our understanding of factors favourable for gold mineralization should improve the effectiveness of future exploration programs.

8.1.8 Applied Neural Network Method to a Data Set Representative of those Used in Exploration

In Chapter 7, neural networks are used to estimate the potential for Archaean orogenic lode gold deposits in the Kalgoorlie case study area. This work addresses the question of whether a neural network is an effective method for mineral prospectivity mapping. The results (in particular, percentage correct classification rates) show that the neural networks do learn the underlying patterns in the data and predict the locations of deposits for new patterns different to those in the training set. The mineral prospectivity maps produced using the trained networks also show that neural networks predict the locations of the known deposits in a geologically meaningful way. These results are obtained using a database that is typical, in terms of its size and complexity, of geoscience data sets used by mining companies for exploration, and therefore provides a realistic test of the neural network method.

Applying a simple approach, similar to that used in the pilot study, it is possible to

produce a prospectivity map in which 27% of the known deposits (≥ 1000 kg TCG) are contained in 2.8% of the total area, which corresponds to the top two prospectivity classes in a nine-class prospectivity map (see the *mapstats* file on the attached CD-ROM, vol. 1). This result is obtained with the 10-20-1 network which gives the best overall test set classification results (overall, 76.5%; deposits, 77.1%). The neural network that produced the best classification for all the test-set patterns then served as a benchmark against which other networks can be tested.

Using training sets augmented with the addition of random noise or using fuzzy membership values significantly improves this ability to define a small proportion of the area which contains a large proportion of the deposits. For example, maps produced with a network trained using ± 10 normally-distributed noise and a hybrid fuzzy-neural network captured 25% of the deposits in 1.3% of the area and 27% of the deposits in 1.4% of the area, respectively (*lm_cat_10_20_1_normal5pcnt_r7_log* and *lm_fuzzy_dda_10_20_1_r8_log* in file *mapstats*, CD-ROM vol. 1). These methods used to improve the neural-network performance are discussed in more detail below. It should be noted that although Knox-Robinson & Groves (1997a) reported much better results in a study of the potential for Archaean orogenic gold deposits using fuzzy systems (i.e. in terms of percentage of deposits in percentage of the area), lithologies other than greenstone were excluded from the analysis.

8.1.9 Investigated Factors Affecting the Performance of a Neural Network Mineral Prospectivity Method

Factors affecting the performance of a neural-network approach to prospectivity mapping are the main subject of Chapter 7. An unexpected result of this work is that many of the neural network parameters, such as the number of hidden layers and units, and training algorithm, have only a relatively small effect on generalization performance and map quality. Other factors, such as transformation of the inputs representing distance (inverse and log) and the use of buffer limits for layers describing the nearest fault or lithological boundary (e.g. strike or chemical contrast, respectively), also have relatively minor (but negative) effects on the results. Only capture efficiency statistic D/A , and possibly $D \times (D/A)$ increase if narrow buffers are used. However, the results for the hybrid fuzzy-neural networks (discussed below) suggest that buffer limits may be implemented more effectively using fuzzy membership functions.

Factors affecting the type and form of the inputs to the neural networks have the most significant effect on the results. In increasing order of effect on the test set classification

performance, these factors are:

1. number of inputs,
2. criteria used to select inputs,
3. encoding of inputs; i.e. raw, scaled inputs versus fuzzy membership values, and
4. size of training sets.

It should be noted that the main effect of the use of fuzzy membership inputs is on the quality of the mineral prospectivity maps produced and on the capture efficiency statistics.

Each of these factors is investigated in Chapter 7, and the results are only summarized here. A comparison of networks trained using 10 and 17 inputs, selected using the same criteria, shows that 17 layers produce significantly better performance than that obtained by using 10 inputs or 25 (i.e. all available) input variables. Of the following criteria used to rank and select input GIS layers:

1. layer from each evidence category with highest D/A value,
2. D/A and $D \geq \sim 20\%$,
3. $D \times (D/A)$, and
4. $D \times (D/A)$ and $D \geq \sim 20\%$ and $D/A \geq \sim 3$,

the $D \times (D/A)$ criterion gives the best results. Networks trained with 10 layers selected using the highest $D \times (D/A)$ values produce the highest (average and best) results for classification of the test set (overall and deposit patterns), the capture efficiency statistic, D/A , and area under the ROC curve. For networks with 17 inputs, this criterion also gives the highest (average and best) values for overall test-set classification and D/A , and area under the ROC curve.

The last two factors affecting performance, shown above, highlight major limitations of the neural network method; that is,

1. train set size is limited by number of known deposits, and
2. it is a data-driven rather than a knowledge-driven method.

Both these limit or exclude neural networks from being applied to exploration in new areas where few known deposits exist. The most significant improvements in generalization and map quality in this study are achieved by attempting to address these limitations by improving the amount and type of training data; that is, through the augmentation of the training set with random noise and use of fuzzy membership inputs. These two topics are discussed in separate sections below.

8.1.10 Augmented Limited Training Data Using Random Noise

The need for large amounts of training data potentially limits the use of the neural network to well-explored areas where there are abundant previously-discovered mineral occurrences and deposits. This is also the main factor affecting the performance of MLP neural networks trained using the backpropagation algorithm in mineral potential mapping. Data used to train neural networks in mineral prospectivity applications contain just two classes; a number of rare deposits and a vast number of non-deposit examples. Due to the need to represent classes within the data population in roughly equal proportions in the training data, the overall size of the training data sets is limited by the small number of known deposits.

To overcome this problem, random noise was added to the original training patterns in order to create additional synthetic deposit training data. Through the addition of noise to the original deposit training data, the number of deposit training patterns was increased from approximately 50 to 1000. Experiments in Chapter 7 on the effect of the number of deposit patterns available for training in the Kalgoorlie case study area show that both the classification performance of a trained network, and quality of the resultant prospectivity map, increase significantly with increased numbers of deposit patterns.

The use of random noise to create additional synthetic deposit-patterns helps overcome the lack of deposit patterns that limits the training set sizes. Training with the larger noise-augmented training data sets results in significantly increased:

1. **Classification performance.** The percentage of correct classifications significantly improves for the independent test set (overall) as well as for deposit patterns in the test set. For example, using $\pm 40\%$ uniform random noise, the test-set classification performance increases from 67.9% and 68.0% to 72.8% and 77.1% for the average of 10 networks for test data set overall and test-set deposit patterns, respectively.
2. **Measures of map quality.** For example, for $\pm 40\%$ uniform random noise, the statistics D/A increases from 8.2 to 17.9, $D \times (D/A)$ increases from 105 to 226, and the area under the ROC curve increases from 0.79 to 0.87. Generally, these improvements in performance apply to both the average and best results for D/A and area under the ROC curve, although, in the case of $D \times (D/A)$, only the average values increase.

Increasing the size of the training-stop data set in addition to the training set results in a further increase in average classification performance.

For $\pm 40\%$ uniform random noise, the average percent classification of the training set increases from 72.8% to 73.5% (overall) and from 77.1% to 77.4% for deposit patterns, D/A decreases from 17.9 to 14.7, $D \times (D/A)$ increases from 226 to 296, and the area under the ROC curve remains unchanged.

More work is needed to determine whether uniform or normally-distributed noise is more effective. Although $\pm 40\%$ uniform random noise (network topology: 10-20-1) gives the best average results (72.8%, 77.1%, 17.9, 226, 0.87 for the percentage correct classification of the test set overall, test-set deposit patterns, D/A , $D \times (D/A)$, and area under the ROC curve, respectively), $\pm 5\%$ normally-distributed noise gives the best results (i.e. 79.0%, 85.1%, 19.0, 269, 0.87).

The method described here is not limited to MLP networks and could be applied to increase the number of patterns available for training for other types of neural networks or in other applications in which training data are rare or difficult or expensive to obtain.

8.1.11 Used Fuzzy Membership Values as Neural Network Inputs

The results of experiments in Chapter 7 demonstrate that using input GIS layers, in which the cell values represent fuzzy membership values, is an effective method of combining subjective geological knowledge with empirical data in a neural-network approach to mineral prospectivity mapping.

Two types of fuzzy membership layers are used:

1. **Objective fuzzy membership layers.** Statistical relationships between known gold deposits and the GIS-layer variable are used to determine the fuzzy membership values (e.g. favourable host-rock type and favourable contact type). This type of fuzzy-membership input is a useful alternative to the 1-of-n coding commonly used for categorical inputs, particularly if there are a large number of classes (e.g. host-rock type). It has the advantage of reducing the size of the input feature vectors, thus saving computer memory, and reduces the likelihood that the network will overfit the data because there are too many weights in relation to the size of the training data.
2. **Subjective fuzzy membership layers.** The assignment of fuzzy membership value, although based on geological field data, is purely subjective (e.g. favourable rheological contrast). It is shown in Chapter 6 that, in the case of rheological

contrast, a subjectively estimated input can be superior to objective data if those data are inconsistent or not extensive enough to be representative at a regional scale.

The average performance statistics are generally similar for both methods. However, a comparison of the single networks that produced the best overall test-set performance shows that using fuzzy membership values to represent the host-rock geology input results in significantly improved values for the overall test-set performance and capture efficiency statistic $D \times (D/A)$, and higher values for D/A and the area under the ROC curve.

8.1.12 Extended Use of Fuzzy Inputs to Create a Hybrid Fuzzy-Neural Network

Traditionally, mineral prospectivity methods are either entirely data-driven or entirely knowledge-driven. However, there is a need, particularly in new exploration areas, to combine very limited quantitative data with conceptual models or exploration criteria derived from mature areas. An extension of the concept of using fuzzy membership values in order to represent categorical data types as inputs is to use fuzzy membership values for *all* the network inputs. Such a system effectively represents a simple modular form of hybrid fuzzy-neural network system.

The main advantage of fuzzy membership inputs is that they enable a large range of subjective data (e.g. favourability of tectonic environment, host stratigraphy, or reactivation along major faults) which are currently used in regional exploration programs but which would not normally be included in an empirical neural-network approach.

8.1.13 Compared Neural Network, Fuzzy and Hybrid Fuzzy-Neural Network Systems

Hybrid fuzzy-neural systems produced slightly poorer and fuzzy systems produced significantly poorer generalization performance than neural networks, but significantly better map quality statistics (i.e. D/A and $D \times (D/A)$ and area under ROC curve). The highest overall test-set classification accuracies though, were obtained with networks using only fuzzy inputs (i.e. 79.0% for the best 10 input network with layers selected with the category criteria, Table 7.38, and 79.0% for the best 17 input network with layers selected using the $D \times (D/A)$ criteria, Table 7.40).

The very high values for capture efficiency statistics (D/A , $D \times (D/A)$) for systems with

fuzzy inputs are probably due to the very small proportion of cells which are assigned high prospectivity values (see histograms of the output values for the three types of systems, Fig. 7.14). In the case of fuzzy systems, this is most likely a result of the increasive nature of the gamma function at high gamma values. High output values would be rare since they would then depend on the relatively rare conjunction of a high number of favourable inputs at a single location. Hybrid systems also have high capture efficiency ratio values but for slightly different reasons. It is likely that the use of fuzzy membership functions used to transform the raw input values causes the trained hybrid fuzzy-neural network to combine the inputs in a more additive way.

The poorer generalization performance of the fuzzy, and to a lesser extent, the fuzzy hybrid systems is interpreted as the result of the way the fuzzy membership functions, which define the favourable variables, simplify and smooth out spatial relationships and ultimately narrow the definition of what constitutes highly favourable locations for gold deposits. Perhaps two thirds of the deposits fit the model implicit in the fuzzy membership functions and this, together with the small number of cells, leads to high D/A and $D \times (D/A)$ ratios. Other deposits that do not fit this simple model are not recognized and contribute to the poorer generalization results.

Prospectivity maps presented in Chapter 7, using hybrid fuzzy-neural networks, clearly reflect the geology and structure in the input GIS maps, but, at the same time, appear to smooth some of the noise and artifacts, which are apparent in neural-network maps, without the loss of information that is apparent in maps produced using the fuzzy systems.

Thus, the hybrid fuzzy-neural systems have several advantages compared with either the neural network or fuzzy systems, that is,

1. ability to incorporate prior knowledge,
2. good generalization as reflected in best test-set classification performance,
3. very high values for map quality statistics, and
4. mineral prospectivity maps with low noise, no artifacts and high level of geological detail.

8.2 Achievable Improvements to Existing Study

8.2.1 Combine Factors that Improved Performance - Augmented Training Data with Fuzzy Inputs

As noted above the most significant increases in generalization ability and map quality result from modifying the quantity and type of training data; i.e. the augmentation of the training data with random noise, use of fuzzy membership values as inputs, and the use of input variables selected with the $D \times (D/A)$ criterion. Combining these factors is likely to lead to a further increase in performance.

None of these factors depends on the type of neural network. Recently, other types of networks have been tested in mineral prospectivity applications. In particular, the work of Harris & Pan (1999) and Singer & Kouda (1999a) suggests that it may be possible to achieve better results with probabilistic and general regression neural networks than with MLP networks.

8.2.2 Maximize Use of Limited Training Data with a Leave-One-Out Training Strategy

Increasing the number of deposit patterns through the addition of random noise is one way of training a neural network with limited known deposit examples. Other procedures for training a network when data are scarce include cross-validation (Stone, 1974) and the leave-one-out method. Cross-validation allows a high proportion of the data to be used to train the network by splitting the data into, for example, 10 segments and withholding one of the portions as a test set and training the network using the remaining nine tenths of the data. In this case the network would be trained 10 times. Each time a different segment is reserved for testing. This is referred to as 10-fold cross-validation. The validation error is calculated by averaging all the results. The leave-one-out procedure (sometimes referred to as the jackknife) refers to the case where only a single pattern is set aside in each training run for testing. An advantage of the leave-one-out procedure is that it can provide measures of confidence for comparing the classification performance of two networks (Duda *et al.*, 2001).

Another method designed to improve the generalization ability, when patterns for a particular class of patterns are scarce, is interactive reinforcement training (Wong *et al.*, 1997b). This method reinforces the effect of classes of patterns which are represented in

the training set in low numbers by duplicating them.

8.2.3 Use of Fuzzy Membership Functions to Implement Narrow Distance Buffers

It is shown in Chapter 7 (Tables 7.19-7.22) that, although narrow buffers in distance and strike and contrast layers, result in poorer generalization performance, the values of the capture efficiency statistics, D/A and $D \times (D/A)$ are significantly improved. Setting the value for cells where the distance exceeds the buffer limits to the maximum distance for distance layers or to a contrast of zero for contrast layers is analogous to using a simple step function with a threshold. It would probably be more effective to implement these buffers using inputs in the form of fuzzy membership values and modifying the form of the fuzzy membership functions to reflect these limits.

8.2.4 Input Standardization, Target Values and Sigmoid Function

In this study, inputs are scaled to the range $[0,1]$, target values to 0.1 and 0.9, and a sigmoid function of the form:

$$f(net) = \frac{1}{1 + e^{-net}} \quad (8.1)$$

(where net is the weighted, summed input to the processing unit) is used. Duda *et al.* (2001) recommend that inputs be standardized so that the average and variance for each feature component over the entire data set is set to zero and 1.0, respectively. They also suggest using a hyperbolic tangent sigmoid of the form:

$$f(net) = a \tanh(bnet) = a \left[\frac{e^{+bnet} - e^{-bnet}}{e^{+bnet} + e^{-bnet}} \right] \quad (8.2)$$

and target values of +1 and -1 for target category and non-target categories, respectively.

8.2.5 Use of a Continuous Rather than Binary Target Variable

A difficulty with the present method of training the networks using binary target values is that deposits are effectively treated as a single class. This is despite the fact that the total gold resource for the 120 known deposits ranges from 1050 to 1,246,500 kg tons of contained gold for the giant Kalgoorlie Golden Mile deposit. An alternative to using binary values to predict the similarity of patterns to deposit patterns in the training data set is to train the network to predict the total contained gold in each grid cell (Knox-Robinson,

1994; Knox-Robinson *et al.*, 1996). This may facilitate learning since the target values are likely to be less often contradictory. For example, due to the regional scale of the GIS data, there may be little evidence present in the GIS input layers for some small deposits. Therefore, input-variable values associated with small deposits may actually be more similar to those of barren cells than large deposits, yet, with binary target values, the network must produce the same output value for both cases.

8.2.6 Elimination of Redundant Inputs

Although considerable effort was put into selecting relevant input variables, redundant attributes were not identified and eliminated. In Chapter 4, it is demonstrated that neural networks are more robust than fuzzy systems with respect to redundant and irrelevant input variables. However, network performance is likely to be improved if redundant attributes can be removed (Langley & Sage, 1994). Training a network, which has a large number of input variables, with a small number of training patterns, may cause the network to over-fit the data. Various techniques are available to do this. For example, Bishop (1995) and Duda *et al.* (2001) suggest the use of principal component analysis to reduce the dimensionality of the inputs, and Milne (1995b), Gedeon (1996) and Milne (1999) developed methods for analysing the trained weights matrix in a trained network to determine which inputs are significant.

8.2.7 Use of Self Organizing Maps for Improved Split of Training Data

In this study, the training data were randomly split ten times between training, training-stop and test data and the performance of the trained network for each split was compared. The characteristics of the resultant data sets are important because the performance of the trained network on the test data set can only be a reliable guide to the performance on completely new data if the training sets are statistically similar. In addition, training with the early-stopping method also requires that the training and test sets are statistically similar. A more efficient means of achieving an optimal split has been suggested by Wong *et al.* (1996a), Fung *et al.* (1997) and Fung & Wong (1999). They used a self organizing map to classify training-data vectors into 6 to 8 classes. Training sets based on a selection of patterns with low or mean quantization errors (i.e. difference between each pattern and the centroid of a class) gave the best results. The remaining data were used for the test set.

8.3 Extensions to This Work

8.3.1 Development of Rule-based Hybrid Fuzzy Systems

The good results obtained with hybrid fuzzy-neural network systems in this study suggest that the application of hybrid systems to mineral prospectivity mapping should be further investigated. Fuzzy and neuro-fuzzy inference systems have been successfully used in engineering systems such as automatic control and computer vision (Jang *et al.*, 1997; Kasabov & Kozma, 1999). In contrast to the fuzzy systems used in mineral prospectivity systems, these engineering systems use *if-then* rules, whereby: 1) rules are evaluated by fuzzifying crisp input values using fuzzy membership functions, 2) multiple antecedents are combined using an implication method (Mamdani & Assilian, 1975; Sugeno, 1985), 3) rules may be weighted, 4) rules are combined using an aggregation method, and 5) a defuzzification method is used to convert the fuzzy membership function representing the aggregated rules to a crisp output value (Jang & Sun, 1995; Jang & Gulley, 1995). In neuro-fuzzy inference systems, the fuzzy inference system is trained using a backpropagation algorithm, and input and output pairs. Hybrid neuro-fuzzy systems are discussed in Appendix A (Section A.2.5). Systems of this sort could have advantages for geoscience applications like mineral prospectivity mapping, in which there is often a mix of conceptual knowledge and data, but the rules can only be expressed in vague or imprecise terms.

8.3.2 Estimates for Accuracy of Prediction

An increasingly important problem for mining companies in assessing alternative exploration opportunities is that of risk management (Lerche, 2002). At present, it is difficult in the case of neural network and fuzzy systems to answer questions about how accurate the predictions are or perhaps how wrong they could be.

8.3.3 Investigate Factors Affecting the Approximation of Network Outputs to Probabilities

Following on from the problem of estimating the accuracy of prospectivity estimates is the need to determine the conditions under which the outputs most closely approximate probabilities. For classification problems, this probability is the posterior probability of class membership $p(C_k|\mathbf{x})$, where C_k is the k th class, and $\mathbf{x}$ is the input feature vector. Bishop (1995) and Duda *et al.* (2001) suggest using; 1) one output neuron per class,

2) target values of 0 and 1, and 3) the sum of squares error function. Bishop (1995) notes that techniques such as re-training the network on patterns which are incorrectly classified alters the class-conditional density functions and are therefore not applicable if the network is to generate probabilities as outputs. Duda *et al.* (2001) also suggest using an exponential rather than a sigmoidal activation function, that is:

$$f(net) \propto \exp^{net} \quad (8.3)$$

Bishop (1995) also describes methods for checking how closely the outputs approximate posterior probabilities and a method for re-scaling the network outputs if the prior probabilities, $P(C_k)$ for the classes in the data population are different from those of the training data.

Although, theoretically, outputs represent probabilities, this is based on the assumption of an infinite amount of training data. In practice, where data are finite, outputs approximate probabilities. Therefore, further work is needed to determine how closely the network outputs approximate probabilities in mineral prospectivity and the factors which affect the approximations in mineral prospectivity applications.

8.3.4 Rule Extraction from Trained Neural Networks

To discover the reasons why a neural network correctly produces high prospectivity estimates for particular patterns could be useful in two ways. First, an understanding of input variable values associated with large deposits could help test and refine current exploration criteria and second, the combination of input variable values required to produce particular responses could be reformulated as if-then rules and used in fuzzy or neuro-fuzzy rule-based systems.

Preliminary work by Gedeon & Turner (1993) and Gedeon & Treadgold (1997) suggests that one way of extracting rules from a neural network could be based on a causal index method. A causal index is the correlation between the neural network inputs and outputs. For example, if an *input* is always on, or has a high value when a particular *output* is on, or has a high value, then the correlation between the input and the output is high, and the input can be said to have caused the output. In a modification of this simple approach, the rate of change of the output with respect to the input is measured, in order to eliminate correlations that are due to chance. This form of causal index is determined by changing the value of a single input from 0 to 1 while the other inputs are held constant. This is repeated for all the inputs and then the resultant curves can be interpreted to yield rules involving *AND* and *OR*.

8.3.5 Uncertainty of Mineral Prospectivity Estimates

One important aspect of a neural network method for mineral prospectivity mapping that has not been investigated in this study is the uncertainty of prediction. Whilst various methods for the estimating uncertainty are available for the weights-of-evidence method (Bonham-Carter *et al.*, 1989; Bonham-Carter & Agterberg, 1990; see discussion in Section 4.6.7, page 134), these methods can not be applied to a neural-network method. However, an estimate of uncertainty associated with the prospectivity map could be obtained using a Monte Carlo simulation.

For the neural network method uncertainty in the prediction arises from error in the input variables and error associated with network training. Sources of error in neural-network-based prospectivity estimates are due to; 1) random selection of patterns corresponding to barren cells for training sets, 2) randomly splitting training data into training, training-stop and test sets random initial weights, and 3) random initial weights. Random errors drawn from distributions appropriate for each input variable could be added to the network inputs to obtain a range of prospectivity estimates for each grid cell. Processing of the inputs, to which errors are added, could be repeated for different random initial weights and selections of training sets so that error associated with training of the neural networks could be simulated. Uncertainties based on the variance and standard deviation of the predictions for each cell could then be represented as additional maps.

8.4 Concluding Statement

Neural networks are shown to be an effective and promising new method for integrating regional exploration data sets to estimate the potential for mineral deposits in a given district. The pilot study establishes that neural networks produce geologically reasonable results. In addition, neural networks are shown to perform at least as well as both the most commonly used statistical methods, weights of evidence, and the conceptual fuzzy systems method, while offering several advantages over these techniques. The methodology established in this study is not restricted to use on a regional scale or in 2-D, and could potentially be used at a mine scale in 3-D.

Statistical methods developed as part of the Kalgoorlie Terrane case study can be applied independently of a neural network approach to mineral prospectivity mapping. These graphical statistical methods are useful for quantitatively assessing exploration criteria, which can be expressed in terms of features in a regional-scale GIS database within the

framework of a mineral-systems approach. A mineral-systems, rather than a deposit-model, approach is important because it also enables prior geological knowledge to be incorporated into a neural network analysis in the form of novel derived layers using features which are appropriate to the regional scale of the GIS database.

This study demonstrates the effectiveness of a neural network approach in established exploration areas where large amounts of data are available and there are numerous deposits. However, experiments on the effect of deposit numbers available for training highlight the fact that neural networks are not well suited to greenfields areas where there are few data. Methods for extending the applicability of the neural network methods to new exploration areas are investigated in this study, for example, through the augmentation of the deposit training patterns using the addition of random noise, and the inclusion of prior knowledge through the use of fuzzy membership values as inputs. The preliminary results for this latter approach are promising and point the way for future research in which knowledge- and data-driven systems can be combined in the form of hybrid fuzzy-neural network systems.

Neural networks are capable of recognizing the underlying patterns in multisource geoscience data sets. Whilst the results of this study demonstrate that neural networks are effective in identifying areas containing known mineralization, it is their ability to generalize and to predict prospective areas for new deposits that makes them a useful tool for mineral exploration.

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Appendix A

Additional Mineral Prospectivity Mapping Methods: Review of Theory and Literature

This appendix contains two sections. The first part contains a review of the theory and literature describing mineral prospectivity methods in addition to those which are applied in this thesis. In the second part, a number of neural network architectures that represent alternatives to the multilayer perceptron and which are potentially useful for the estimation of mineral prospectivity are examined. These are the probabilistic (PNN), general regression (GRNN), radial basis function (RBF) and self-organizing feature map (SOFM) or Kohonen neural networks and a hybrid neuro-fuzzy system. These networks have been chosen because they have been shown to be useful for a wide range of applications, and secondly these architectures span a range of neural network paradigms.

A.1 Additional mineral prospectivity methods

A.1.1 Boolean Algebra

Boolean algebra and index-overlay are the simplest procedures for combining geoscience data sets. In Boolean algebra, features in each layer are treated as binary variables. For raster data, if a feature is present, the cell value is set to one otherwise the cell value is set to zero. Boolean AND and OR operators are then used to combine the different binary

layers. The binary favourability value of a particular grid location is given by:

$$S = \begin{cases} 1 & : \text{ if } (condition) \text{ TRUE} \\ 0 & : \text{ otherwise} \end{cases} \quad (\text{A.1})$$

where *condition* is a Boolean expression containing AND, OR and NOT operators and a binary variable representing the grid cell value for each thematic layer. Bonham-Carter (1994) has suggested the use of the Boolean *OR* operator in cases where favourable evidence for mineralization is rare.

The Boolean AND operator was used by Bates (1959) in a study to determine the factors controlling the location of uranium-vanadium deposits in the Colorado Plateau area of Colorado and Utah, USA. Bates (1959) selected predictor variables by testing the strength of the correlation between ranked values of candidate predictor variables and the ranked production of known deposits in tons.

George & Bonham-Carter (1989) used the Boolean AND operator to combine layers containing principal components scores for biogeochemical data, buffered faults, and bedrock geology to predict the favourability for gold deposits in the Star Lake area of Saskatchewan, Canada. They argued that a simple approach using Boolean logic is appropriate when exploration is at an early stage and low numbers of known deposits preclude the use of statistical methods.

A.1.2 Index-Overlay

A disadvantage of the Boolean algebraic method is that all evidence maps are treated as being of equal importance. The index overlay method overcomes this problem by allowing a constant weight factor to be assigned to each map layer. For binary input maps the overall favourability index, F , for an individual grid cell is given by:

$$F = (w_1x_1 + w_2x_2 + w_3x_3 + \dots + w_Nx_N) / \sum_i^N w_i \quad (\text{A.2})$$

where x_i is the binary value of the i_{th} predictor variable, N is the number of binary input maps and w_i is the subjectively chosen weight assigned to the i_{th} map (Bonham-Carter, 1994). The features represented by binary variables could be simple ones such as the presence of a particular rock type or they could be represented by the logical union of

more than one feature; e.g. *anomalous Au OR anomalous Ag*. The score is normalized to the range $[0, 1]$ by dividing the weighted sum (numerator) by the maximum possible score represented by the sum of the weights (denominator).

Koch *et al.* (1981) used an index overlay method to calculate scores for uranium prospectivity for two degree quadrangles in Colorado based on point located data and subjectively chosen weights and a mixture of binary and metric predictor variables.

Bonham-Carter (1994) described an index overlay method for multiclass maps in which weights are assigned to each class within each map in addition to the weights for each map type. the Index overlay method has also been used in a recent study by Carranza & Hale (1999) to classify the nickeliferous-laterite potential of an area in the north-eastern part of the Phillipines.

The favourability index is given by equation A.3:

$$F = (w_1c_{1i} + w_2c_{2i} + w_3c_{3i} + \dots + w_Nc_{Ni}) / \sum_i^N w_i \quad (\text{A.3})$$

where

- w_i = the weight for the i^{th} map layer,
- c_{ji} = is the weight for the i^{th} class of the j^{th} map
- N = the number of map layers.

A modelling procedure similar to the one described above was employed by Reddy & Koch (1988) to combine 13 geophysical, geological, and geochemical map layers to predict the favourability for silver deposits in the Butte, Dillon, Hamilton and Elk City two degree quadrangles in Idaho and Montana, USA. A variety of statistical procedures were used to select a set of control cells. The value of weighting factors for each class within a map were set equal to the fraction of control cells having that attribute value. Weights were assigned to classes within map layers but weights were not assigned to the map layers themselves.

Moore & Gregory (1989) applied an index overlay method to produce a geological map for an area with poor outcrop near Halifax, Nova Scotia. They used a statistical measure of correlation between the input maps to define weighting factors for each class within each input map.

The advantage of the binary and index overlay methods lies in their simplicity. However,

disadvantages of these methods include the following points.

- The methods are subjective. In the Boolean method the decision whether to use the *AND* or *OR* operator and the choice of cutoff values used to convert multiclass input maps to binary format are subjective. The choice of weighting factors in both binary and multiclass index overlay methods is also subjective.
- Both Boolean and binary index overlay methods limit the information in the input maps to just the presence and absence of a feature.
- The methods are based on a linear additive model and therefore cannot model complex non-linear relationships. Also due their linear nature, the methods are likely to over-estimate the favourability index in cases where some input layers are correlated or contain redundant information.

A.1.3 Multiple Linear Regression

Multiple linear regression analysis is a statistical technique which is used to predict and explain the relationship between a single independent variable and several independent variables (also referred to as explanatory variables). The regression equation has the form:

$$Y_i = b_0 + b_1X_{1i} + b_2X_{2i} + \dots + b_nX_{ni} \quad (\text{A.4})$$

where Y_i is the predicted value of the dependent variable for the i^{th} observation, b_0 is the Y-axis intercept, $b_1 \dots b_n$ are regression coefficients, and $X_1 \dots X_n$ are the independent (predictor) variables. Multiple regression analysis uses a mathematical procedure known as least squares to estimate the values of $b_0 \dots b_n$ such that the sum of the squared errors is minimized, that is:

$$\sum_{i=1}^n (Y_i - \hat{Y}_i)^2 \quad (\text{A.5})$$

where Y_i and $\hat{Y}_i$ are the actual and predicted values of the i_{th} observation, respectively.

The weights denote the relative contribution of the individual predictor variables to the overall result.

In the form of multiple regression shown in equation A.4, the independent and dependent

variables can only represent interval or ratio data (rather than ordinal or categorical variables; Hair *et al.*, 1998).

In order to build a multiple linear regression model, an approach known as stepwise regression is used. New variables are added to the model in steps and only retained if a test (partial F-test criterion) shows that the new variable significantly improves the model. At each stage, previously entered explanatory variables are re-tested to see if they are still significant. If not, they can be eliminated from the model. In this way a minimal model incorporating the most effective explanatory variables is produced.

Multiple linear regression was one of the earliest and most popular methods used in mineral-prospectivity mapping (e.g. Kelly & Sherriff, 1969; Sinclair & Woodsworth, 1970; De Geoffroy & Wignall, 1970, 1971). For example, Sinclair & Woodsworth (1970) used multiple regression to combine 12 geological data sets to produce separate contoured favourability maps of total ore tonnage, average ore grade, and total dollar value for an area near Terrace, British Columbia, Canada, in which Cu-Pb-Zn-precious metal vein deposits occur. Independent variables included the percentage of a cell occupied by rocks belonging to a particular formation and distance from the centre of a cell to the nearest plutonic rock. A control area of contiguous cells covering the best explored part of the study area was used to develop the regression model. The resulting model was then used to provide estimates for all the cells in the area.

Assumptions required in order to apply multiple regression analysis are:

- linearity: the relationship between the dependent and independent variables is linear
- normality: the values of Y are normally distributed at each value of X
- homoscedasticity: that the variation around the line of regression does not change over the range of X values
- that there is no significant correlation between predictor variables

A difficulty with the use of multiple regression in mineral prospectivity studies is that geological variables are often not normally distributed and few studies present scatter plots or residual plots to demonstrate that the normality assumption is satisfied. Where variables are not normally distributed, variables can be transformed so that the frequency distribution becomes as near-normal as possible. For example De Geoffroy & Wignall (1971) used $\ln(Y)$ instead of Y for the dependent variable and $\ln(1+x)$ in place of X for all the independent variables. Sinclair & Woodsworth (1970) used other transformations; for example $\arcsin(\sqrt{X/100})$ in place of X, the dependent variable representing the percentage of plutonic rocks.

Multiple regression analysis cannot be used where the dependent variable is binary (e.g. deposit present or absent). To overcome this restriction, some researchers have used: Multiple regression analysis cannot be used where the dependent variable is binary (e.g. deposit present or absent). To overcome this restriction, some researchers have used:

- very large grid cells (in order to guarantee that every cell contains a deposit or at least a percentage of all the rock types in the study, or
- total metal value per cell (thus in some cases effectively grouping several mineralization types together).

Some examples include Sinclair & Woodsworth (1970) who estimated grade, tonnage, and total dollars for 4×4 mile cells, Hodgson & Troop (1988) who used $\log(\text{Au oz./cell})$, Agterberg *et al.* (1972) used $\log(\text{Cu tonnage/cell})$ for 10×10 km, and De Geoffroy & Wignall (1971) who used the total ore value in 10×10 mile cells. Some examples include Sinclair & Woodsworth (1970) who estimated grade, tonnage, and total dollars for 4×4 mile cells, Hodgson & Troop (1988) who used $\log(\text{Au oz./cell})$, Agterberg *et al.* (1972) used $\log(\text{Cu tonnage/cell})$ for 10×10 km, and De Geoffroy & Wignall (1971) who used the total ore value in 10×10 mile cells.

A.1.4 Multiple Discriminant Analysis

Multiple Discriminant Analysis (MDA) is used when the dependent variable is categorical (as with logistic regression) and independent variables represent metric data. In contrast to logistic regression, MDA is capable of handling dependent variables with more than two classes. Similar to multiple regression, discrimination is achieved by using a linear combination of independent variables multiplied by weights. The analysis procedure is based on a sample of the data and involves an attempt to find the combination of independent variables and appropriate values of the weight for each variable that maximizes the variance between groups relative to the variance within groups. The discrimination function has the following form:

$$Z_{ji} = a + w_1X_{1i} + w_2X_{2i} + \dots + w_nX_{ni} \quad (\text{A.6})$$

where

$$\begin{aligned} Z_{ji} &= \text{discriminant } Z \text{ score for the } i^{th} \text{ observation of the } j^{th} \text{ predictor variable} \\ a &= \text{Y-intercept} \end{aligned}$$

$$\begin{aligned}w_k &= \text{discriminant weight for independent variable } k \\x_{ki} &= \text{independent variable } k \text{ for the } i^{th} \text{ observation}\end{aligned}$$

In order to classify observations belonging to two groups for example, the discriminant scores are calculated for each observation and a cut-off score (called the critical Z score) is selected to divide the results into two groups. The approach can be extended to more than two groups.

Prelat (1977) applied MDA to VMS deposits in central Norway to produce a contoured map for gridded data showing the probability that the grid cell belongs to the group of cells containing VMS mineralization. Predictor variables were selected from a group of 36 geological and structural features, and aeromagnetic data. Prelat (1977) transformed the raw data to bring the distributions closer to normality using the following functions: $\sqrt{x+k}$, $\log(x+k)$, and $\arcsin(x+k)$, where x is the value of the raw variable and k is a constant. Probabilities were calculated from discriminant Z scores. The probability that a cell belongs to one of the two groups is a function of the squared Euclidean distance (in multidimensional input space) between the cell and the mean of the group being considered.

The discriminant analysis method is dependent on the following assumptions:

- multivariate normality of independent variables,
- equal variance and covariance for the classes, and
- absence of significant multicollinearity between variables (Prelat, 1977; Hair *et al.*, 1998).

Ramsayer & Bonham-Carter (1974) described an adaptive pattern recognition algorithm based on MDA to class sediment formations on the basis of binary input data on the presence or absence of fossils and other characteristics. De Geoffroy & Wignall (1971) compared a form of MDA, which they refer to as Bayesian classification analysis, with multiple regression. The result of this MDA method is a raster-based map showing cells coloured according to 4 classes of probability of belonging to a group for which ore values exceeded \$2M (Canadian).

A.1.5 Cluster Analysis

Cluster Analysis is a multivariate technique that has been applied to problems of mineral prospectivity (Briggs & Press, 1977; Nikolenko, 1980). The purpose of the technique is to group objects (e.g. grid cells in a GIS) according to the similarity of their characteristics. In the study by Briggs:1977, input variables are continuous and the output variable is binary (mineralized or barren). Unlike multiple regression and multiple discrimination analysis where the problem of which predictor variables to use is determined as part of the method, in cluster analysis, the researcher must specify which independent variables are to be used. Cluster analysis is very sensitive to the inclusion of irrelevant variables and to outliers (Hair *et al.*, 1998).

An example of the use of cluster analysis is the study by Briggs & Press (1977). They applied a simple form of cluster analysis to predict uranium-bearing areas on the Colorado Plateau, USA. Geological structural, and topographic data sets were converted to binary form. Variables (or features in GIS layers) were then selected to characterize mineralized areas on the basis of whether the features satisfy equation A.7:

$$\text{IF } (K_{deposits} < N_{feature} / N_{cells}) \text{ AND } (N_{feature} / N_{cells} < K_{barren}) \text{ THEN select feature} \quad (\text{A.7})$$

where $K_{deposit}$ and K_{barren} are cutoff percentages, which are different for each data set, $N_{feature}$ is the number of cells in which the feature occurs and N_{cells} is the number of cells. The same procedure was applied to barren areas within the control area. The classification criterion for a particular cell is given by equation A.8;

$$\begin{aligned} \text{IF } (N_{deposit\ traits} > N_{barren\ traits}) \quad \text{THEN} \quad classification &= \text{Uranium-bearing} \\ \text{ELSE} \quad classification &= \text{barren} \end{aligned} \quad (\text{A.8})$$

A.1.6 Factor Analysis

Characteristic analysis is a multivariate statistical technique that has been applied by Botbol (1971); Botbol *et al.* (1978); McCammon *et al.* (1983, 1986) to the identification of exploration targets. The method is similar to factor analysis. Agterberg (1989a) has described it as a simplified form of principal component analysis. A set of mineralized cells (together with some prospective non-mineralized cells to make the model more general) are

selected to represent a particular type of deposit. The parameters in various raster-based input layers containing both these *model* cells and the regional-scale area to be explored are transformed to binary form.

Locations that are favourable for mineralization are assigned a value of 1 and other areas are assigned 0. Favourable areas were defined as anomalous areas for the purpose of the study of part of the Ag-Pb Coeur D'Alene district by Botbol *et al.* (1978). The choice of model cells and the selection of input layers requires subjective judgement and Botbol *et al.* (1978) notes that these choices have a critical effect on the output.

The favourability for a cell is calculated using Equation A.9:

$$f = a_1x_1 + a_2x_2 + \dots + a_nx_i \quad (\text{A.9})$$

where a_i represents the weights for each of the n binary (or ternary) variables x_i . Once the model cells and parameters have been chosen, the weights for each variable shown in Equation A.9 are determined by solving the matrix equation:

$$(X'X)\mathbf{a} = \lambda\mathbf{a} \quad (\text{A.10})$$

where λ is the largest eigenvalue of $(X'X)$ and X is the $m \times n$ matrix of n binary or ternary transformed parameter values for the m selected *model* cells. The weights $a - i$ are scaled so that the values of the favourability function are in the range $[-1,+1]$. The favourability value is interpreted as a measure of similarity of the values in Equation A.9 for a particular cell to those selected to represent the deposit (i.e. the model cells).

In a further development of the method, ternary variables were introduced (where 1 = favourable, 0 = unevaluated, and -1 = unfavourable) along with truth tables for combining the ternary variables with logical *AND*, *OR*, and *NOT* (McCammon *et al.*, 1983, 1986). Kobayashi *et al.* (1994) has used this ternary form of characteristic analysis to estimate the potential for unconformity-type uranium deposits in the Alligator Rivers region of the Pine Creek Geosyncline, Northern Territory, Australia.

A.1.7 Expert Systems

Expert systems are computer systems that attempt to automate the sort of tasks that normally require a human expert (Cawsey, 1998)¹. Expert systems have often been applied to diagnostic tasks, which include medical diagnosis (e.g. the MYCIN system, Shortcliffe, 1976), fault-finding, configuring computer systems (e.g. McDermott, 1982), and mineral exploration (e.g. Duda *et al.*, 1978).

The basic components of an expert system are a set of facts and some interpreter controlling the application of the rules (Cawsey, 1998). Facts are represented as a set of IF-THEN rules that lead to a conclusion that is true if the evidence is true. A simple rule can be represented as a single piece of evidence E implying a single hypothesis H ; i.e. IF *evidence is true* THEN *hypothesis is true* (Fig. A.1a). In more complex rules, the IF condition contains multiple pieces of evidence (Fig. A.1b).

Figure A.1. Form of simple IF-THEN rules in an expert system; a) single piece of evidence implying a single hypothesis and b) multiple pieces of evidence.

The type of expert systems used in two important geological applications (Duda *et al.*, 1978; Reddy *et al.*, 1992) is a rule-based inference systems in which the main inference mechanism used is forward chaining. Forward chaining systems are primarily data-driven (Cawsey, 1998). Rules are organized into a hierarchical network in which the rules (statements about evidence and hypotheses) are linked as shown in Figure A.2. In a forward-

¹Expert systems are also referred to as knowledge-based systems.

Figure A.2. Linking of rules in an expert system through forward chaining.

chaining system, rules are linked so that the hypothesis from one rule becomes the evidence for the next rule and so on. Rules are invoked under the control of the interpreter only when evidence contained in the IF part of the rule is available.

Using the example of Kuroko-type VMS deposits, the nodes represent items of field evidence and/or geological hypotheses. For example, D_1 = limonite casts near the intrusive contact, C = sulphide mineralization, B = economic mineralization, and A = VMS mineralization.

A key feature of expert systems used in mineral exploration is the ability to deal with uncertainty or incomplete evidence. A procedure called Bayesian updating is used. The prior probability of the geological statement at the end of the arrows in Figure A.2 is updated depending on whether field evidence is available. In a simple Bayesian system, the evidence is assumed to be either definitely present (i.e. true) or definitely absent (i.e. false).

The following discussion is based on a description of an expert system designed for mineral exploration by Stackhouse & Boyd (1985). An odds-likelihood formulation of Bayes' rule is used to update the probabilities according to the type of evidence available. It is derived as follows. The prior probability, $P(H)$, of a hypothesis H (e.g. the area represented by

a grid cell is favourable for gold mineralization) can be updated if there is some evidence E available using the odd-likelihood formulation of Bayes' rule:

$$P(H|E) = \frac{P(E|H)}{P(E)} \cdot P(H) \quad (\text{A.11})$$

where

$$\begin{aligned} P(E|H) &= \text{the conditional probability of evidence } E \text{ given } H \\ P(H|E) &= \text{the updated or posterior probability of } H \text{ given } E \end{aligned}$$

An equivalent expression for the probability that H is not true given evidence E is shown in equation A.12:

$$P(\bar{H}|E) = \frac{P(E|\bar{H})}{P(E)} \cdot P(\bar{H}) \quad (\text{A.12})$$

where $\bar{H}$ means “not H ”.

For example, the prior probability of a porphyry copper deposit, $P(H)$, could be determined as the number of grid cells containing deposits divided by the total number of cells in the study area. This represents the probability that any cell selected at random contains a deposit. Evidence E in the form of the presence of argillic alteration could be used to update this prior probability. $P(E)$ could be calculated from the number of cells in the study area in which argillic alteration is present, and $P(E|H)$ represents the number of cases where argillic alteration (E) is present given the location corresponds to a deposit (hypothesis, H).

The odds, $O(H)$, of an event H is equal to the ratio of the probability that the event occurs to the probability that the event does not occur and is given by:

$$O(H) = \frac{P(H)}{1 - P(H)} \quad (\text{A.13})$$

From this definition, it follows that:

$$O(H|E) = \frac{P(H|E)}{P(\bar{H}|E)} \quad (\text{A.14})$$

$$O(H) = \frac{P(H)}{P(\bar{H})} \quad (\text{A.15})$$

The odds-likelihood form of Bayes' rule is obtained by dividing equation A.11 by equation A.12 and using equations A.14 and equation A.15 to replace the probability ratios with odds:

$$O(H|E) = \frac{P(E|H)}{P(E|\bar{H})} \times O(H) \quad (\text{A.16})$$

A similar expression is obtained for the case where the evidence is absent:

$$O(H|\bar{E}) = \frac{P(\bar{E}|H)}{P(\bar{E}|\bar{H})} \times O(H) \quad (\text{A.17})$$

If the evidence E is definitely present, the strength of a rule is represented by the ratio LS^1 . This is obtained by rearranging equation A.16:

$$LS = \frac{P(E|H)}{P(E|\bar{H})} = \frac{O(H|E)}{O(H)} \quad (\text{A.18})$$

If the evidence E is definitely absent, the rule strength is represented by the ratio² LN (obtained by rearranging equation A.17 as follows:

$$LN = \frac{P(\bar{E}|H)}{P(\bar{E}|\bar{H})} = \frac{O(H|\bar{E})}{O(H)} \quad (\text{A.19})$$

Rearranging equations A.18 and A.19 gives the equations used of for updating probabilities:

$$O(H|E) = LS \times O(H) \quad (\text{A.20}) \quad O(H|\bar{E}) = LN \times O(H) \quad (\text{A.21})$$

These formulas are only useful if there is just one item of evidence. LS , LN , and $P(H)$ (from which $O(H)$ is obtained) are estimated subjectively by an expert.

In order to extend this basic approach to updating prior probabilities to cases where two or more pieces of evidence are combined, the assumption that evidence is conditionally independent is made (Bonham-Carter, 1994). For n items of evidence, Bayes rule (equation A.11) becomes:

¹The ratio LS is known as the likelihood ratio for sufficiency or sufficiency ratio.

²The ratio LN is known as the likelihood ratio for necessity or necessity ratio.

$$P(H|E_1 \cap E_2 \cap \dots \cap E_n) = \frac{p(E_1 \cap E_2 \cap \dots \cap E_n|H)}{P(E_1 \cap E_2 \cap \dots \cap E_n)} \times P(H) \quad (\text{A.22})$$

Applying equation A.13 to convert the left-hand side and the term $P(H)$ to odds gives:

$$O(H|E_1 \cap E_2 \cap \dots \cap E_n) = \frac{p(E_1 \cap E_2 \cap \dots \cap E_n|H)}{p(E_1 \cap E_2 \cap \dots \cap E_n|\bar{H})} \times O(H) \quad (\text{A.23})$$

If events $E_1 \dots E_n$ are assumed to be conditionally independent then:

$$P(E_1 \cap E_2 \cap \dots \cap E_n|H) = P(E_1|H) \times P(E_2|H) \times \dots \times P(E_n|H) \quad (\text{A.24})$$

Substituting the right-hand of equation A.24 into the numerator of equation A.23 and using a similar expression for the denominator gives:

$$\begin{aligned} O(H|E_1 \cap E_2 \cap \dots \cap E_n) &= \frac{P(E_1|H)}{P(E_1|\bar{H})} \times \frac{P(E_2|H)}{P(E_2|\bar{H})} \times \dots \times \frac{P(E_n|H)}{P(E_n|\bar{H})} \times O(H) \\ &= \prod_{i=1}^N LS_i \times O(H) \end{aligned} \quad (\text{A.25})$$

Similarly for the case where all the evidence is absent:

$$O(H|\bar{E}_1 \cap \bar{E}_2 \cap \dots \cap \bar{E}_n) = \prod_{i=1}^N LN_i \times O(H) \quad (\text{A.26})$$

Equations A.25 and A.26 are only applicable if the evidence is definitely true (present) or definitely false (absent). The rule strengths, LS and LN , and the prior probabilities (which are converted to odds using equation A.13 for use in the equations shown above) represent the facts that are stored in the expert system. These are estimated *subjectively*.

Expert systems constructed for mineral prospectivity by Duda *et al.* (1978), Reddy *et al.* (1992) and Stackhouse & Boyd (1985) take the degree of certainty to which the user believes the evidence exists into account. The probability that an item of evidence exists (or is true) given a particular observation Ob concerning that evidence is denoted by $P(E|Ob)$. In this case LS_i and LN_i are replaced by a quantities that Reddy *et al.* (1992) refer to as the effective likelihood ratios:

$$LE = \frac{O(H|Ob_i)}{O(H)} \quad (\text{A.27})$$

$$\bar{L}E = \frac{O(H|\bar{O}b_i)}{O(H)} \quad (\text{A.28})$$

Consequently, in the case of uncertainty about evidence, instead of equations A.25 and A.26, we have:

$$O(H|Ob_1 \cap Ob_2 \cap \dots \cap Ob_n) = \prod_{i=1}^N LE_i \times O(H) \quad (\text{A.29})$$

$$O(H|\bar{Ob}_1 \cap \bar{Ob}_2 \cap \dots \cap \bar{Ob}_n) = \prod_{i=1}^N \bar{L}\bar{E}_i \times O(H) \quad (\text{A.30})$$

For example, $P(E|Ob)$ could indicate the probability that an argillic alteration zone exists given a degree of alteration or proportion of certain minerals. $P(E|Ob)$ can vary between two extreme cases. The probabilities for the following three conditions can be calculated:

1. if the evidence E is true then $P(E|Ob) = 1$ and $P(H|Ob) = P(H|E)$,
2. if the evidence E is false then $P(E|Ob) = 0$ and $P(H|Ob) = P(H|\bar{E})$, and
3. if no observations are available concerning the evidence for a deposit, e.g. argillic alteration, then the probability of the evidence is just the prior probability $P(E)$ so that $P(E|Ob) = P(E)$ and $P(H|Ob) = P(H)$.

These conditions define the three end points of the segments in the piecewise linear function illustrated in in Figure A.3.

The values of these three points are defined in the following way. As noted previously prior probabilities of evidence $P(E)$ and deposits $P(H)$, and rule strengths (in equations A.18 & A.19) are estimated by an expert based on statistics of deposit examples and stored in the system. The right-hand side of equations A.18 & A.19 together with the prior probabilities yield the quantities $O(H|Ob_i)$ and $O(H|\bar{Ob}_i)$.

The user of the system then estimates $P(E|Ob)$ subjectively based on some field observation. The value of $P(H|Ob)$ is obtained by interpolating the piecewise linear function in Figure A.3 and then used to update the rule strengths $LE_i = O(H|Ob_i)/O(H)$. Given the rule strengths and the prior probability, the posterior probability of a deposit can then be calculated using equation A.25.

$P(H|Ob)$ can also be estimated using the following formula (Reddy *et al.*, 1992):

Figure A.3. Interpolation of a piecewise function in the PROSPECTOR expert (after (Stackhouse & Boyd, 1985)). system

$$P(H|Ob) = \begin{cases} P(H|\bar{E}) + \frac{P(H) - P(H|\bar{E})}{P(E)} P(E|Ob) & \text{if } 0 \leq P(E|Ob) < P(E) \\ P(H) + \frac{P(H|E) - P(H)}{1 - P(E)} [P(E|Ob) - P(E)] & \text{if } P(E) \leq P(E|Ob) \leq 1 \end{cases} \quad (\text{A.31})$$

The system described by Stackhouse & Boyd (1985) applies the following processing steps.

1. The system asks the user in an interactive session to provide an estimate of the certainty of the evidence; e.g. -5 indicates “*definitely not*”, 0 indicates “*don’t know*”, and +5 indicates “*definitely yes*”.
2. The system converts this rating to a probability $P(E|Ob)$. In a map-based processing system, the value of $P(E|Ob)$ would be stored as the grid cell values of a map.
3. The piecewise linear function (Fig. A.3) is interpolated to obtain an estimate of $P(H|Ob)$
4. The rule strengths (also referred to as the effective likelihood ratio; equations A.27 & A.28 are calculated)
5. Multiple pieces of evidence are combined using equations A.29 and A.30.

Systems like PROSPECTOR (Duda *et al.*, 1978), its GIS-based successor (Katz, 1991), POLOG (Stackhouse & Boyd, 1985), and the MAPS system developed by Reddy *et al.* (1992) use fuzzy logic in addition to Bayesian updating to combine pieces of uncertain

evidence. The following operators, *min* and *max* (analogous to the Boolean *AND* and *OR*) are used;

$$P(E|Ob) = \min_i P(E_i|Ob) \quad (\text{A.32})$$

$$P(E|Ob) = \max_i P(E_i|Ob) \quad (\text{A.33})$$

Before attempting to evaluate the advantages and disadvantages of expert systems in mineral prospectivity analysis it is necessary to note that the type of expert system examined here is a rule-based system that uses mainly forward chaining as the inference mechanism similar to that used in many mineral prospectivity studies (e.g. PROSPECTOR, Duda *et al.*, 1978).

Many geoscience applications of expert systems have been documented in the literature. Review articles include Fabbri & Kasvand (1988) and Yatabe & Fabbri (1988, 1989). Yatabe & Fabbri (1988, 1989) examined 37 geological expert systems. More recent examples of the application of expert systems in the geosciences are given by Dimitrakopoulos *et al.* (1994)

The best known expert system that has been applied to mineral exploration is called PROSPECTOR. This is a rule-based system that mainly uses the forward chaining and the type of Bayesian updating described above as the inference mechanism (Duda *et al.*, 1978)). Although its main mode of operation is non-spatial and involves matching field observations to ore deposit models, PROSPECTOR also has a map-based mode used for drill-site selection. In this latter mode, input in the form of digital geological, structural, geochemical and geophysical maps can be combined to produce a raster-based favourability map for porphyry system mineralization. Duda *et al.* (1978) has produced a favourability map for the Island Copper deposit in British Columbia, Canada. In later work, a favourability map was produced, that predicted extensions to the Mt Tolman porphyry molybdenum deposit. The extensions were later confirmed by drilling (Duda, 1980; Campbell *et al.*, 1982). Katz (1991) adapted a public domain GIS package (MAPS) to emulate the map-based functionality of the PROSPECTOR system. In order to validate the new system, Katz combined 26 input maps consisting of geological, geophysical and geochemical data to duplicate the original Island Copper deposit analysis by Duda *et al.* (1978). Reddy *et al.* (1992) developed an expert system in conjunction with a commercial GIS and applied the system to a regional scale evaluation of the favourability for VMS deposits in the Snow Lake area, Manitoba. In this study, geological evidence (e.g. lithology, alteration and proximity to intrusive contacts) was converted to a series of binary input maps.

Although expert systems that have been discussed contain knowledge about the association

of field evidence and geological hypothesis and deal with uncertainty, the systems are difficult and time-consuming to construct. A new deposit model and set of rules must be developed for each deposit type and this requires both a domain expert and someone skilled in eliciting and converting expert knowledge into a form that can be used by the system. There is also the assumption that the deposit models correctly represent all deposits both known and unknown (Reddy *et al.*, 1992). Despite the formalism of the Bayesian updating and inference networks, the prior probabilities and likelihood ratios, which form the basis of all predictions, are subjectively estimated (Duda *et al.*, 1978; Duda, 1980). In addition, in systems like PROSPECTOR, the user is required to subjectively estimate the certainty of the evidence. Finally, all the systems use Bayesian updating as the main inference method require the assumption of conditional independence between the evidence maps in order to combine multiple items of evidence for a single hypothesis (Agterberg, 1989a).

A.1.8 Logistic Regression

Logistic regression is a type of multivariate analysis that is used to predict a dependent variable that can take only one of two values (i.e. a binary variable). It is a similar technique to multiple regression and also performs a similar function to two-group discriminant analysis but differs in that it directly predicts the probability of an event occurring and assumes a non-linear relationship between the independent variables and the dependent variable. The regression equation for the logistic model has the following form:

$$\ln[\text{Odds}(D)] = b_0 + b_1 + b_1X_{1i} + b_2X_{2i} + \dots + b_nX_{ni} \quad (\text{A.34})$$

where b_0 to b_n are coefficients whose values are determined by using a set of control data for which both the dependent and independent variables are known, n is the number of independent variables, X_{ji} is the value of the i^{th} observation of the j^{th} predictor variable, and $O(D)$ is the odds of event D . The relationship between the probability and odds of an event is given by equation A.13:

The odds is equivalent to the ratio of the probability that an event will occur to the probability that the event will not occur. Event D could represent the occurrence of a deposit in a grid cell for which data for many variables are known.

A mathematical procedure known as the maximum likelihood procedure is used in an iterative manner to determine the coefficients b_0 to b_n . Once the coefficients have been determined, the equation can be used to predict the values of the log of the odds ratio,

known as the logit, which corresponds to the left-hand side of equation A.34. The logit can be converted to a probability estimate in two steps. First the estimated odds ratio is determined using equation A.35:

$$O(D) = e^{\ln[O(D)]} \quad (\text{A.35})$$

In the second step, the odds ratio is calculated to probability using equation A.36:

$$P(D) = \frac{O(D)}{1 + O(D)} \quad (\text{A.36})$$

Logistic regression was first applied to the analysis of mineral prospectivity by Agterberg (1974) who compared the use of multiple linear and logistic regression to predict the probability of occurrence of Archaean Ni-Cu sulphide and Cu-Zn deposits. The percentages of 8 rock types and combinations of rock types in 10×10 km cells were used as the predictor variables (giving a total of 37 variables). The dependent variable was a categorical variable with binary values representing the presence and absence of a deposit in a cell. Agterberg (1974) attempted to overcome the problem of the control area not being sufficiently representative of the study area by using deposit cells together with the 8 neighbouring cells for 87 deposits over a very large area (850000 km^2) as the control cells to develop the logistic model. The model was then used to estimate the probability of deposit occurrence in a much smaller area (254000 km^2). Agterberg (1974) concluded that the logistic model produces better results than multiple regression if there are few deposit occurrences

Chung & Agterberg (1980) also used logistic regression and the proportion of 5 rock types to produce a map depicting the probability of occurrence of VMS deposits in part of Newfoundland, Canada. Three classes of probability were displayed as a grey-scale image.

In another study, Chung (1983) used an interactive graphic system to analyze multivariate geoscience data called SIMSAG. They compared logistic regression and multiple linear regression methods for prospectivity mapping. The logistic model was based on 16 independent variables representing geology, lake sediment geochemistry, airborne magnetic and radiometric survey data, gravity and topography. The result of the analysis was a contoured probability map for uranium occurrences in the Kasmere Lake area, Manitoba, Canada.

The advantage of logistic regression compared with multiple regression is that the method is less affected when assumptions that independent variables follow a normal distribution

Figure A.4. Form of the logistic function showing the relationship between the dependent and independent variables. The dependent variable shown on the y-axis represents the probability of an event. This curve was produced using the function, $f(x) = 1/(1 + e^{-x})$.

and that there is no correlation between independent variables (Hair *et al.*, 1998).

Agterberg (1974) and Chung & Agterberg (1980) have noted that the logistic regression method gives better results than multiple linear regression in situations where there are few known deposits. The logistic model has been used by Agterberg *et al.* (1981) in preference to the Poisson model when events consisting of one or more deposits have been defined to avoid local clustering effects.

Use of the logistic model assumes a very specific type of relationship. Whereas the multiple linear regression model assumes the relationship between the dependent and independent variable is linear so that the dependent variable can be predicted by a linear combination of predictor variables, the logistic regression assumes the relationship between the dependent and independent variables is a logistic one of the form shown in Figure A.4. The latter relationship is shown in equation A.37:

$$P(D) = \frac{e^{b_0 + b_1 + b_1 X_{1i} + b_2 X_{2i} + \dots + b_n X_{ni}}}{1 + e^{b_0 + b_1 + b_1 X_{1i} + b_2 X_{2i} + \dots + b_n X_{ni}}} \quad (\text{A.37})$$

A.1.9 Dempster-Shafer Evidential Belief Theory

Dempster-Shafer evidential belief theory is the basis of a method of probabilistic reasoning that involves subjective judgement about the credibility of evidence that is used to support a proposition. One of the reasons for interest in the method as a means of integrating spatial geoscience data sets is that it deals with uncertainty in evidence explicitly and

allows an estimate to be made for each probability estimate.

Figure A.5. An example illustrating partial belief in evidence and support

The key difference between ordinary probability and Shafer's theory can be illustrated by the following example adapted from Schum (1994). Let us suppose a geologist, P, reports that there is a deposit at the top of a mountain (referred to as hypothesis, H, in Fig. A.5), without any further evidence, we might judge that there is a 90% chance that P is credible and a 10% chance that P isn't. This means that the evidence together with what is believed about P supports H to degree 0.9, i.e. evidential support is 0.9.

There are three main rules in Shafer's scheme for allocating evidential support. These are:

- support (S) is assigned a number such that $0 \leq S \leq 1$,
- the values of S always sum to 1.0 across the power set. The power set represents the collection of all possible subsets of the set of hypotheses. For example, in Figure A.5 above, the power sets is $\{\{H\}, \{\bar{H}\}, \{H, \bar{H}\}, \emptyset\}$
- for the empty set $\emptyset$, $S = 0$

Despite the fact that these rules look similar to those for ordinary probability, there is a major difference in regard to how the remaining 0.1 evidential support in Figure A.5 is

interpreted and what is implied if P is not credible. In the Bayesian model, it is assumed that there is a Boolean phenomena, which either does or does not exist; i.e. the only possibilities are, H , (a deposit exists) and $\bar{H}$, (a deposit does not exist). Consequently, if P is not credible then H is not true so $\bar{H}$ is true and the remaining 0.1 of support *must* be assigned to hypothesis, $\bar{H}$.

Evidential belief theory differs from ordinary probability by allowing for uncertainty in the following way. If geologist P is not credible, it does not mean there is no deposit. Although P being credible is compatible with H , P not being credible is compatible with both H and $\bar{H}$ and so 0.1 of evidential support remains uncommitted; i.e. on the basis of the present evidence, it might go to H or to $\bar{H}$.

Similarly, while $P(H) = 0$ in ordinary probability means that event H is impossible, evidential support $S\{H\} = 0$ means that the evidence available is incompatible with H . Conversely, $S\{H_1, H_2, H_3\} = 1.0$ means the evidence could mean H_1 , H_2 , or H_3 are true but not in any discernible proportions among these.

Concept of the Belief Functions

Central to evidential belief theory is the possibility of allocating evidential support to combinations of hypothesis. For example, for multiple hypotheses, H_1 , H_2 , H_3 , where H_1 = epithermal gold deposit, H_2 = porphyry copper deposit, and H_3 = no deposit. The collection of possible combinations or subsets (known as the power set) is $\{H_1\}$, $\{H_2\}$, $\{H_3\}$, $\{H_1, H_2\}$, $\{H_1, H_3\}$, $\{H_2, H_3\}$, $\{H_1, H_2, H_3\}$ and empty set $\emptyset$. Table A.1 shows a set of example values used in the following discussion of evidential belief theory concepts from Schum (1994). In this example, $\{H_1 H_2\} = 0.1$ means that evidential support for the hypothesis that there is either an epithermal gold or porphyry copper deposit is equal to 0.1. If $S\{H_1\} = 0.5$ and $S\{H_2\} = 0.2$ then the support committed to the idea “that there is an epithermal deposit ” also supports $\{H_1, H_2\}$; i.e. there is some kind of deposit. The same applies to $S\{H_2\}$.

The combination of two different sets of evidence is performed using Dempster’s rule. Applying the rule gives a new basic probability number which is equivalent to degree of support for the hypothesis provided by the combined evidence. This discussion follows Schum (1994) in referring to the support, S , provided by evidence. Instead of S , Shafer (1976) uses the term, basic probability assignment (bpa). $S(C)$ is the combined evidential support (or bpa) for two independent bodies of evidence, 1 and 2 for hypothesis C in some frame of discernment. (The frame of discernment is the set of hypotheses being

Table A.1. Values of variables used to illustrate evidential belief theory concepts for the power set of hypothesis in $F = \{H_1, H_2, H_3\}$ after Schum (1994). The belief functions $S\{\}$, $Bel\{\}$, $Dou\{\}$, $Pl\{\}$ are explained in the text.

Belief	Power set of hypotheses in $F = \{H_1, H_2, H_3\}$							
Function	$\{H_1\}$	$\{H_2\}$	$\{H_3\}$	$\{H_1H_2\}$	$\{H_1H_3\}$	$\{H_2H_3\}$	$\{H_1H_2H_3\}$	$\emptyset$
$S\{\}$	0.5	0.2	0.0	0.1	0.0	0.1	0.1	0.0
$Bel\{\}$	0.5	0.2	0.0	0.8	0.5	0.3	1.0	0.0
$Dou\{\}$	0.3	0.5	0.8	0.0	0.2	0.5	0.0	1.0
$Pl\{\}$	0.7	0.5	0.2	1.0	0.8	0.5	1.0	0.0

considered.) Focal elements are subsets in a frame of discernment that have non-zero support. Dempster's rule is given by:

$$S\{C\} = \frac{\sum_{A_i \cap B_j = C} S_1(A_i) S_2(B_j)}{1 - \sum_{A_i \cap B_j = \emptyset} S_1(A_i) S_2(B_j)} \quad (\text{A.38})$$

where the numerator is the product of all the focal element pairs with intersections equal to subset C, the denominator represents all focal element intersections, which equal an empty set, S_1 and S_2 refer to the support assignments made for items of evidence 1 and 2 and A_i and B_j refer to hypotheses. The meaning of equation A.38 as it applies to the combination of two gridded geoscience data sets used to estimate prospectivity is illustrated in Figure A.6 below. The frame of discernment is $F = D, \bar{D}$, where the two hypotheses are D : *the grid cell contains mineralization* and $\bar{D}$: *the grid cell is barren*. Evidence, e_1 could represent airborne magnetic data in GIS layer 1 and e_2 could represent solid geology in GIS layer 2.

Belief denoted $BelA$, for any group of hypotheses indicates the total amount of evidential support committed to A or any hypotheses that are subsets of A. In the example discussed above, if $A = \{H_1, H_2\}$ and nonempty subsets of A are $\{H_1\}$, $\{H_2\}$ and $\{H_1, H_2\}$, then:

$$Bel\{H_1, H_2\} = S\{H_1\} + S\{H_2\} + S\{H_1, H_2\} = 0.5 + 0.2 + 0.1 = 0.8 \quad (\text{A.39})$$

This indicates that the belief that the evidence means one of the hypotheses in $\{H_1, H_2\}$ is true. For H_1 there are no subsets so $Bel\{H_1\} = S\{H_1\}$.

Figure A.6. An illustration of the relationship between belief, uncertainty, doubt and plausibility in Dempster-Shafer belief theory (modified from Flack, 1995).

Doubt that the evidence means one of the hypotheses in A is true is defined by equations A.40 and A.41:

$$Dou\{A\} = Bel\{\bar{A}\} \quad (\text{A.40})$$

where $A = \{H_1\}$ and $\bar{A}$ represents hypotheses incompatible with A ; i.e. $\bar{A} = \{H_2, H_3\}$:

$$Dou\{H_1\} = Bel\{H_2, H_3\} = S\{H_2\} + S\{H_3\} + S\{H_2, H_3\} = 0.3 \quad (\text{A.41})$$

Plausibility of an hypothesis A is the total amount of support that is, or might possibly be, committed to A given by:

$$Pl\{H_1\} = S\{H_1\} + S\{H_1, H_2\} + S\{H_1, H_3\} + S\{H_1, H_2, H_3\} \quad (\text{A.42})$$

The concept is that for hypothesis H_1 , each of the subsets $\{H_1, H_2\}$, $\{H_2, H_3\}$, $\{H_1, H_2, H_3\}$ may contain uncommitted support specifically for H_1 that could, if additional evidence were available, be assigned to H_1 . So in an extreme case all of the uncommitted support assigned to sets in which H_1 appears could be allocated to H_1 . The total is the upper probability or plausibility of $\{H_1\}$.

Uncertainty indicates how uncertain we are about the evidence and is represented by the interval, $[Bel\{A\}, Pl\{A\}] = [0.5, 0.7]$.

These quantities are represented graphically in Figure A.6 (Flack, 1995). In the cross tabulation of hypotheses in Figure A.7, the elements represent the intersections of the sets shown at the left and bottom margins of the table. Note that the intersection of D and $\bar{D}$ is an empty set $\emptyset$.

$S_1(D)$ refers to the degree of support from the value at a particular grid cell in the data

		S_1			
Evidence 1	0.9	$\{D\}$	$\{D\}$	$\{\emptyset\}$	$\{D\}$
	0.2	$\{\bar{D}\}$	$\{\emptyset\}$	$\{\bar{D}\}$	$\{\bar{D}\}$
	0.1	$\{D, \bar{D}\}$	$\{D\}$	$\{\bar{D}\}$	$\{D, \bar{D}\}$
			$\{D\}$	$\{\bar{D}\}$	$\{D, \bar{D}\}$
		S_2	0.5	0.3	0.2

Grid cell value in layer 1

Grid cell value in layer 2

Evidence 2

Figure A.7. Values of support used to illustrate Dempster's rule (after Schum, 1994).

set 1 from the proposition; “deposit in grid cell ” and $S_2(\bar{D})$ refers to support assignments based on the cell values for data set 2.

Pairs of support assignments (shown in the column labelled S_1 and in the row labelled S_2) corresponding to the hypothesis D are multiplied and summed to give the numerator in equation A.38. Pairs for which the intersection corresponds to the empty set $\emptyset$ are used to determine the denominator. Applying Dempster's rule to the example shown in Table above gives:

$$S(D|e_1, e_2) = \frac{S_1(D|e_1)S_2(D|e_2) + S_1(D|e_1)S_2(D, \bar{D}|e_2) + S_2(D|e_2)S_1(D, \bar{D}|e_1)}{1 - [S_1(D|e_1)S(\bar{D}|e_2) + S(\bar{D}|e_2) + S(\bar{D}|e_1)S(D|e_2)]} \quad (\text{A.43})$$

where $S(D|e_1, e_2)$ is the support assignment for hypothesis D on the basis of combined evidence, e_1, e_2 .

In an application of Dempster-Shafer evidential belief theory to combining data sets for mineral exploration, Moon & So (1995) simplified the equation for the support assignment for an hypothesis (equation A.43). The sum of the support assignment over the frame of

discernment must equal 1.0, that is:

$$S(D|e_1) + S(\bar{D}|e_1) + S(D, \bar{D}|e_1) = 1 \quad (\text{A.44})$$

Re-arranging equation A.44, gives the following expression for $S(D, \bar{D}|e_1)$:

$$S(D, \bar{D}|e_1) = 1 - S(D|e_1) - S(\bar{D}|e_1) \quad (\text{A.45})$$

Moon & So (1995) further simplified Equation A.43 by making the following substitutions:

$$\begin{aligned} a &= S(D|e_1) \\ a' &= S(\bar{D}|e_1) \\ b &= S(D|e_2) \\ b' &= S(\bar{D}|e_2) \end{aligned} \quad (\text{A.46})$$

and from A.45:

$$\begin{aligned} 1 - a - a' &= S(D, \bar{D}|e_1) \\ 1 - b - b' &= S(D, \bar{D}|e_2) \end{aligned} \quad (\text{A.47})$$

The resultant simplified form of equation A.43 is given by:

$$S(D|e_1, e_2) = \frac{ab + a(1 - b - b') + b(1 - a - a')}{1 - ab' - a'b} \quad (\text{A.48})$$

Since we are dealing with a hypothesis that has no subsets; i.e. D , the belief function value is the same as the support assignment:

$$Bel(D|e_1, e_2) = \frac{ab + a(1 - b - b') + b(1 - a - a')}{1 - ab' - a'b} \quad (\text{A.49})$$

The uncertainty, $U(A) = PL(A) - Bel(A)$, is calculated by determining the plausibility. The plausibility is defined as:

$$Pl(A) = 1 - Bel(\bar{A}) \quad (\text{A.50})$$

where $\bar{A}$ is the subset of hypotheses incompatible with A . In this case, the plausibility is calculated with equation A.51:

$$Pl(D|e_1, e_2) = 1 - \frac{a'b' + a'(1 - b' - b) + b'(1 - a' - a)}{1 - a'b - ab'} \quad (\text{A.51})$$

where quantities on the right hand side are defined in equation A.48. To combine n data sets, Dempster's rule must be applied $n - 1$ times. Each time the result of the previous combination becomes one of two input data sets that is combined in the next step.

The benefits of the Dempster-Shafer approach are

- that it offers an approach to handling uncertainty that is similar to the way people think about uncertainty
- it allows a map to be produced that shows the degree of uncertainty about how the evidence supports the proposition; “*area represented in the cell is favourable for mineralization*”.
- the method handles missing data well; an estimate of favourability can be made as long as the cell is covered by at least one data set.

There are some problems with the Dempster-Shafer method. It is unclear what effect a the lack of independence of some of the sources of evidence has on the results. Shafer states that the pieces of evidence to be combined with Dempster's rule must be distinct bodies of evidence (Shafer, 1976) and the multiplication of focal terms in the numerator in equation A.43 is based on the product rule for independent events used in ordinary probability. However, it is common for geoscience data sets to be correlated with one another (Bonham-Carter, 1994; Singer & Kouda, 1999a).

An *et al.* (1992) suggest that evidential independence depends on the frame of discernment that is chosen. They cite an example involving two airborne magnetic surveys. They interpreted the surveys to be evidentially dependent if the surveys are used to prove a hypothesis that a deposit is located at a location but evidentially independent if the surveys are used to prove the hypothesis that a magnetic anomaly exists at the location. The problem here is that, although many intermediate hypotheses are used complex inference networks in expert systems, in most mineral prospectivity studies there is generally just one relevant hypothesis namely; “*mineralization is present* ” so according to An *et al.* (1992), all the layers would be evidentially dependent.

There are several further potential problems in the application of the Dempster-Shafer approach. Moon (1990) highlights the need to assign the degrees of support to values in the various evidence map layers according to the relative importance of the data layers. The support assignment or basic probability assignments are subjective and unless a logical framework exists for the assignment of the values such as an expert system, then it may be difficult for different geologist to produce similar results.

Evidential belief theory has been applied to the classification of satellite imagery (e.g. Lee *et al.*, 1987; Peddle & Franklin, 1992; Peddle, 1995). Lee *et al.* (1987) compared Bayesian and Dempster-Shafer approaches to the integration of multiple data sources and found that both methods produced similar results. A Dempster-Shafer approach has also been applied to the integration of geoscience data sets in mineral prospectivity studies. Moon (1990) subjectively assigned degrees of support to classes within airborne magnetic, EM, Ground EM, and solid geology maps to produce support (i.e. favourability), plausibility, and uncertainty maps for iron and base metal deposits in the Farley Lake area of Manitoba, Canada.

In a later study of the same area, An *et al.* (1992) produced a rule-based expert system that combined Boolean AND and OR operators with the Dempster-Shafer method. In this way, they combined 12 data sets to produce favourability and uncertainty maps for base-metal deposits. Belief functions were also used to quantify the uncertainty associated with each rule. An & Moon (1993) applied an expert system incorporating a Dempster-Shafer method to base-metal exploration in the Snow Lake area. Seven geology and geophysical map layers were combined to produce favourability and uncertainty maps.

The Dempster-Shafer method is applied in the PLAYMAKER expert system which was designed to assist geologists estimate the potential of new prospects in a hydrocarbon field (Cheong *et al.*, 1993).

A.1.10 Decision Trees

A decision tree is a method in the field of artificial intelligence that is used to perform classification tasks. A classification task is one where things are assigned to an enumerable set of possible categories or classes based on a set of properties or input features (Quinlan, 1993). For example, in medical diagnosis, the input features are patient symptoms and the output categories are possible diseases. A set of example classifications (both positive and negative) are required. Decision tree systems represent a type of machine learning because the model is constructed inductively by generalizing from specific examples (Cawsey,

1998). This is known in machine learning terminology as supervised learning.

Decision-tree induction systems try to construct the simplest tree that correctly classifies all the training data. A decision tree consists of leaves which represent output classes and nodes at which the input features are used in questions designed to split the examples into groups. Figure A.8 shows an example of a decision tree for determining whether someone coming to a doctor with chest pains has had a heart attack Cawsey (1998). The diagnosis is performed by answering the yes/no questions posed by the system.

The system selects the features that are the best predictors of the outcomes and places these at the root of the tree. The tests are constructed in order to split the examples into as homogeneous groups as possible. The best split is one that reduces the overall misclassification of the examples. Once the tree is constructed using training data, it can be used to classify new cases. In the inference system C4.5 developed by Quinlan (1993), the tree is converted to a set of rules. The rules have the form:

$$L \longrightarrow R \quad (\text{A.52})$$

where the left-hand side consists of a set of attribute tests joined by Boolean AND operators and the right-hand side is a class that the objects belong to. The system examines the list of rules and applies the first one for which the left-hand side condition is true. The classification is set to the class on the right-hand side.

Decision trees have been used in geoscience applications by Bui *et al.* (1997, 1998) and Reddy & Bonham-Carter (1991b). Bui *et al.* (1998) used features based on lithology, digital elevation, terrain attributes (slope & aspect) and LANDSAT MSS (range, mean and variance of each band) as inputs to C5.0 (a decision tree classification system) to predict the soil types in the upper Darling Basin area, NSW. Correct classification rates of 76% and 83% for two different training data sets were achieved. Reddy & Bonham-Carter (1991b) used a decision-tree system to classify the potential for VMS mineralization in the Snow Lake area, Manitoba, Canada using lithology, alteration type and intensity, and proximity to lithological contacts.

The most important limitation of induction systems like C4.5 is that they require that classes are sharply defined. Clearly, in a mineral prospectivity application, classes like “*favourable host rock for mineralization present*” and “*favourable host rock for mineralization absent*” are gross simplifications which ignore the range between the extremes. An end-member of one class may be very similar to extreme members of an other class yet they are treated as being different.

Figure A.8. Illustration of a decision tree (after Cawsey, 1998)

The prediction of continuous values is not possible in C4.5 and tasks in which a continuous-valued class is broken up into vague categories (as is done in fuzzy logic) are problematical (Quinlan, 1993).

Quinlan (1993) has noted that decision-tree systems do not perform well when;

- irrelevant attributes exist,
- the data are noisy ,
- concept complexity is high (equated with fragmented regions in feature space),
- the classification task is probabilistic, and
- the number of training examples close to some of the decision boundaries in hyper-dimensional feature space are low.

The first and second points suggest that decision-tree systems are quite sensitive to noise. Walker & Moore (1988c) observed that noisy training data caused the CART decision-tree system to introduce unnecessary nodes and sub-trees to account for the data.

Decision-tree systems appear to require very large training sets. For example, Bui *et al.* (1998) reported that in order to achieve good precision for soil classification maps, 20-25% of the cells in 1:250000 maps and 35% of cells in 1:100000 maps were used as training data.

A.1.11 Canonical Correlation

Canonical Correlation is a multivariate statistical technique that is similar to multiple regression in that the general form of the model is linear. Whereas multiple regression predicts a single dependent variable from a set of multiple independent variables, canonical correlation simultaneously predicts multiple dependent variables (Hair *et al.*, 1998). The form of the canonical correlation equation is:

$$b_1Y_1 + b_2Y_2 + b_3Y_3 + \dots + b_nY_n = a_1X_1 + a_2X_2 + a_3X_3 + \dots + a_nX_n \quad (\text{A.53})$$

X and Y can be either metric or categorical data type. The left-hand and right-hand sides of equation A.53 are linear composites of variables called canonical variates. The result of the analysis is to find the set of a and b that maximize the correlation between the linear composites (Sharma, 1995)

Pan & Harris (1992) used the canonical correlation method to produce a favourability map

for epithermal Au-Ag vein deposits in the Walker Lake quadrangle of Nevada and California. For the purposes of the study, Pan & Harris (1992) distinguished between explanatory and target variables. Explanatory variables are those that can be measured throughout the study area and only provide indirect evidence for mineralization; e.g. airborne magnetic anomalies. Target variables provide direct evidence of mineralization and are likely to be available in only very well explored areas; e.g. mineral occurrences or gold anomalies in stream sediment geochemical samples. In the canonical correlation method is capable of predicting more than a single dependent or target variable. In addition to favourability for a deposit, Pan & Harris (1992) also used hydrothermal alteration, Tertiary intrusives and Au-Ag occurrences as dependent variables (i.e. Y_1 , Y_2 , and Y_3 on the left-hand side of equation A.53 above). The independent or explanatory variables consisted of a set of eight geological, structural, geophysical and geochemical variables.

The method requires a well explored training area where the target and explanatory variables (Y and X , respectively) are known in order to develop the model. Once the values of $a_1 \dots a_n$ and $b_1 \dots b_n$ were established, the favourability was determined using the right-hand side of equation A.53 as:

$$\hat{F} = a_1X_1 + a_2X_2 + a_3X_3 + \dots + a_8X_8 \quad (\text{A.54})$$

Pan & Harris (1992) argue that defining favourability in terms of multiple target variables avoids ambiguities in the meaning attached to favourability and helps to capture important genetic ingredients of the ore formation process in the model. Yet the information captured by their use of Tertiary intrusives as a target variable (to define the presence of a heat source) could also be achieved by making it one of the explanatory variables and using a standard multiple linear regression model.

The major assumption underlying canonical correlation is that the relationships between independent and dependent variables (e.g. equation A.53) are assumed to be linear. Deviations from linearity can sometimes be corrected by transforming one of the variables, however if after the transformation the assumption is not satisfied then the relationship can not be modelled by canonical correlation (Hair *et al.*, 1998).

A.2 Additional Neural Network Architectures

A.2.1 Probabilistic Neural Networks

The probabilistic neural network (PNN) is a three layer multilayer feedforward network, which is based on a statistical algorithm developed by Meisel (1972). Specht (1990) reformulated the algorithm as a neural network. MLP networks rely on heuristic approaches to determine the network topology (i.e. the number of hidden nodes) and optimal values of system parameters (e.g. learning rate and momentum). MLP networks also require long training times and training may lead to a local rather than a global minimum. In contrast, the PNN directly implements Bayes' decision strategy and is guaranteed to approach an optimal solution (Bayes' optimal decision surface) as the number of training samples increase (Masters, 1993b; Zaknich, 1999).

PNNs are best suited to pattern classification problems. The following summary of the theory of PNNs is drawn from Masters (1993b), Bishop (1995), Fausett (1994), and Zaknich (1999). In pattern classification, patterns are represented by a feature vector; $\mathbf{x}^n = (x_1, x_2, x_3, \dots, x_n)$ and training vectors are used to estimate the probability of an unknown vector belonging to a particular class.

The optimum decision rule is the one which minimizes the probability of misclassification. This can be achieved if the unknown feature vector $\mathbf{x}$ is assigned to the class C_k for which the posterior probability $P(C_k|\mathbf{x})$ is the largest. This decision strategy is referred to as Bayes' decision rule. According to this rule vectors belong to a class C_k if:

$$P(C_i|\mathbf{x}) > P(C_j|\mathbf{x}) \text{ for all } i = 1, 2, 3, \dots, N \text{ and } i \neq j \quad (\text{A.55})$$

The cost associated with misclassifying vectors from the different classes is assumed in equation A.55 to be equal. Bayes' theorem can be used to restate equation A.55 as;

$$P(C_i|\mathbf{x}) = \frac{p(\mathbf{x}|C_i)P(C_i)}{p(\mathbf{x})}$$

$$\text{where } P(\mathbf{x}) = \sum_{j=1}^N (P(\mathbf{x}|C_j)P(C_j)) \text{ for all } i = 1, 2, 3, \dots, N \text{ and } i \neq j \quad (\text{A.56})$$

Substituting the right hand side of equation A.56 and a similar expression for class j and discarding the term $p(\mathbf{x})$ which is common to both sides in equation A.55 gives:

Figure A.9. Example of Bayes' decision rule classification (after Bishop, 1995).

$$P(C_i)P(\mathbf{x}|C_i) > p(\mathbf{x}|C_j)P(C_j) \text{ for all } i = 1, 2, 3 \dots, N \text{ and } i \neq j \quad (\text{A.57})$$

where

- $P(C_i)$ = the prior probability that an unknown vector belongs to class C_i
- $p(\mathbf{x}|C_i)$ = the class conditional probability density function that an unknown vector is $\mathbf{x}$ given that it belongs to class C_i
- $P(C_i|\mathbf{x})$ = the posterior conditional probability that an unknown vector belongs to class C_i given that the vector is $\mathbf{x}$
- $p(\mathbf{x})$ = the probability density that a vector is $\mathbf{x}$ irrespective of its class membership

The decision rule is illustrated with a simple case shown in Figure A.9. (after Bishop (1995)). The probability of misclassification is minimized if the decision boundary between the two regions R_1 and R_2 representing classes C_1 and C_2 is located where the two probability density curves cross. Consequently, the unknown pattern for which the value of feature $x = a$ is assigned to the class with the highest posterior probability ($g(\mathbf{x}) = p(x|C_k)P(C_k)$). In Figure A.9, $g_2(x) > g_1(x)$ so the vector is assigned to class 2.

The Bayes' optimal decision rule (equation A.57 above) is often written as (Zaknich, 1999):

$$h_i f_i(\mathbf{x}) > h_j f_j(\mathbf{x}) \text{ where } i \neq j \quad (\text{A.58})$$

where

h_i	=	the prior probability that vector $\mathbf{x}$ belongs to class C_i
$f_i(\mathbf{x})$	=	the class conditional probability density function that an unknown vector is $\mathbf{x}$ given that it belongs to class C_i
$g_i(\mathbf{x})$	=	the Bayes' decision function, $g_i(\mathbf{x}) = h_i f_i(\mathbf{x})$

and where the cost of misclassification is assumed to be equal for all classes and is therefore discarded because it does not contribute to the decision.

In order to apply equation A.58, both the prior probability h_i and the class probability density function $f_i(\mathbf{x})$ must be estimated. The probability density function or PDF is estimated from the training sample using a method developed for univariate data by Parzen (1962) and later extended by Cacoullos (1966) to multivariate data.

The Parzen PDF estimator uses the sum of small multivariate spherical Gaussian basis functions centred on each training sample vector (Zaknich, 1999). Masters (1995) has illustrated the concept in terms of a classification problem shown in Figure A.10 below. Figure A.10 shows an unknown sample (symbol “?”) representing a vector with just two components which must be classified as either belonging to population X or O . A nearest-neighbour method would assign class O to the unknown sample. The method based on the Parzen PDF estimator assigns a sphere of influence to each training sample. The function representing the sphere of influence has its largest value at zero distance and diminishes to very small values for large distances. The method involves finding the sum of this function for all training set members of each population. The class of the unknown sample is then set to the class having the largest sum (i.e. greatest combined influence).

The Parzen PDF estimator used to implement the PNN is given by Zaknich (1999) as:

$$f_i(\mathbf{x}) = \frac{1}{(2\pi)^{p/2} \sigma^p M_i} \sum_{j=1}^{M_i} \exp \frac{-\|\mathbf{x} - \mathbf{x}_{ij}\|^2}{2\sigma^2} \quad (\text{A.59})$$

where

i	=	class number
j	=	pattern number
$(\mathbf{x}_{ij})$	=	j^{th} training (or weight) vector from class i
$(\mathbf{x})$	=	unknown vector to be classified (referred to as the test vector)
M_i	=	number of training vectors in class i
p	=	dimension of vector x
σ	=	smoothing factor that controls the width of the area of influence
$f_i(\mathbf{x})$	=	PDF estimate for the i^{th} class equal to the sum of the multivariate

Figure A.10. An example of a classification problem involving two classes; shown as X or O (after Masters, 1993b). The feature vectors have two components and can therefore be plotted in a plane. The unknown sample to be classified is shown as “?”). A nearest-neighbour method would assign class O to the unknown sample. In contrast, the Parzen PDF estimator which assigns a sphere of influence to each training sample, would assign the unknown sample to class “ X ”.

$$\|\mathbf{x} - \mathbf{x}_{ij}\|^2 = \begin{array}{l} \text{spherical Gaussian distribution centred at each of the training} \\ \text{vectors } \mathbf{x}_{ij} \\ \text{the length of the vector representing the difference between the} \\ \text{unknown vector } \mathbf{x} \text{ and the training vector } \mathbf{x}_{ij}. \text{ This is equivalent} \\ \text{to the squared Euclidean distance measure.} \end{array}$$

The value of the PDF function $f_i(\mathbf{x})$ must be evaluated separately for each class. In equation A.59, the function actually evaluates the average of the multivariate Gaussian (normal) distributions for all the training vectors belonging to the same class. The computation of equation A.59 is sometimes simplified in the following ways (Zaknich, 1999; Masters, 1993b):

- the factor $1/M_i$ is eliminated when $g_i(\mathbf{x}) = h_i f_i(\mathbf{x})$ is calculated because it is assumed that $h_i \propto M_i$ i.e. the proportion of vectors of class i in the training set M_i is equal to the prior probability of class i vectors in the population. Note that this assumption cannot hold for mineral prospectivity applications where the two classes of vectors represent deposit and non-deposit cells. For example, in training neural networks it is standard practice to set the numbers of training examples in each class to be approximately equal (this was done in the pilot study in Chapter 4) but the ratio of non-deposit to deposit vectors in actual data population is likely to be

more than 1000 to 1.

- if vectors $\mathbf{x}$ and $\mathbf{x}_{ij}$ are normalized to unit length then the expression $\frac{-\|\mathbf{x}-\mathbf{x}_{ij}\|^2}{2\sigma^2}$ reduces to $(Z_{ij} - 1)/\sigma^2$ where $Z_{ij} = \mathbf{x} \cdot \mathbf{x}_{ij}$
- the factor $\frac{1}{(2\pi)^{p/2}\sigma^p}$ is the same for all classes and is therefore discarded because it does not contribute to the classification.

Thus $g_i(\mathbf{x}) = h_i f_i(\mathbf{x})$ is reduced to:

$$g_i(\mathbf{x}) = \sum_{j=1}^{M_i} \exp \frac{Z_{ij}-1}{\sigma^2} \text{ where } Z_{ij} = \mathbf{x} \cdot \mathbf{x}_{ij} \quad (\text{A.60})$$

As a result of the simplification, the calculation required has been reduced to a dot product ($\mathbf{x} \cdot \mathbf{x}_{ij}$) and an exponential function.

The architecture of the PNN is shown in Figure A.11. The input units represent the components of a test or unknown vector and distribute the values to the pattern units. There is a pattern unit for each vector in the training data set. There are N classes denoted by $M_1, M_2, \dots, M_N$. The links from each of the inputs $x_1, x_2, \dots, x_p$ to the pattern unit within class 1 for example indicate that the difference between the input vector components and the stored training data set vector (represented by the pattern unit) is to be calculated and stored. These squared Euclidean distances are summed for each class to give $g_i(\mathbf{x})$ (refer to equation A.58) and the class of the input vector is set to the class with the largest value of $g(\mathbf{x})$.

The smoothing parameter is equivalent to the standard deviation of the spherical Gaussian functions. The effect of different choices of smoothing parameter, σ on the form of the probability density functions for two classes is shown in Figure A.12a-c (based on Masters, 1993b, 1995 and Zaknich, 1999). Patterns in Figure A.12a-c are represented as points in the horizontal plane, corresponding to the tip of the vectors. Only two features are shown and therefore the vectors have only two components. At very small values of σ , the system is equivalent to a nearest neighbour classifier. At larger values, the classifier is a maximum likelihood function.

Training in a PNN network consists of comparing a set of stored training vectors $\mathbf{x}$ with an independent set of test vectors $\mathbf{x}_{ij}$ for which the classification is known, in order to find a value for the smoothing parameter, σ that gives the best classification accuracy. A single value of sigma is used for all classes. In contrast to the back-propagation algorithm,

Figure A.11. Architecture of a probabilistic neural network (PNN) adapted from Zaknich (1999). See text for explanation.

this is a one-pass process. If there is not enough data for both a training and test set then a procedure called the hold-one-out method can be used for testing (Bishop, 1995).

Practical descriptions of the use of PNNs have been given by Masters (1993b, 1995) and Zaknich (1999). In a study on the classification of crop types using PNNs, Serpico & Vernazza (1996) found that PNNs were faster to train and easier to configure than MLP networks but training time for the PNN grew proportionally to the size of the training set.

Masters (1993b) warns that the PNN is more sensitive than most types of neural network to training sets that do not cover all possible classes in the data population and states that an MLP network is likely to give better generalization performance in cases where only a few training samples are available. In a study in which a PNN was used to classify deposits, Singer & Kouda (1997b) noted that unknown samples which do not belong to any of the classes represented in the training set are likely to be incorrectly classified by the network. On the other hand, Zaknich (1999) has stated that sparse samples are

Figure A.12. The effect of different choices of smoothing parameter, σ on classification in a PNN; a) $\sigma = 0.1$, b) $\sigma = 0.5$, c) $\sigma = 0.225$, and d) $\sigma = 5.0$. Patterns are represented as points in the horizontal plane, corresponding to the tip of the vectors. At very small values of σ , the system is equivalent to a nearest neighbour classifier. At larger values, the classifier is a maximum likelihood function.

adequate for good performance from PNN networks. Although this appears to contradict Master's observations, it is possible that a PNN could perform well if the few training samples that are available happen to fall very close to the modal values for the population and the variance in the vector component values is low.

PNNs have been used on a variety of classification problems. Zaknich (1997) compared the use of PNN and MLP networks for edge detection in order to characterize aluminium hydroxide particles produced in the Bayer process for aluminium refining. He reported that a simple MLP, PNN and a more complex MLP resulted in classification accuracies of 85%, 91%, and 95%, respectively.

Singer & Kouda (1997b) used a PNN to classify deposits into 8 deposit types based on the presence or absence of 58 ore and alteration minerals. They reported better performance for the PNN (88% classification accuracy) than the PROSPECTOR II expert system (83%) in which a range of lithological, geochemical and other attributes were used in addition to mineralogy. Another of their results illustrates the importance of selecting the most useful features as inputs. They found that the addition of an input feature indicating whether the marine volcanic rocks in the vicinity of the deposit were mafic or felsic improved the classification rate (for the training-stop set) from 88% to 98%.

In a related study by Singer & Kouda (1997a), deposits were classified into 28 categories instead of 8 deposit as described above. The agreement between classes assigned by the neural network and those assigned by experts was only 58% Singer & Kouda (1997a) explained this poorer than expected performance as follows; 1) the training data for the first study consisted of deposits that had been described in scientific studies whereas those in the second study were from regional mineral databases, and 2) experts used data which were not available to the network. These results highlight the importance of ancillary and expert knowledge.

In a recent study, Singer & Kouda (1999a) have compared the performance of the PNN and weights-of-evidence methods for the prediction of mineral potential for VMS deposits in the Chisel Lake-Anderson Lake area, Manitoba, Canada. Twenty-three variables were used to classify areas into deposit and non-deposit groups. The correct classification rates of 99.3% for PNN and 83% for the weights-of-evidence method were obtained for an independent training-stop data set containing 7 deposit and 3223 non-deposit cells. Large differences between correct classification rates were obtained using; 1) a combination of training and test data sets consisting of all the available data, and 2) a training-stop set consisting of half the data (where the other half was used for training and test sets). The differences

were interpreted to indicate over-fitting (learning of noise rather than general patterns in the data) caused by the large number of variables (23) in relation to the small size of the training data set representing deposits (8). Singer & Kouda (1999a) stated that the PNN handled correlated input variables well compared to the weights-of-evidence method, which was adversely affected by small to moderate correlations leading to upward biased probabilities.

Harris & Pan (1999) also examined the use of a PNN for mineral prospectivity analysis. They compared a PNN to general regression (GRNN) and MLP neural networks, logistic regression and discriminant analysis and found that the PNN gave the best results. A feature of their study was an analysis of how the percentages of correctly classified mineralized and barren cells varied with the choice of cutoff probability used to make the classification. The PNN performed better than the other methods because it produced the highest percentages of correct classification of both mineralized and barren cells over a wide range of cutoff probabilities (86.7% and 93.8%, respectively for the combined training, test and training-stop data sets). An interesting aspect of their study was that Harris & Pan (1999) used software that calculated the value of the smoothing factor σ for each input variable (rather than a single value for all classes). This enabled Harris & Pan (1999) to interpret the relative contribution of the input variables to the classification. Sigma values in the range 0.01–0.1 were interpreted to have been practically ignored by the network, whereas inputs with sigma values in the range 1.80–2.95 were regarded as being moderately to very important.

Some of the advantages of PNNs include;

- the output can be used to calculate Bayesian posterior probabilities
- the decision surfaces are guaranteed to approach Bayes' optimal boundaries unlike MLP networks in which training can result in a local rather than global minimum
- training is fast and easy
- outliers in the data are handled well

Disadvantages of PNNs include;

- performance depends strongly on having a training set that accurately represents the data (i.e. it is important that all classes and variation in the classes are represented, (Masters, 1993b, 1995), and
- memory requirements are large because all training vectors are stored and all vectors are processed each time an unknown vector is classified.

A.2.2 General Regression Neural Networks

The General Regression neural network (GRNN) is another network developed by Specht (1991) which is very similar to the PNN. The GRNN is suitable for both function approximation and pattern classification. Like the PNN, the GRNN uses radial basis functions in a Parzen kernel estimator and stores each training vector in its structure. The GRNN is based on methods for estimating regression functions from noisy data (Bishop, 1995). Bishop (1995) explains that the goal of learning in a network is to find a smooth mapping from input vectors $\mathbf{x}$ to an output vector $\mathbf{y}$, which captures the underlying structures of the data without fitting the noise in the training data as part of the model. In a GRNN, this optimal mapping is achieved by performing a regression with the target data as a dependent variable and the input data as the independent variable. The regression value is equivalent to the conditional average, $\langle t|\mathbf{x} \rangle$, of the target data, where t is the target output, and $\mathbf{x}$ is the input to the network; this is illustrated in Figure A.13 below.

Figure A.13. Schematic illustration of the concept behind the GRNN network (after Bishop, 1995). Dots represent the data points and circles represent the Gaussian kernel functions. The regression curve is given by conditional average, $\langle t|\mathbf{x} \rangle$, of the target data, where t is the target output and $\mathbf{x}$ is the input to the network.

The network mapping which minimizes a sum-of-squares error function is given by the conditional average of the target data. Here we consider a mapping from a single input variable x to a single target variable t . At any given value x_0 of the input variable, the network output $y(x_0)$ is given by the average of t with respect to the distribution $p(t|x_0)$ of the target variable, for that value of x .

The concept behind the general regression neural network has been explained by Bishop (1995) who states that under certain circumstances the optimal mapping of the inputs to the output for a network that minimizes a sum-of-squares error function is given by the conditional average of the target data. That is, the minimum of the error function occurs when;

$$y(\mathbf{x}) = \langle t|\mathbf{x} \rangle \quad (\text{A.61})$$

$$= \int_{-\infty}^{\infty} t p(t|\mathbf{x}) dt \quad (\text{A.62})$$

$$= \frac{\int_{-\infty}^{\infty} t p(\mathbf{x}|t) dt}{\int_{-\infty}^{\infty} p(\mathbf{x}|t) dt} \quad (\text{A.63})$$

where the independent variable is assumed to be a vector, $\mathbf{x}$, and the dependent variable t is a scalar, $y(\mathbf{x})$ is the network output, $p(t|\mathbf{x})$ is the conditional density and $p(\mathbf{x}|t)$ is the joint probability density function. This result is based on the assumptions that; 1) the data set is sufficiently large, and 2) the number of adaptive weights is sufficiently large (Bishop, 1995). Equation A.62 is the standard formula for the expected value of a continuous random variable $\langle t|\mathbf{x} \rangle$ (Berenson & Levine, 1996).

For a set of training data $\{\mathbf{x}_i, t\}$ where $i = 1, 2, \dots, N$, the probability density $p(\mathbf{x}, t)$, can be modelled by using a Parzen kernel estimator based on the data set. If a Gaussian kernel function is used the estimator takes the form:

$$\hat{p}(\mathbf{x}, t) = \frac{1}{N} \sum_{n=1}^N \frac{1}{(2\pi\sigma^2)^{(d+c)/2}} \exp \left\{ -\frac{\|\mathbf{x} - \mathbf{x}_i\|^2}{2\sigma^2} - \frac{\|t - t_i\|^2}{2\sigma^2} \right\} \quad (\text{A.64})$$

where;

$\hat{p}(\mathbf{x}, t)$	=	the estimated value of the joint probability density
d	=	dimensionality of the input space
c	=	dimensionality of the output space
N	=	number of training pairs
$(\mathbf{x})$	=	unknown or test vector
$(\mathbf{x}_i)$	=	i^{th} training vector (stored in network)
t_i	=	target value for the i^{th} training example
t_i	=	target value for the test vector
σ	=	smoothing parameter determined during network training
$\ \mathbf{x} - \mathbf{x}_i\ ^2$	=	the square of the Euclidean distance between the test and training vectors (equivalent to their dot product, $\mathbf{x} \cdot \mathbf{x}_i$)

Substituting equation A.64 into A.63 and some manipulation gives estimated value of the target data (Masters, 1995):

$$\hat{y}(\mathbf{x}) = \frac{\sum_{n=1}^N t_i \exp\{-\|\mathbf{x} - \mathbf{x}_i\|^2 / 2\sigma^2\}}{\sum_{n=1}^N \exp\{-\|\mathbf{x} - \mathbf{x}_i\|^2 / 2\sigma^2\}} \quad (\text{A.65})$$

where $\hat{y}(\mathbf{x})$ is the value of the target variable; predicted by the network (i.e. network output). Equation A.65 is known as the *Nadaraya-Watson* estimator (Nadaraya, 1964; Watson, 1964) and it is this procedure that was re-discovered and formulated as a neural network by Specht (1991).

Although, the GRNN can be extended to handle multidimensional output (Zaknich, 1999) in the network proposed by Specht (1991), the target output is a scalar value. Equation A.65 shows that the regression value $y(\mathbf{x})$ is the weighted average of all the values t_i . Huang & Williamson (1994) noted that when the smoothing factor σ approaches zero, $\hat{y}(\mathbf{x})$ assumes the value t_i associated with the value x_i and when σ becomes very large the value of $\hat{y}(\mathbf{x})$ becomes the mean of all t_i values. For intermediate values of σ just the values of t_i in a small neighbourhood contribute to the estimate of the target value.

The architecture of the GRNN is shown in Figure A.14 (Zaknich, 1999). It is very similar to that of the PNN. All the components of the input vector (three are shown) are presented to the network and the input units calculate the Euclidean distance measure (small input layer circles); then the Parzen window function (similar to the activation function) is performed (large circles in input layer). At the output units, the product of y_i with the output of the activation function is calculated (corresponding to the numerator in equation A.65). The signal that is not modified corresponds to the denominator in equation A.65. The two output units perform the summations in numerator and denominator of equation A.65. The output unit performs the division in equation A.65.

Training in a GRNN network consists of finding a single value of the smoothing parameter σ which minimizes the mean square error (MSE) between the network output and the desired output for the test data set. This is done by trial and error. The vector pairs $\{\mathbf{x}, t\}$ of the training data set are incorporated into the network structure (i.e. pattern units contain $\mathbf{x}_i$ and output units store t in Fig. A.14). The mean square error (MSE) for a GRNN with a single output unit is given by:

$$MSE = \frac{\sum_{p=1}^N (\hat{y}_p - u_p)^2}{N} \quad (\text{A.66})$$

Figure A.14. Architecture of a general regression neural network (Zaknich, 1999).

A plot of MSE versus the smoothing parameter σ shows that the variation of MSE with σ is smooth and has a broad minimum (Zaknich, 1999). Although trial and error can yield a suitable value of σ , a convergent optimization algorithm based on recurrent parabolic curve fitting has also been used (Zaknich & Attikiouzel, 1993).

The strengths and weaknesses of the GRNN are similar to those of the PNN discussed previously (refer to page 482). The main advantages of the GRNN are;

- the faster training time compared to the MLP network,
- the fact that there is just one parameter to adjust compared to many in the MLP (learning rate, momentum, batch or pattern update, and the number of hidden nodes) and
- the problem of training in MLP networks leading to a local instead of a global minimum does not exist.

Zaknich (1999) has noted that the fact that the centres of the radial basis functions are determined by the training data vectors means that the network can not be overtrained.

Huang & Williamson (1994) compared the performance of GRNN and MLP networks for two tasks related to oil exploration. For the task of predicting the total organic carbon content of rocks in exploration wells based on wire-line log data. Although a 4-4-1 MLP network performed slightly better than the GRNN, Huang & Williamson (1994) noted that much more time was required to determine the topology and to train the MLP network. In addition, they found that the GRNN required fewer patterns in order to be trained than the MLP network. A second task was the identification of the dominant source rocks (carbonate, deltaic, and marine shale oil) based on the carbon isotopic profiles (i.e. carbon isotopic ratios for 11 crude oil distillation fractions). Only the GRNN was applied to this task. A 95% correct classification rate was achieved including the identification of 6 out of 7 incomplete patterns.

In a comparative study of different mineral prospectivity methods, Harris & Pan (1999) found that a GRNN performed very well but was slightly poorer than the PNN. Using a cut-off value of 0.5 at the network output to categorize input vectors as mineralized (≥ 0.5), the PNN classed 13.6% of the total cells in the study area as mineralized (68.2% correct) versus 13.5% (59.5%) for the GRNN.

A.2.3 Radial Basis Neural Networks

The radial basis neural network (RBFNN) is a type of kernel classifier that uses radial basis activation functions in the hidden layer that depend on a measure of distance between the input vector and the training vector associated with the pattern unit. As in the PNN and GRNN, a smoothing factor controls the diameter of the units receptive field (Broomhead & Lowe, 1988; Moody & Darken, 1989). In contrast with PNN and GRNN networks though, the weights associated with hidden units are not determined by a single training vector and the smoothing parameter σ can be set to different values for each hidden unit (Schalkoff, 1997). Like the GRNN, the RBFNN can be used as a universal function approximator as well as a classifier (Park & Sandberg, 1991).

The concept behind the RBFNN is closely related to distance-weighted regression (Zaknich, 1999). Figure A.15 shows the architecture of an RBFNN. The value computed by each output unit represents the weighted sum of radial basis functions (e.g. Gaussian) that depends on the distance between the input vector to the centroid in input space corresponding to the hidden unit as follows:

Figure A.15. Architecture of a radial basis function neural network (adapted from Zaknich, 1999)

$$y_k(\mathbf{x}) = \sum_{i=1}^M w_{ki} f_i(\|\mathbf{c}_i - \mathbf{x}\|, \sigma_i) \quad (\text{A.67})$$

where;

$y_k(\mathbf{x})$	=	k^{th} output vector
$\mathbf{x}$	=	input vector
w_{ki}	=	weight vector from the i^{th} hidden layer node to the k^{th} output node
c_i	=	centroid of the i^{th} hidden layer node
σ_i	=	smoothing factor for the i^{th} hidden layer node
M	=	number of hidden layer nodes
$f_i(\cdot)$	=	$\exp\{-\ \mathbf{c}_i - \mathbf{x}\ / (2\sigma_i^2)\}$, a Gaussian radial basis function with a smoothing factor, σ_i

Training involves finding suitable values for the position of the centroids (i.e. the position in multidimensional space occupied by the input vectors) represented by the hidden units c_i ; weights from hidden units to output units, w_{ki} ; and the smoothing factors σ_i , for the radial basis functions associated with each hidden layer unit. Although many procedures to do this have been developed, training generally consists of two stages; 1) determination of RBF centroids, and 2) determination of σ_i and the weights from the hidden to output

layer (Schalkoff, 1997).

Various methods exist for determining the centroids, weights and smoothing factors $\mathbf{c}_i$, (w_{ki} and σ_i , respectively) are described by Zaknich (1999);

1. selecting $\mathbf{c}_i$ uniformly or randomly and using Singular Value Decomposition to solve for w_{ki} and σ_i . Each cluster centre or centroid is then represented by a hidden layer unit. The weights are optimized by minimizing an error function (e.g. sum of squares) representing the error between the actual network output and the desired output over the vectors in the training set.
2. orthogonal least squares learning (Chen *et al.*, 1991)
3. use of k-means clustering to determine $\mathbf{c}_i$, a k-nearest neighbour heuristic to determine σ_i , and multiple linear regression to determine w_{ki} (Leonard & Kramer, 1991). The k-means clustering algorithm groups vectors according to a Euclidean-distance measure of similarity.
4. Karri & Frost (1999) compared estimates of σ_i based on the standard deviation of the output vector and by plotting the root-mean-square (RMS) error against σ_i for the training and test data and choosing the value of σ that gave the minimum RMS error.

The value of σ determines how smoothly the network output fits the training data and therefore how well the underlying function is represented and how well the network is able to generalize to new data (Bishop, 1995).

Advantages of the RBFNN include;

1. the fact that the number of basis functions (and therefore hidden layer units) is determined by the complexity of the mapping between the inputs and outputs. This contrasts with the PNN and GRNN, in which the training data set size determines the number of pattern units.
2. there is no local minima problem as in the MLP network (Kasabov, 1996)
3. training is an order of magnitude faster than a comparable MLP network (Kasabov, 1996)

Kasabov (1996) has pointed out that a disadvantage of the RBFNN is that it may not be clear how many hidden units to use and that the choice may adversely affect the performance of the network.

RBFNN have been applied to control applications. One example in mineral processing is the work of Karri & Frost (1999). They used a RBFNN to predict the AlF_3 concentration in electrolyte in electrolysis cells in the aluminium smelting process.

A.2.4 Kohonen Neural Networks

The self-organizing feature map (SOFM), also known as a Kohonen network, uses an unsupervised training scheme (Kohonen, 1982, 1988, 1990). Instead of presenting both inputs together with the correct outputs to the network during training (as in supervised training for MLP, PNN and GRNN networks), just the inputs are used and the network develops its own clustering of the data. Another difference to the networks architectures previously discussed is that the SOFM is almost always used as classifier rather than a universal function approximator like the MLP network, GRNN and RBFNN.

The way in which multidimensional feature space is divided into complex decision regions in order to perform a classification differs between neural network architectures (Lippmann, 1989). MLP networks divide feature space using hyperplanes. In RBFNN and GRNN and PNNs, decision regions are formed by radial basis functions or kernels. The SOFM is an exemplar classifier, in which classification of an unknown feature vector is based on the identity of the training examples that are nearest to the input in multidimensional feature space (Lippmann, 1989). These differences are summarized in Figure A.16

The architecture of the SOFM is shown in Figure A.17. The SOFM is usually arranged into two layers. There is an input unit for each component of the input feature vector. Each of these input units is connected to every unit in the output layer. The output layer is usually arranged as a two-dimensional grid. After the presentation of each input pattern during training, units in the output layer compete with one another to learn. Just the output unit which is closest to the input vector (in terms of distance between the vectors in multidimensional feature space) together with a group of units in the neighbourhood adjacent to the winning cell have their weights adjusted (i.e. learn).

Prior to training, raw data must be pre-processed. Masters (1993b) recommends performing a linear scaling to convert raw inputs to a symmetrical range; e.g. $[-1, +1]$ and normalizing training and test vectors to unit length. This latter step is performed as follows (Strang, 1993);

$$\hat{\mathbf{x}} = \frac{x_i}{l} \quad \text{where } i = 1, 2, \dots, N \quad (\text{A.68})$$

Figure A.16. Range of methods used by neural network types to divide multidimensional feature space into decision regions in order to classify patterns (after Lippmann, 1989).

A. Probabilistic neural network: class probability density functions are estimated using the sum of small multivariate spherical Gaussian distributions centred at each training sample vector. Bayes' decision rule is implemented to assign an unknown vector to the class that it has a maximum likelihood of belonging to.

B. Multilayer perceptron: class regions within multidimensional feature space are divided by decision surfaces known as hyperplanes. MLP networks contain nodes which calculate the weighted sum of the inputs and transform this with a non-linear function. The position of the hyperplanes depend on the connection weights linking the nodes and the threshold or bias input to the nodes.

C. Radial basis function neural network: this type of network contains a hidden layer with radial basis activation (spherical Gaussian). functions that are connected in parallel. These radial basis functions (also referred to as kernel functions) are defined by parameters which control their centroid and spread and are designed to overlap in feature space. Training involves adjusting the parameters and optimizing the output-layer weights which control the linear combination of the kernel functions. Classification of an unknown vector is made according to the class of the output unit with the highest activation.

D. Kohonen network or self-organizing feature map: unknown input vectors are assigned to the same class as the output node that the unknown vector is closest to (in terms of the Euclidean distance in feature space). Output nodes are trained to represent the centroid of clusters of vectors using labelled training examples.

Figure A.17. Architecture of a Kohonen neural network (modified from Dowla & Rogers, 1995; Dayhoff, 1990)

$$l = \|\mathbf{x}\| = \sqrt{\sum_{i=1}^N x_i^2} \quad (\text{A.69})$$

where;

- $\hat{x}_i$ = new value of the i^{th} component of input vector $\mathbf{x}$
- x_i = raw value of the i^{th} component of $\mathbf{x}$
- $\|\mathbf{x}\|$ = length of $\mathbf{x}$
- N = dimensionality of $\mathbf{x}$

According to Masters (1993b) a disadvantage of normalization is that it discards absolute magnitude information. Masters (1993b) proposed using a procedure called z-axis normalization to create an additional synthetic input to overcome the problem.

In order to train the network, weights are initialized to small random values. Then the following two steps are applied;

- determine the output unit with a weight vector that best matches the training input vector; this output node is referenced as the winner,
- update the weight vector of the winner and a neighbourhood of surrounding cells to increase their alignment (i.e. similarity) to the input vector.

The effect of this form of training is to create regions in the output layer that are sensitive to clusters or classes of input patterns. The use of neighbourhoods ensures that once the

learning algorithm has converged, vectors corresponding to output units that are close on the output layer grid respond to similar input patterns; i.e. vectors that are close in input feature space. This means that the patterns are topologically ordered in the output layer (also called the feature map).

The best matching unit is the output unit c with the minimum Euclidean distance between its weight vector and the input vector. This distance is given by;

$$d_c = \min_j \| \mathbf{x} - \mathbf{w}_j \| \quad (\text{A.70})$$

where;

$$\begin{aligned} d_c &= \text{distance for the best matching unit } c, \text{ i.e. the minimum} \\ &\quad \text{distance of all the output-unit vectors } j \\ \mathbf{x} &= \text{input vector for a single training pattern} \\ \mathbf{w}_j &= \text{weight vector associated with the output unit } j \end{aligned}$$

Weights for the best matching unit and its neighbours are updated according to the rule;

$$\mathbf{w}_j(k+1) = \mathbf{w}_j(k) + h_{cj}(k) (\mathbf{x}(k) - \mathbf{w}_j(k)) \quad (\text{A.71})$$

where;

$$\begin{aligned} \mathbf{x} &= \text{input vector for a single training pattern} \\ \mathbf{w}_j &= \text{weight vector associated with the output unit } j \\ k &= \text{time expressed as the training iteration count } k \\ h_{cj}(k) &= \text{neighbourhood kernel function at time } k \end{aligned}$$

The neighbourhood kernel is defined as the area around the best matching output unit c . Usually, the neighbourhood kernel is decreased linearly with time until it reaches a limit of one. At this point the *fine tuning* phase of training continues until some limit is reached. The neighbourhood kernel function at iteration k is given by;

$$h_{cj}(t) = \begin{cases} \alpha(k) & \text{if the unit } j \text{ is within the neighbourhood } N_c(k) \\ 0 & \text{otherwise} \end{cases}$$

where

$h_{cj}(k)$	=	neighbourhood kernel function
$\alpha(k)$	=	learning rate; monotonically decreasing function of time
$N_c(k)$	=	current neighbourhood around best matching output unit

Both the learning rate α and the neighbourhood radius N_{cj} should decrease according to some monotonically decreasing function of time as training progresses until some minimum is reached. Masters (1993b) has recommended a learning rate of 0.5 and Kohonen (1988) recommended that the neighbourhood N_{cj} should be initially set to half the diameter of the output grid. In order that local areas of the output layer specialize their response to certain classes of input patterns, it is important that the learning rate decreases rapidly with distance (Masters, 1993b). This can be achieved by applying a Gaussian function to decrease the learning rate according to the distance measured on the output grid between best matching unit and its neighbours. (Zaknich, 1999):

$$h_{cj}(k+1) = \alpha(k) \exp\{-\|\mathbf{r}_c - \mathbf{r}_j\|^2 / 2\sigma^2(k)\} \quad (\text{A.72})$$

$h_{cj}(t)$	=	neighbourhood kernel function
$\alpha(k)$	=	learning rate; monotonically decreasing function of time
$\sigma(k)$	=	spread parameter for Gaussian function centred around best matching unit c
$\mathbf{r}_c$	=	vector representing the position of the best matching unit c on output grid
$\mathbf{r}_j$	=	vector representing the position of unit j on output grid

Training is halted when the weight changes become insignificant. Masters (1993b) has suggested a number of heuristics to determine; 1) if the learning rate is sufficient, 2) if more output units to represent outlier patterns are required, 3) to optimize specialization by identifying units that represent too wide a variety of patterns, and 4) when to stop training. Hecht-Nielsen (1991) has proposed a conscience algorithm to deal with output units that do not represent any patterns during training.

Once the network has been trained, clusters on the output grid must be labelled to indicate the classes so unknown input patterns can be classified (Beale & Jackson, 1990). This is done using training patterns for which the class is known.

The SOFM network is useful as a clustering algorithm since the number of features in the input feature vector is reduced to clusters represented graphically on the two dimensional output grid. However, Rogers & Kabrisky (1991) have likened the attempt to identify patterns, which span a multidimensional feature space, on the basis of their associations

with units on a 2-D grid to trying to identify animals after they have been squashed flat on the side of a road. Also Masters (1993b) has noted that the SOFM is a weak classifier since it has no hidden units and is therefore strictly linear in its response.

A number of applications of SOFM's have been reported in the geosciences. Maurer *et al.* (1992) have used an SOFM in combination with a fuzzy-logic inference system to identify classes of seismic events as part of an attempt to automate monitoring networks used to verify nuclear test ban treaties. Fung *et al.* (1995) was able to classify six lithologies from wire-line log data using a combination of an SOFM and a Learning Vector Quantization algorithm. Yudong *et al.* (1994) applied an SOFM to predict the presence and absence of mineralization at 25 sample locations. Twenty input variables consisting of assay values of 8 elements and the presence or absence of various structural features (e.g. proximity to certain types of lithological contacts) and rock types were used. Output classes were *mineralized* and *not mineralized*. Yudong (1994) also applied an SOFM to the classification of gossan types using geochemical and mineralogical inputs.

Clare & Cohen (2001) compared an SOFM and a K-means clustering algorithm to perform a cluster analysis on regional stream sediment analyses (comprising 33 elements and 1677 sub-catchments). They found that although the two methods produced similar results, the SOFM was relatively unaffected by the presence of outliers and non-normal populations. Clare & Cohen (2001) produced a series of maps for each cluster identified by the network by colouring catchment areas according to their degree of similarity between the feature vector for that catchment and the vector associated with the particular cluster represented by the output layer of the trained network. A mineral prospectivity map based on this principle was constructed using the PROSPECT EXPLORER software package by Clare *et al.* (1997). In this case the map is coloured according to the similarity of vectors associated with grid cells and the cluster type representing anomalous characteristics associated with mineralization.

STRATIMAGIC is another commercial system that incorporates an unsupervised neural network classifier (Addy, 1998; Neri, 1999). The system produces seismic facies maps based on the trace shapes (due to phase, frequency and amplitude) in seismic reflection data. Textural classes can be labelled using patterns associated with wells where the lithologies are known.

A.2.5 Hybrid Fuzzy-Neural Network Systems

Since the early 1990's there has been considerable interest in methods for combining neural networks and fuzzy systems. Much of the research has been directed towards solving complex non-linear control problems in engineering (Jang & Sun, 1995; Kasabov, 1996). The reason for combining the two methods is that they appear to complement one another. Whilst both methods can deal with uncertain and imprecise inputs, neural networks represent a data-driven approach, whereas fuzzy systems represent a conceptual approach. Neural networks can detect very complex patterns in data but fuzzy systems are able to incorporate expert knowledge, which neural networks cannot do directly. It has been shown that combining the two approaches can increase performance and speed up system development (Lazzerini *et al.*, 1999). Huang *et al.* (1996) found that a modified version of the fuzzy neural network proposed by Lin & Cunningham (1995) resulted in faster convergence and a lower test set error than an MLP network, which was trained using the backpropagation algorithm.

Three main ways of combining neural networks and fuzzy systems have been described in the literature (Gupta & Rao, 1994; Jang & Sun, 1995; Kasabov, 1996)

1. fuzzy neurons,
2. multi-modular hybrid neural network-fuzzy systems, and
3. adaptive network-based fuzzy inference systems (ANFIS).

In fuzzy neurons, the computations are based on fuzzy membership functions (Yamakawa, 1990). Modular hybrid neural network-fuzzy systems contain fuzzy inference and neural network systems which act together in a sequential modular way. The neural network inputs and outputs are crisp whereas the fuzzy system uses fuzzy linguistic variables. Consequently, conversions to and from fuzzy variables (referred to as fuzzification and defuzzification,) must be performed. This type of system is described by Kasabov & Jain (1990, 1993), Kasabov *et al.* (1994), and Masters (1993b). Kohonen (1988) describes a speech recognition system in which a self-organizing map is used for the low-level task of phoneme recognition and a fuzzy inference system is used to apply rules about word context to improve the accuracy of the system.

A class of systems called adaptive fuzzy inference systems (ANFIS) has been developed independently by Jang (1991, 1993), Lin & Lee (1991), and Wang & Mendel (1992). In these systems, fuzzy *if-then* rules and membership functions are represented as nodes in a feedforward network structure. The membership functions can be adapted through super-

vised training and a hybrid backpropagation-least mean squares learning algorithm (Jang & Sun, 1995). The advantage of ANFIS's are that they; 1) achieve better performance than either fuzzy systems or neural networks alone and 2) they can incorporate linguistic knowledge from experts (in the form of stored rules) and adapt to numerical training data. ANFIS's have been applied to control a steam engine-boiler system (Mamdani & Assilian, 1975), control part of a steel rolling mill (Funabashi *et al.*, 1995), analyze of ultrasonic images, (Pavlopoulos *et al.*, 2000), assist in medical diagnosis (Zahlmann *et al.*, 2000), and diagnose faults in motors (Fuessel, 2000).

Comparison of Boolean and Fuzzy Inference

Both the modular and adaptive fuzzy systems depend on a fuzzy inference procedure. An inference procedure is used to derive conclusions from a set of fuzzy *if-then* rules and one or more conditions. In two-valued Boolean logic, the fundamental rule of inference is called *modus ponens* (Cawsey, 1998), which is summarized as:

$$A \wedge (A \rightarrow B) \rightarrow B \quad (\text{A.73})$$

It states that the truth of a proposition B can be inferred from the truth of a condition A and the implication $A \rightarrow B$. For example, a rule such as “*if distance to fold axis is low then favourability for gold deposits is high*” can be represented in the following syllogism.

premise 1	(fact)	x is A
premise 2	(rule)	If x is A then y is B
<hr/>		
conclusion		y is B

In Boolean logic, the premise and conclusion can either belong to the set *true* completely or not at all. In contrast, in fuzzy set theory, a variable can belong to a set partially and the degree of membership is expressed as a real number in the range $[0,1]$ (Zadeh, 1965).

Fuzzy membership functions are used to quantify the x is A and y is B parts of premises 1 and 2 in the syllogism above. For example, if crisp sets in the *if-then* rule; “*if distance to fold axis is high*” are replaced by fuzzy sets then the rule becomes; “*if distance to fold axis is low then favourability for gold deposits is more or less high*”. The rule can be represented as a syllogism as follows;

premise 1	(fact)	x is A'
premise 2	(rule)	If x is A then y is B
<hr/>		
conclusion		y is B'

where A' is close to A and B' is close to B (Jang & Sun, 1995).

Processing Steps in a Fuzzy Inference System

Processing in a fuzzy inference system consists of the following steps;

1. convert input variables to membership degree (fuzzification) using fuzzy membership functions,
2. combine antecedents to determine the *firing strength* of rules using fuzzy operators (e.g. fuzzy *AND* and *OR*),
3. calculate consequent membership functions (MFs) based on the firing strength using an implication operator,
4. combine the consequent MFs (i.e. output of rules) using an aggregate operator, and
5. conversion of fuzzy membership degree to crisp values (defuzzification),

In a single fuzzy *if-then* rule of the form

If x is A then y is B ,

the first two steps are required to evaluate the premise or antecedent part of a fuzzy *if-then* rule. The *if*-part of the rule “ x is A ” is called the premise or *antecedent* while the *then*-part of the rule is called the “ y is B ” is called the *consequent* or conclusion.

The first five steps are illustrated in a example (Fig A.18; adapted from Jang *et al.*, 1997). All of the processing steps listed above are discussed in the following sections. The system only contains two rules in which the parameters are the *distance to the nearest fault or shear zone* and the *rheological contrast at the nearest lithological boundary*. Two fuzzy variables for each rule, low and high, express the degree of favourability of the conditions in map cells for gold deposits. The discussion focusses on the rule 1 in Figure A.18.

The first step is to convert crisp values of distance (= 1000 m, in left-hand column) to a membership degree for the fuzzy set *low*. From the fuzzy membership function for *distance is low*, it can be seen that the degree is approximately 0.9. The rheological contrast (=

8, in column 2) belongs to the fuzzy set *rheological contrast moderate* to a degree 0.2 (Fig. A.18).

In the second step, the two input conditions in rule 1 are combined using a fuzzy AND operator. In the example shown in Figure. A.18, AND operator is implemented by taking the minimum of the fuzzy membership degrees for the two antecedent parts of the rule (indicated by the horizontal dashed line which is continued across to the right-hand column).

The third step is to determine the output of the rule. The output of each rule is a fuzzy membership function (shown the right-hand column, Fig. A.18). This membership function describes the degree to which crisp values of “favourability for gold deposits” belong to the fuzzy set *low*. This output fuzzy membership function is modified according to the degree to which the input conditions of the rule are satisfied. The approach is as follows; if the input conditions to a rule are only partially fulfilled, then the result of the rule can only be partially fulfilled. Consequently, the minimum value of the input conditions (horizontal dashed line at $y = 0.2$) is used to truncate the output fuzzy membership function for rule 1.

The fourth step is to combine the results of the rules. In this example, the *max* is used to take the maximum value of the output membership functions for rules 1 and 2, giving an aggregate membership function. The fifth step is to convert this aggregate membership function to a single crisp value. This is done by taking the x -value corresponding to the centroid (i.e. centre of mass) of the shape.

Conversion of Input Variables to Membership Degree using Fuzzy Membership Functions

A fuzzy set $A = \{(x, \mu_A(x)) \mid x \in X\}$ can be represented as a sequence of value/membership pairs; for example, $\{(1/0), (2/0), (3/0.5), (4/1), (5/0.5), (6/0)\}$. Another way of representing a fuzzy set is with a membership function such as the ones shown in Figure A.18 above and in Figure 2.1 on page 24). In Figure 2.1, the linguistic variable *amount of gold* has three fuzzy values; i.e. background, weakly anomalous, and strongly anomalous, each of which is represented by a fuzzy set.

As noted in Section 2.2.3 on page 21, the definition of a membership function is often subjective. In real-time control applications, membership functions composed of straight-line segments are often chosen because of their simplicity and computational efficiency

Figure A.18. An example of a Mamdani fuzzy inference procedure for two rules and two premises. The Mamdani inference system uses the max-min composition, and $\min$ and $\max$ for the for the T-norm (AND) and T-conorm (OR) operators, respectively (modified from Jang & Gulley, 1995).

(Kosko, 1992). An example is the triangular membership function. It is specified by three parameters a , b and c , which determine the x coordinates of the three corners. The membership value is given by Schalkoff (1997):

$$\mu_{triangle(a,b,c)} = \max \left[\min \left(\frac{x-a}{b-a}, \frac{c-x}{c-b} \right) \right] \quad (\text{A.74})$$

In applications where real-time response is not critical and an neural network is used to simulate the behaviour of a fuzzy inference system, smooth non-linear membership functions such as the Gaussian or generalized bell (sigmoidal) (Halgamuge & Glesner, 1994) function can be used. Equations A.75 and A.76 shown the bell and Gaussian membership functions, respectively (Schalkoff, 1997);

$$\mu_{bell(x,a,b,c)} = \frac{1}{1 + \left\| \frac{x-c}{a} \right\|^2 b}, \quad \text{where } b > 0 \quad (\text{A.75})$$

$$\mu_{Gaussian(x,c,\sigma)} = \exp[-(x-c)/\sigma]^2 \quad (\text{A.76})$$

In equation A.76, c and σ represent the centre and width of the membership function, respectively. Both the form of the fuzzy membership function (Masters, 1993b) and the number of fuzzy values used to represent the fuzzy variable is crucial for a fuzzy system (Kasabov, 1996). For example, the variable *temperature* could be represented by linguistic variables and corresponding fuzzy sets, *very cold*, *cold*, *medium*, *hot*, and *very hot*. Kosko (1992) used seven fuzzy values and trapezoidal membership functions with a 25 functions are discussed in detail by Schalkoff (1997) and Kasabov (1996).

Using Fuzzy Operators to Evaluating the Firing Strength of Rules

Fuzzy membership values express the degree to which each part of the antecedent of a rule is satisfied. Where the antecedent is composed of multiple parts as in the rule;

If x is A and y is B then z is C ,

fuzzy operators are used to combine the two fuzzy membership values in the antecedent to obtain a single number which describes the *firing strength* of the rule.

Fuzzy intersection is applied to antecedents linked with *AND* and a fuzzy union is applied to antecedents linked with *OR* (step 2 in Fig A.18). The most common method for combining antecedents linked with *AND* is to use the *min* (minimum) operator. The intersection of two fuzzy sets A and B is a fuzzy set C whose membership function (MF) is related to the MFs for A and B by;

$$\mu_C(x) = \min(\mu_A(x), \mu_B(x)) = \mu_A(x) \wedge \mu_B(x) \quad (\text{A.77})$$

The union of two fuzzy sets (i.e. those combined with *OR*) is implemented using the maximum method;

$$\mu_C(x) = \max(\mu_A(x), \mu_B(x)) = \mu_A(x) \vee \mu_B(x) \quad (\text{A.78})$$

A variety of other fuzzy operators are available. For example, a general class of operators known as T-norm operators that include the *prod* (product) operator are used to perform fuzzy intersection. Similarly, there are also a variety of fuzzy union operators called T-conorm operator (e.g. the probabilistic *OR* operator, $\text{prob}(a, b) = a + b - ab$). In addition a range of *parameterized* T-norm and T-conorm operators have been proposed (Jang *et al.*, 1997) to perform fuzzy *AND* and *OR* functions, respectively.

Using Implication Operators to Calculate Consequent Membership Functions

In fuzzy implication, the antecedent part of the *if-then* rule is represented by a single number (referred to as the firing strength of the rule). The output of a rule or consequent is an entire fuzzy set represented as an MF. Fuzzy implication involves modifying the consequent MF according to the degree to which the antecedent part of the rule is satisfied.

Two main implication methods are used in the Mamdani fuzzy model. These are the *min*, which truncates the output fuzzy set, and the *algebraic product* function, which scales the output fuzzy set. The consequent membership is modified using the *min* function in step 3 in Fig A.18).

Using Aggregate Operators to Combine the Output of Rules

In the Mamdani inference system (Mamdani & Assilian, 1975), the truncated output fuzzy membership functions obtained for each rule are combined with the fuzzy OR function (implemented using the *max* operator; step 4 in Fig A.18). This procedure is applicable if the conclusions of the rules have the same domain for the fuzzy set (e.g. all the rules represent degrees of membership of the fuzzy set *favourable for gold deposits*; Masters, 1993b). Other methods, depending on the inference model used (e.g. Sugeno or Tsukamoto models) include the *sum* (the sum of the output of each rule) and the probabilistic OR function (Jang & Sun, 1995). Kosko (1992) has suggested that arithmetic addition of membership functions gives better results although this option is only appropriate where max-product composition is used.

Conversion of Fuzzy Membership Degree to Crisp Values (Defuzzification)

In the Mamdani inference system the result of combining the outputs of each rule is a single fuzzy membership function. Defuzzification is the process of converting this aggregate output fuzzy membership function to a single crisp value. The crisp value can be obtained from the following characteristics of the aggregate fuzzy membership function (Fig. A.19);

1. centroid of area (the most widely used method),
2. bisector of area,
3. mean of the range of the crisp variable over which the membership degree is at a maximum,
4. smallest of maximum (the smallest value of the crisp variable over which the membership degree is at a maximum), and
5. largest of maximum (the largest value of the crisp variable over which the membership degree is at a maximum).

In practice the need to perform defuzzification in the Mamdani fuzzy inference system has two disadvantages. First, it is time consuming to compute and second, the process is not easily subject to rigorous mathematical analysis (Jang & Sun, 1995). In the Sugeno fuzzy model, which overcomes this problem, fuzzy rules have the form;

$$\text{If } x \text{ is } A \text{ and } y \text{ is } B \text{ then } z = f(x, y)$$

Figure A.19. Methods for converting the aggregate output fuzzy membership function to a single crisp value. This process is known as defuzzification (see text for explanation; from Jang *et al.*, 1997).

where A and B are fuzzy sets in the antecedent, and $z = f(x, y)$ is a crisp function in the consequent. The output $f(x, y)$ is either a constant (zero-order Sugeno model) or a first-order polynomial (first-order-Sugeno model).

How Rules are Represented in a Neuro-Fuzzy Inference System

Figure A.20 shows the ANFIS architecture used to implement a simple fuzzy system consisting of two input variables x and y and two rules. This structure corresponds to a first-order Sugeno model with the following rules;

If x is A_1 and y is B_1 then $f = p_1x + q_1y + r_1$

If x is A_2 and y is B_2 then $f = p_2x + q_2y + r_2$.

These rules are represented within the ANFIS by the links between layer 1 and layer 2. In order to illustrate this, the rules above have are applied to a geological example giving;

If *Distance* is low and *Contrast* is low then favourability is high

If *Distance* is high and *Contrast* is high then favourability is moderate

where distance is the distance to the nearest fault or shear zone, contrast is the rheological contrast between adjacent rock units at the nearest lithological boundary, and favourability is the favourability for gold deposits.

The output of nodes in layer 1 are fuzzy membership values which express the degree to which the input variables belong to the fuzzy set represented by a particular node. In Figure A.20, the top node in layer 2 receives input from node 1 indicating the degree to which *distance* is low and an input from the node 4, indicating the degree to which *contrast* is low. Links corresponding to rules 1 and 2 are shown in red and blue, respectively.

The example has been simplified so that the rules for this example illustrating the Sugeno system in Figure A.20 are the same as those used in the example of a Mamdani fuzzy model shown in Figure A.18. Normally, the rules would cover a complete range of fuzzy sets in the antecedent (i.e. *low*, *moderate* and *high* for both input variables and the output MF's of the rules would comprise *low*, *moderate* and *high* favourability). Thus, for two variables (*distance* and *contrast*, both of which can belong to three fuzzy sets (*low*, *moderate* and *high*), nine rules would be required to cover all combinations.

Although, the general procedure for the Mamdani and Sugeno fuzzy models illustrated in Figures A.18 and A.20 is the same, the processing steps are performed differently. In the Mamdani model shown, the rule firing strength is determined using the *min* function, the rule output MF is truncated using *min* function, the aggregate output of all rules is determined with the *max* function, and defuzzification is performed using the centroid of area of the aggregate MF. In contrast, in the Sugeno model (Fig. A.18), the rule firing strength is determined using the *prod* function, the rule output MF is determined using a first-order polynomial expression involving the input variables and the overall output is calculated as a crisp value, without defuzzification, by calculating the weighted average of the rule outputs (calculated using the normalized firing strengths).

Architecture of an Adaptive Neuro-Fuzzy Inference System (ANFIS)

The functionality of the layers in the ANFIS (Fig. A.20) are summarized from Jang & Gulley (1995), Jang & Sun (1995) and Jang *et al.* (1997) below.

Layer 1 Inputs are converted to fuzzy membership values by applying fuzzy membership functions as follows;

$$\begin{aligned} O_{1,i} &= \mu_{A_i}(x) \text{ for } i = 1, 2 \\ O_{1,i} &= \mu_{B_i}(y) \text{ for } i = 3, 4 \end{aligned}$$

where x and y are input variables, μ_{A_i} and μ_{B_i} are membership functions, and $O_{1,i}$ represents the output of the i^{th} node in layer 1. Input variables are converted to

Figure A.20. ANIFS architecture for two rules and two variables using a Sugeno fuzzy inference model. Layer 1 converts inputs to fuzzy membership values using fuzzy membership functions that are specified by three parameters (a , b and c). In layer 4, the output of each rule is given by a first-order polynomial containing three parameters (p , q and r). These parameters are adapted during training. Links corresponding to rules 1 and 2 are shown in red and blue, respectively (modified from Jang & Gulley, 1995).

fuzzy membership values according to parameterized fuzzy membership functions, such as the bell function;

$$\mu_{bell}(x,a,b,c) = \frac{1}{1 + \left\| \frac{x-c}{a} \right\|^2 b}, \quad \text{where } b > 0$$

The parameters a , b , and c are different for each node and are *adapted* during training.

Layer 2 The output of each node in this layer represents the firing strength of the rules which are obtained by calculating the product of the inputs;

$$O_{2,i} = w_1 = \mu_{A_i}(x) \mu_{B_i}(y),$$

where $i = 1, 2$ (rule number). The fuzzy AND operator is implemented using the *prod* function. The number of nodes in layer 2 is equal to the number of rules in the fuzzy system.

Layer 3 Nodes in this layer calculate the normalized firing strengths of the i^{th} rule;

$$O_{3,i} = \bar{w}_1 = \frac{w_i}{w_1 + w_2},$$

where $i = 1, 2$ (rule number) and $\bar{w}_1$ is the normalized firing strength.

Layer 4 Each node in this layer takes the normalized firing strength of a single rule from the previous layer as its input and determines the shape of the fuzzy set that represents the consequent or output of the rule. Using the first-order Sugeno fuzzy implication model, the output of the i^{th} node of layer 4 is given by;

$$O_{4,i} = \bar{w}_i f_i = \bar{w}_i(p_i x + q_i y + r_i),$$

where $i = 1, 2$ (rule number), $\bar{w}_i$ is the normalized firing strength and p_i , q_i and r_i are *adaptable* consequent parameters.

Layer 5 The node in this layer aggregates the outputs of the two rules by summing them;

$$O_{5,i} = \sum_i \bar{w}_i f_i,$$

where $i = 1, 2$ (rule number), and $\bar{w}_i$ is the normalized firing strength, and f_i is the first-order polynomial $f_i = (p_i x + q_i y + r_i)$ representing the output of rule i .

As noted previously, the Mamdani fuzzy inference system shown in Figure A.18 uses the max-min composition (i.e. minimum, and *min* and *max* for the for the T-norm (*AND*) and T-conorm (*OR*) operators, respectively. The corresponding ANFIS network to implement this system would be slightly different to the Sugeno fuzzy model shown in Figure A.20. First, in the layer 2, the *min* function would be used to combine the precedent parts of the rules (i.e. firing strength). Second, the calculation of the normalized firing strengths in layer 3 is not required. Fourth, the polynomial functions in layer 4 nodes would be replaced by a single node that uses the *max* function to aggregate the output fuzzy membership function from all the rules. Finally, the function of layer 5 would be to apply a discrete approximation algorithm to calculate the centroid of the aggregate output fuzzy set to give a single crisp output value.

Training to Adapt Fuzzy Membership Parameters and Weights in an ANFIS

Two layers in the ANFIS contain adaptable parameters that are modified during training. Each node in layer 2 contains three premise parameters that determine the shape of the fuzzy membership functions used to convert inputs to fuzzy membership degrees. There is a separate membership function for each fuzzy variable (e.g. *low* and *high* distance, and *low* and *high* rheological contrast). In layer 4, each node contains three consequent parameters. These are the coefficients in the polynomial functions used to calculate the rule outputs. There is a node for each rule in layer 4.

Hybrid learning is performed in two steps. In a forward pass, the premise (membership function) parameters are fixed, and the signals are calculated up to layer 4. This is done for all the training input and output pairs. In layer 4, the consequent parameters are estimated by the least squares method using the formula for the Least Squares Estimator (LSE) (equation A.85; see discussion below) or the recursive least squares procedure (Jang *et al.*, 1997). Once the consequent parameters have been determined, the overall output and therefore the errors for each training pattern can be calculated. In the backward pass, the consequent signals are fixed and the error signals are propagated backwards to layer 2. The premise parameters are then updated using a gradient descent method similar to that described in Section 2.4.5. The update formula for a generic parameter α is given by;

$$\Delta\alpha = -\eta \frac{\partial^+ E_p}{\partial \alpha} \quad (\text{A.79})$$

where η is the learning rate, E_p is the error measure for pattern p , and ∂^+ is the ordered partial derivative (Jang *et al.*, 1997).

Expanding the formula given in step 4 above, the overall output f of the ANFIS can be re-written as;

$$\begin{aligned} y &= \bar{w}_1(p_1x + q_1y + r_1) + \bar{w}_2(p_2x + q_2y + r_2) \\ y &= (\bar{w}_1x)p_1 + (\bar{w}_1y)q_1 + (\bar{w}_1)r_1 + (\bar{w}_2x)p_2 + (\bar{w}_2y)q_2 + (\bar{w}_2)r_2 \end{aligned} \quad (\text{A.80})$$

This can be considered as a linear expression where the consequent parameters are the coefficients. In order to represent this linear equation in more general terms, the consequent parameters p_1, q_1, r_1, p_2, q_2 and r_2 are replaced with $\theta_1, \dots, \theta_n$, x and y are replaced with input vector $\mathbf{u} = [u_1, \dots, u_p]^T$, and $\bar{w}_1x, \bar{w}_1y, \bar{w}_1r_1, \bar{w}_2x, \bar{w}_2y$ and $\bar{w}_2r_2$, are replaced with $f_1 \dots f_n$ which are functions of $\mathbf{u}$, giving;

$$y = \theta_1 f_1(\mathbf{u}) + \theta_2 f_2(\mathbf{u}) + \dots + \theta_n f_n(\mathbf{u}). \quad (\text{A.81})$$

This equation is a linear regression function. An equation can be written relating each pair of input feature vectors and target output values in the training data set. For m training patterns and n parameters this gives a set of m linear equations;

$$\left\{ \begin{array}{lcl} f_1(\mathbf{u}_1) \theta_1 + f_2(\mathbf{u}_1) \theta_2 + f_n(\mathbf{u}_1) \theta_n & = & y_1 \\ f_1(\mathbf{u}_2) \theta_1 + f_2(\mathbf{u}_2) \theta_2 + f_n(\mathbf{u}_2) \theta_n & = & y_2 \\ \vdots & & \vdots \\ f_1(\mathbf{u}_m) \theta_1 + f_2(\mathbf{u}_m) \theta_2 + f_n(\mathbf{u}_m) \theta_n & = & y_m \end{array} \right. \quad (\text{A.82})$$

This can be written in matrix notation as:

$$\mathbf{A} \theta = \mathbf{y}, \quad (\text{A.83})$$

$$\text{where; } \mathbf{A} = \begin{bmatrix} f_1(\mathbf{u}_1) & \cdots & f_n(\mathbf{u}_1) \\ \vdots & \vdots & \vdots \\ f_1(\mathbf{u}_m) & \vdots & f_n(\mathbf{u}_m) \end{bmatrix}, \quad \theta = \begin{bmatrix} \theta_1 \\ \vdots \\ \theta_n \end{bmatrix}, \quad \mathbf{y} = \begin{bmatrix} y_1 \\ \vdots \\ y_n \end{bmatrix}$$

The least squares estimator (LSE) $\hat{\theta}$ is the best solution of the system of linear equations which minimizes the sum of squared error $\|\mathbf{A} \theta - \mathbf{y}\|^2$ and satisfies the *normal equation*;

$$\mathbf{A}^T \mathbf{A} \theta = \mathbf{A}^T \mathbf{y}, \quad (\text{A.84})$$

and provided that $\mathbf{A}^T \mathbf{A}$ is singular, $\hat{\theta}$ is unique (Jang *et al.*, 1997). The LSE $\hat{\theta}$ is given by;

$$\hat{\theta} = (\mathbf{A}^T \mathbf{A})^{-1} \mathbf{A}^T \mathbf{y}. \quad (\text{A.85})$$

Jang *et al.* (1997) also describes a recursive method for calculating the least squares estimator.

Advantages of Hybrid Neuro-Fuzzy Inference Systems

At present there are no applications of hybrid neuro-fuzzy systems in the geosciences. Sun & Jang (1993) have applied an adaptive network-based neuro-fuzzy inference procedure to data classification. A hybrid modular fuzzy neural network system for selecting optimal sites for land development using geographic data has been described by Kasabov & Trifonov (1993).

Although neuro-fuzzy systems are varied in their architecture and mode of operation, general advantages of a combined approach include;

1. a combined approach allows both expert knowledge and training data to be incorporated into the system

2. performance of hybrid systems is often superior to that of the component systems used individually, and
3. modular hybrid and adaptive fuzzy inference systems are often easier to develop than alternative neural network or static fuzzy systems.

Appendix B

Documentation of GIS Databases

B.1 Directory Structure of GIS Databases on CD-ROM

CD volume 1 contains a copy of all the primary and derived ARCVIEW GIS thematic layers and associated database tables used in the Kalgoorlie case study. In addition, CD volume 1 contains the code for C++ programs used in the Tenterfield pilot study and the MATLAB scripts and functions used in the Kalgoorlie case study, and a text file which explains the meaning of the abbreviated ARCVIEW layer names.

CD volume 2 contains mineral prospectivity maps and input GIS layers in GEOSOFT format, and software to install a GEOSOFT viewer.

B.2 Metadata for the GIS Data Sets

B.2.1 What are Metadata?

Metadata provides information about the characteristics of a data set. For example, metadata at a summary level of detail describe the content, geographic extent, date of collection or compilation, positional accuracy, source and contact details for the custodian of the data set. This enables data sets to be indexed and allows potential users to determine which data exist for a particular geographic location, assess the usefulness of the data for a specific purpose, and acquire the data set or obtain further information from the custodian.

Table B.1: Directory structure of GIS databases on the CD-ROM

CD-ROM 1	
Directory name	Description
<i>polygon_layers</i>	Vector (point, line & polygon) layers; e.g. deposits, faults and solid geology
<i>raster_layers</i>	Raster layers (cell size = 100 m); i.e. all derived GIS layers
<i>info</i>	ARCVIEW attribute tables for vector layers; e.g. MINDEX deposit DB
<i>arcview.apr</i>	ARCVIEW project file for Kalgoorlie GIS database
<i>Matlab programs</i>	MATLAB scripts and functions for pre- & post-processing, neural networks, and fuzzy logic
CD-ROM 2	
Directory name	Description
<i>geosoft maps</i>	Top-level directory containing input GIS layers and prospectivity maps
<i>maps neural</i>	Neural-network mineral prospectivity maps; entire study area
<i>maps noise</i>	NN-prospectivity maps created with noise-augmented training sets
<i>maps fuzzy systems</i>	Fuzzy logic mineral prospectivity maps
<i>maps fuzzy neural</i>	Fuzzy-neural-network mineral prospectivity maps
<i>maps detail neural</i>	Neural-network mineral prospectivity maps; area around Coolgardie
<i>maps detail noise</i>	Noise-augmented, NN mineral prospectivity maps; area around Coolgardie
<i>maps detail fuzzy</i>	Fuzzy logic mineral prospectivity maps; area around Coolgardie
<i>maps detail fuzzy neural</i>	Fuzzy-neural-network mineral prospectivity maps; area around Coolgardie
<i>maps base map</i>	Base map with geographic and AMG coordinates and scale
<i>maps location</i>	Maps of Western Australia showing location of study area
<i>grids</i>	Raster layers used to create input GIS and prospectivity maps
<i>input gis layers</i>	Input layers and prospectivity maps with geographic and AMG coordinates
<i>tbl</i>	Tables required by GEOSOFT for legend colour schemes

Detailed metadata provides information that may be needed by users to access, process and interpret the data supplied in digital format by transfer or purchase from another organization. For example a thematic layer in a GIS package may be stored in Arc/Info Export Format or MAPINFO Interchange Format (MIF) or the scheme used to encode an image may be Band Interleaved by Line (BIL), Band Interleaved by Pixel (BIP) or Band Interleaved Sequential (BSQ). Entities, attributes and domains for information stored in database tables must be documented in order for users to correctly interpret and maintain the data.

Metadata are particularly important for digital geospatial data sets because metadata is not normally a part of the data set itself. In contrast, a paper map usually contains printed information about the date of compilation, projection, grid system and details of the individuals and organization responsible for producing it. Further, the content and method used to encode digital data may not be clear as it is for a paper map with a legend.

B.2.2 Metadata Standards

The metadata used to document the data sets used in this study follow the recommendations of the Australia New Zealand Land Information Council (ANZLIC) and the United States Federal Geographic Data Committee (FGDC).

Australia New Zealand Land Information Council (ANZLIC) Guidelines

ANZLIC is the main body responsible for coordinating the management of geospatial information in Australia. One of the main tasks of ANZLIC is to develop and implement a nationally consistent geographic data directory system using summary-level metadata. ANZLIC has published a guide which defines a minimum number of characteristics, which should be described at the summary level, called core metadata elements ANZLIC (1996). This is the mandatory information required for the national metadata directory system and is general enough to be independent of the type of data involved.

ANZLIC only provides a guide to the content and format for a minimum amount of summary metadata. These core metadata items are also referred to as Page 0 within the hierarchical metadata framework proposed by ANZLIC. In addition to Page 0, state or theme-based directories contain more detailed metadata (referred to as Page 1). These types of metadata contain general descriptions of the data sets and information about the custodian of the data. Agency-based directories collect and maintain more detailed metadata (referred to as Page 2 metadata) in addition to the information prescribed by the standards for the first two categories. The Australian National Geoscience Information System (NGIS) is an example of a theme-based or page-0-type directory and the Minerals and Energy Airborne Geophysics Information Exchange (MAGIX), a Geographic Information System-based register and index of airborne geophysical surveys reported to the Department of Minerals and Energy Western Australia, is an example of an agency-based directory.

Unfortunately, ANZLIC does not provide details on the type and format of metadata to

be included in Page 1 and Page 2 categories. Instead, it is only suggested that additional information be consistent with the corresponding metadata elements in the U.S. Federal Government Data Committee (FGDC) content standard FGDC (1998).

Federal Government Data Committee(FGDC)Guidelines

The U.S. Federal Government Data Committee (FGDC) provides very detailed information about how to document spatial data stored in electronic form. The FGDC standards FGDC (1998) specifies the names, format and type of content for 220 items which describe digital geospatial data sets. The FGDC metadata standard was used as a basis for the draft International Organization for Standardization's metadata standard (ISO Metadata Standard 14056 Part 15).

B.2.3 Metadata Format used in This Study

Both the ANZLIC metadata guidelines and the FGDC metadata standard are used to document the data sets which were used in this study. The ANZLIC guidelines are used for summary information about each data set (e.g. Kalgoorlie data set, Appendix D) or category of data, where a data set has multiple sources (e.g. the Tenterfield intrusion-hosted gold deposit). Additional items from the FGDC metadata standard, which are relevant to the data set being described, are used to provide more detailed information. The format of the metadata presented in this study is the same as that used by the Department of Minerals and Energy, Western Australia, and is based on a sample metadata file for the Bangemall Basin data set provided by Steve Bandy (Manager, Geoscience Data Management, Geological Survey of Western Australia; Bandy, 1997).

B.3 Data Dictionaries for GIS Database Layers

B.3.1 Data Dictionaries for Spatial Attributes

A data dictionary is provided for each thematic layer in the GIS databases. A data dictionary describes the attributes stored in a database table associated with a thematic layer. The attributes are equivalent to the column headings in the table and are also referred to as fields or items. Each data dictionary contains the following information: name of the thematic layer (also referred to as coverage), coverage class (point, line, polygon), and for each attribute; the attribute name, attribute type and a brief description.

In the ARCVIEW GIS package, different attribute types are described by the following codes;

B = binary integers,
 C = a character of ASCII text,
 D = data in format YYYYMMDD,
 F = decimal number stored in internal floating point format,
 I = integer, and
 N = decimal number.

Database tables associated with thematic layers contain two types of attributes; spatial and non-spatial. In ARC/INFO and ARCVIEW, the spatial attributes are generated automatically and appear in the left-most columns of the database table. The internal spatial attributes differ according to whether thematic layer contains point, line or polygon data. The internal spatial attributes generated by Arc/Info for point and polygon coverages are shown in Table B.2 below.

Table B.2: Spatial attributes generated automatically by ARC/INFO for point and polygon coverages

Item names	Type	Item description
AREA	F	Area of polygon calculated by ARC/INFO. Set to zero for point coverages.
PERIMETER	F	Perimeter of polygon calculated by Arc/Info. Set to zero to point coverage.
<coverage_name>#	B	Internal number of point/polygon assigned and maintained by Arc/Info.
<coverage_name>-ID	B	Unique user-assigned point/polygon identifier. If not assigned by user, defaults to <coverage_name>#.

The internal spatial attributes generated by ARC/INFO for line coverages are shown in Table B.3 below. In the ARCVIEW GIS package, there is a single file type for all vector coverages (i.e. all data stored as points, lines and polygons) called a shape file. The spatial attributes generated automatically for shape files are shown in Table B.4 below.

Table B.3: Spatial attributes generated automatically by ARC/INFO for line coverages

Item names	Type	Item description
FNODE#	F	Internal number of the from-node. Arc starts at From-node.
TNODE#	F	Internal number of the to-node. Arc ends at to-node.
LPOLY#	B	Left polygon number assigned and maintained by ARC/INFO.
RPOLY#	B	Right polygon number assigned and maintained by ARC/INFO.
LENGTH	F	Length of arc measured in coverage units.
<coverage_name>#	B	Internal number of arc assigned and maintained by ARC/INFO.
<coverage_name>-ID	B	Unique user-assigned line identifier. If not assigned by user, defaults to <coverage_name>#.

Table B.4: Spatial attributes generated automatically by ARCVIEW for point, line and polygon coverages

Item names	Type	Item description
SHAPE	B?	Type of coverage: point, line or polygon
AREA	F	Area of polygon calculated by ARC/INFO. Set to zero for point coverages.
PERIMETER	F	Perimeter of polygon calculated by ARC/INFO. Set to zero to point coverage.
<coverage_name>#	B	Internal number of point/polygon assigned and maintained by ARC/INFO.
<coverage_name>-ID	B	Unique user-assigned point/polygon identifier. If not assigned by user, defaults to <coverage_name>#.

Appendix C

Metadata for Tenterfield GIS Database

C.1 Location of the Tenterfield Data Set

The Tenterfield data set used for the pilot study described in Chapter 4 corresponds to the area of the Tenterfield 1:100000 sheet (map 9339). The area is located in north eastern New South Wales and represents part of the southern portion of the New England Orogen (Fig. C.1 below).

The boundary of the Tenterfield 1:100000 map sheet is defined in geographic coordinates. Coordinates of the map corners in both geographic coordinates and Australian Map Grid (AMG) coordinates are given in Table C.1. AMG coordinates must be used in conjunction with the zone number, 56. Geographic coordinates based on the Australian Geodetic Datum (AGD66) were converted to the cartesian coordinate system of the Australian Map Grid (AMG66) by applying a Universal Transverse Mercator projection using Redfearn's formulae (Redfearn, 1948; NATMAP, 1986). Ellipsoid parameters used for the conversion are those of the Australian National Spheroid (ANS). All standards used (ANS, AGD66 and AMG66) are standards current at the time of the publication of the Grafton 1:250000 geological map (Brunker & Chesnut, 1976).

Figure C.1. Location of the Tenterfield 1:100000 map sheet area used in the pilot study described in Chapter 4

Table C.1: Location of the Tenterfield 1:100000 map sheet in latitude and longitude and AMG coordinates. The Tenterfield area is located in AMG zone 56.

Corner	Longitude	Latitude	Easting	Northing
	Deg. Min.	Deg. Min.	Metres	Metres
Northwest	152° E	29° S	402597.1	6791591.2
Northeast	152° 30' E	29° S	451299.5	6791900.3
Southeast	152° 30' E	29° 30' S	451535.8	6736501.2
Southwest	152° E	29° 30' S	403069.6	6736188.7
Standards	Ellipsoid Datum Geographic coordinate set Grid coordinates (UTM)		Aust. National Spheroid (ANS) Aust. Geodetic Datum (AGD) AGD66 Australian Map Grid (AMG66)	
Ellipsoid parameters	Semi-major axis Inverse flattening		a = 6,378,160.0 m 1/f = 298.25	
AGD parameters	Initial zone number Initial central meridian longitude Zone width Central scale factor False easting False northing		31 3 degrees 6 degrees 0.9996 500,000 m 10,000,000 m	

In some cases, the Tenterfield data were extracted from larger regional data sets. The airborne geophysical data were acquired over the whole Inverell and Grafton 1:250000 map sheets (Fig. C.1) below) and the main stream sediment geochemistry data set, the NRAC survey of the Upper North East covers portions of the Warwick, Tweed Heads, Grafton, Maclean, Dorrigo, and Coffs Harbour 1:250000 sheet areas.

C.2 Overview of Primary Thematic Layers

Table C.2 lists all the data sets in the Tenterfield GIS package, which were supplied by the Geological Survey of NSW. The coverages shown below are in ARCVIEW shape file format. All image files were supplied in IDRISI image format (designated by the suffix, *img*) except for the *igrrad* image which is in BIL format. The tables are in ARCVIEW tables format. The term Upper North East Region is used by the Geological Survey of NSW and includes portions of the Warwick, Tweed Heads, Grafton, Maclean, Dorrigo, and Coffs Harbour 1:250000 sheet areas. File names of layers in the GIS database are shown in typewriter font.

Table C.2: Primary thematic layers in the Tenterfield GIS database

Layer	Description
uner5ge	Solid geology of the Upper North East region, NSW.
t-geology	Solid geology of the Tenterfield 1:100000 map sheet area (Map 9339).
unew5fa	Regional scale faults and shear zones in the Upper North East region, NSW.
t_struct	Regional scale faults and shear zones in the Tenterfield 1:100000 map sheet area.
t_deps	Mineral deposits and occurrences in the Tenterfield 1:100000 sheet area.
t_nracstrmgc	Tenterfield 1:100000 map sheet subset of Upper North East region stream sediment geochemistry data set.
t_strmgc	Stream geochemistry (mainly Cu, Pb & Zn) over Tenterfield area.
t_whrkgc	Whole-rock geochemistry over the Tenterfield area.
Image Name	Description
igu	U channel radiometric image covering Tenterfield 1:100,000 sheet area.
igth	Th channel radiometric image covering Tenterfield 1:100,000 sheet area.
igk	K channel radiometric image covering Tenterfield 1:100,000 sheet area.
igtc	Total count radiometric image covering Tenterfield 1:100,000 sheet area.
ingrrad	Composite radiometric image over parts of Inverell, and Grafton 1:250000 map sheets. Channels: red = U, green = Th, blue = K). ARCVIEW BIL image format (file suffixes: .bil, .hdr, & .stx).
imag	total intensity magnetic image covering Tenterfield 1:100,000 sheet area.
Table Name	Description
unew5gel2	Details on Quaternary, Tertiary and basin sedimentary units for the Upper North East Region geology coverage, <i>oldage_my</i> .
geolage	Explanation of <i>oldage_my</i> & <i>ynage_my</i> attributes codes in <i>t-geology</i> cover.
geolprov	Explanation of <i>geol_province</i> attribute codes in <i>t-geology</i> coverage.
geolsys	Links tectonostratigraphic division attribute (<i>geolsystem</i>) to <i>t-geology</i> coverage table. via common <i>symbol</i> attribute.
gransuit	Links <i>gransuit</i> and <i>sfsuite</i> and <i>description</i> attributes to the <i>t-geology</i> coverage table via common <i>symbol</i> attribute.
domlith	Links description and colour attributes to <i>t-geology</i> coverage table via the <i>domlith</i> attribute (same as the <i>lithology</i> attribute in <i>t-geology</i> coverage).
depsize	Describes equivalence between the <i>size</i> , <i>size2</i> and <i>value1967a</i> attribute values in the <i>t_deps</i> coverage.
depcodeb	Links <i>label</i> , <i>code</i> , <i>add_commod</i> and <i>examples</i> fields to the mineral deposits coverage, <i>t_deps</i> via <i>code</i> attribute.

C.3 Metadata for Tenterfield GIS Database

The Tenterfield GIS package consists of a number of different unpublished digital geology, geophysics, geochemistry, and deposit location data sets, which were compiled by Robert Barnes at the Armidale Office of the Geological Survey, Department of Minerals and Energy, NSW (Barnes, 1993; Barnes *et al.*, 1995). Since the data sets were collected by different groups at different times and have different geographic extents, there are separate sets of metadata for each of these categories. The data in Section C.4.1 are summarized from unpublished reports held at the Armidale office of the Geological Survey of NSW (Barnes, 1995; Barnes & Suppel, 1995; Barnes, 1997a,b).

C.4 Geological Data

C.4.1 Core Metadata Elements for Geological Data

The core metadata items (Page 0) described in the Australia New Zealand Land Information Council (ANZLIC) metadata guidelines (ANZLIC, 1996) are given in Table C.3 below.

Table C.3: ANZLIC core metadata elements for Tenterfield geological data

<i>Dataset</i>	Title	unew5ge — regional geology layer: Upper North East region, NSW
	Custodian	NSW Department of Mineral Resources
	Jurisdiction	New South Wales
<i>Description</i>	Abstract	Geology of the Upper North East region comprises portions of the Warwick, Tweed Heads, Grafton, Maclean, Dorrigo, and Coffs Harbour 1:250,000 sheet areas including a contribution from NRAC Project S1(C)
	Search Words	GEOSCIENCES, GEOSCIENCES Geology, GEOSCIENCES Geochemistry
	Geographic Extent Name(s)	Warwick 1:250000 Map Sheet, Tweed Heads 1:250,00 Map Sheet, Grafton 1:250000 Map Sheet, Maclean 1:250000 Map Sheet, Dorrigo 1:250000 Map Sheet, Coffs Harbour 1:250000 Map Sheet
<i>Data Currency</i>	Beginning Date	01JAN1971
	Ending Date	01JAN1994

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Table C.3: *continued*

<i>Dataset Status</i>	Progress	Complete
	Maintenance and Update Frequency	Not Known
<i>Access</i>	Stored Data Format	DIGITAL ARC/INFO 7.0.3 under SUNOS, vector coverage, AMG 66
	Available Format Type	ARC/INFO coverage, ARCVIEW shape file
	Access Constraint	Available for research, subject to license agreement.
<i>Data Quality</i>	Lineage	<p>The upper North East Region includes the Grafton 1:250000 sheet, which contains the Tenterfield 1:100000 sheet. Published and unpublished geological maps were compiled onto 1:25,000 topographic maps and then recompiled at 1:100000 scale and further simplified and recompiled at 1:250000 scale.</p> <p>The map was then digitized using INFOMAP and PC ARC/INFO software. The Upper North East region geology (stored as digital coverages: uner_geol and unew5ge) was compiled from both the 1:100000 and 1:250000 scale maps in 1995 (Barnes & Willis, 1989; Barnes, 1997b).</p>
	Positional Accuracy	Most geological boundaries and features have a horizontal accuracy of 10–500 m. Geological reliability is moderate to good. In many parts of the map the terrain is extremely rugged and little detailed geological mapping has been done.
	Attribute Accuracy	<p>Each unit on the geological map is given a letter symbol using a convention described by Stroud (1994). The main attribute in the geology coverage is the litho-stratigraphic unit.</p> <p>The map shows stratigraphic units, which contain several rock types, any one of which may be present at a particular location. Areas were mapped at different levels of detail.</p> <p>Approximately two field days per 1:25,000 map area were spent on reconnaissance checking over the Grafton 1:250000 sheet area.</p>

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Table C.3: *continued*

	Logical Accuracy	The data were checked during the initial map compilations but the new compilation has not been subject to rigorous checking. Some polygons are not fully labelled and some lines overshoot or undershoot and sliver polygons exist.
	Completeness	Attribute data are available for the entire area.
Contact Information	Contact Organization	Geological Survey of NSW
	Contact Position	Senior Geologist
	Mail Address 1	P.O. Box 65
	Mail Address 2	
	Suburb/Locality	Armidale
	State/Locality 2	NSW
	Country	Australia
	Postcode	2350
	Telephone	Australia Fixed Network Number 02 6770 2118 (Armidale) 02 9901 8888 (St Leonards, Sydney)
	Facsimile	02 6770 2121
	Email	barnesr@minerals.nsw.gov.au
Metadata Date	Metadata Date	01SEP1995
Additional Metadata		See Barnes (1995); Barnes & Suppel (1995); Barnes (1997a,b)

C.4.2 Data Dictionary for Regional Geology Layer

The data dictionaries that describe the non-spatial attributes for each thematic layer are presented as separate tables below. The internal spatial attributes are not shown. There is no data dictionary for the structural coverage *t_struct* since it does not contain any non-spatial attributes. Table C.4 shows the data dictionary for the Upper North East Region geology, corresponding to the layer; *uner_geol*.

Table C.4: Data dictionary for the Tenterfield regional geology coverage (Upper North East Region, NSW)

Coverage name: <i>uner-geol</i> ^a		
Coverage type: Polygon		
Item names	Type	Item description
sym_arc	C	Unique code for each polygon used to link data in the <i>sym-geol</i> LUT to the geology coverage.
lpoly	I	Identifier for polygon on the left side of current polygon.
rpoly	I	Identifier for polygon on the right side of current polygon.

C.4.3 Data Dictionary for Tenterfield Geology Layer

The data dictionary for the Tenterfield geology (layer: *t-geol*) is shown in Table C.5 below.

Table C.5: Data dictionary for the Tenterfield 1:100000 map sheet geology coverage

Coverage name: <i>t-geol</i>		
Coverage type: Polygon		
Item names	Type	Item description
mapno	C	Number of NSW Geological Survey 1:100000 map sheet for area.
sym_arc	C	Unique code for each polygon used to link data in the <i>sym-geol</i> LUT to the geology coverage.
mapnum	C	Number of NSW Geological Survey 1:100000 map sheet for area.
geolprov	C	Major geological province in which the unit occurs.
supergp	C	Tectonostratigraphic terranes after Flood & Aitchison (1988).
gpsuite	C	Group or plutonic suite.
subgp	C	Subgroup.
frm_plut	C	Formation or pluton.
bath_no	I	Pluton number listed in confidential report by Chappell & Bryant (1994).
mem_body	C	Member or granite body.
all_strat2	C	Stratigraphic name components for each unit; i.e. supergroup/group or plutonic suite/subgroup/formation or pluton/member of body.
lithology	C	Dominant lithology within a unit (see explanation of codes in C.8 below. Lithological units are generalized and do not follow strict definitions; e.g. <i>granite</i> includes a range of felsic plutonic rocks and not just <i>granite sensu stricto</i>).

continued on next page

Table C.5: *continued*

lith_descr	C	Range of rock types that can be found in mapped units.
oldage_my	I	Code for the oldest age of unit in terms of period or epoch in the geological time scale. below.
yngage_my	I	Code for the youngest age of unit in terms of period or epoch in the geological time scale. below.
oldage_ab	I	Old end of range of absolute ages quoted for unit (Ma) or old end of error range (mainly from Shaw & Flood, 1993).
yngage_ab	I	Young end of range of absolute ages quoted for unit (Ma) or young end of error range.
symbol	I	Colour code for use with the AGSO shade set <i>AGSO.shd</i> .
screen	I	Texture code for use with shadeset <i>CARTO.shd</i> ; applies an overprint on some units.

The *geol_prov* attribute is restricted to the following values;

NEW ENGLAND = all rocks in the basement sedimentary and granite units of the New England Orogen,
 CLARENCE = rocks of the Clarence-Moreton basement sedimentary and granite units, which form most of the northeastern part of the coverage,
 TERTIARY = all Tertiary volcanics, intrusives and sediments,
 COVER = all Quaternary rocks consisting mainly of alluvium and coastal sands.

C.4.4 Data Dictionary for Geological Province Table

Table C.6 shows the data dictionary for the table, *geolprov*.

Table C.6: Data dictionary for database table, *geolprov*

Table name: <i>geolprov</i>		
Item names	Type	Item description
geolprov	C	Geological province; e.g. NEWENGLAND, CLARENCE, AND COVER. This field is used as a foreign key to link this table to the main Tenterfield geology table, <i>t_geol</i> .
description	C	Free form textural description of the packages of rocks found in the province.

C.4.5 Data Dictionary for Tenterfield Granite Suite Table

Table C.7 shows the data dictionary for the Tenterfield granite suite table, *gransuit*.

Table C.7: Data dictionary for database table, *gransuit*

Table name: <i>gransuit</i>		
Item names	Type	Item description
gransuit	I	Code for plutonic suite assigned according to Chappell & Bryant (1994).
sfgsuite	I	Code for plutonic suite interpreted according to Shaw & Flood (1981). The codes are the same as those for <i>gransuite</i> but interpretations of individual units is different.
lgd_pos	I	Legend position. Units with higher numbers are younger.
desc	C	Name of plutonic suite from Chappell & Bryant (1994).
symbol	I	Number code for colour of unit using the <i>AGSOSHD</i> shade set obtained from the Australian Geological Survey Organisation. This field is used as a foreign key to link this table to the main Tenterfield geology table, <i>t_geol</i> .

Values of the lithology attribute are codes defined in the Mineral Resources Land Information System (MRLIS) of the New South Wales Department of Mineral Resources. An explanation of the MRLIS dominant lithology codes is given in Table C.8.

Table C.8: Explanation of MRLIS dominant lithology codes used in *t_geol* attribute table

Lithology code	Description
AMPHIBOL	Amphibolite
ANDESITE	Andesite
BASALT	Basalt
CARBONSED	Carbonaceous sediment
CHERT	Chert
CLAY	Clay
COLLUVIUM	Colluvial/eluvial deposits
CONGLOM	Conglomerate, sedimentary breccia
DIORITE	Diorite
DUNE	Dune and sandplain-unconsolidated sand and silt
ECLOGITE	Eclogite
FERRICRETE	Ferricrete

continued on next page

Table C.8: *continued*

GABBRO	Gabbroic rocks
GNEISS	Gneiss
GRANITE	Granitoids
GRANULITE	Granulite
GRAVEL	Gravel
HORNFELS	Hornfels
IRONSTONE	Oolitic and other ironstones
LATERITE	Laterite
LATITE	Latite
LIMESTONE	Limestone
LUTITE	Mudstone
MONZONITE	Monzonite
MUD	Mud
OTHERMET	Metamorphic rock
OTHERPLUT	Plutonic rock
OTHERSED	Sedimentary rock
OTHERVOLC	Volcanic rock
PEGMATITE	Pegmatite
PHYLITE	Phyllite
QTZMAG	Quartz magnetite/BIF-type rocks
QUARTZITE	Quartzite
RHYOLITE	Rhyolite-dacite
SAND	Sand
SANDSTONE	Sandstone
SCHIST	Schist
SEDMIX	Interbedded clastic rocks, no single dominant lithology
SILCRETE	Silcrete
SLATE	Slate
SYENITE	Syenite
TRACHYTE	Trachyte
ULTRAMAFIC	Ultramafic rock
UMAFICVOLC	Ultramafic volcanic rock
UNCONSED	Unconsolidated sedimentary rock

continued on next page

Table C.8: *continued*

USATPLUT	Undersaturated plutonic rocks (<10% undersaturated minerals)
USATVOLC	Undersaturated volcanic rocks
VOLCSED	Volcaniclastics

C.4.6 Data Dictionary for Tenterfield Dominant Lithology Table

Table C.9 shows the data dictionary for the dominant lithology table, *domlith*.

Table C.9: Data dictionary for database table *domlith*

Table name: <i>domlith</i>		
Item names	Type	Item description
domlith	C	Name of dominant rock type in the geological unit. This field is identical to the <i>lithology</i> field in the main geology table <i>t_geology</i> and is used as a foreign key to link the <i>domlith</i> table to the <i>t_geology</i> table.
desc	C	Explanation of the lithology code. Generally this field is identical to the lithology code.
colornames	I	Code for the colour in the ARC/INFO shade set used in the map legend.

C.4.7 Data Dictionary for Tenterfield Geological Age Table

Table C.10 shows the data dictionary for the Tenterfield geological age table, *geolage*.

Table C.10: Data dictionary for database table, *geolage*

Table name: <i>geolage</i>		
Item names	Type	Item description
class	I	Number code for the geological eras and periods. This field is used as a foreign key to link this table to the main Tenterfield geology table, <i>t_geol</i> .
descriptio	C	The qualifier, <i>undifferentiated</i> , may be used in conjunction with the era or period name—otherwise the description is the same as the <i>label</i> field below.
label	C	Name of geological era or period.

An explanation for the codes used for the ages of the geological units in the Tenterfield geology data attribute table (*t_geol*) is given in Table C.11. The age codes are defined

in the Mineral Resources Land Information System (MRLIS) of the New South Wales Department of Mineral Resources

Table C.11: Explanation of MRLIS age codes used in *t_geol* attribute table

Age code	Description	Age code	Description
100	Cainozoic, undifferentiated	317	Early Permian
109	Cainozoic, undifferentiated?	318	Early Permian?
110	Quaternary, undifferentiated	319	Permian, undifferentiated?
111	Holocene (Recent)	320	Carboniferous, undifferentiated
112	Holocene? (Recent?)	311	Late Carboniferous
115	Pleistocene	312	Late Carboniferous?
116	Pleistocene?	317	Early Carboniferous
119	Quaternary, undifferentiated?	318	Early Carboniferous?
120	Tertiary, undifferentiated	329	Carboniferous, undifferentiated?
121	Pliocene	330	Devonian, undifferentiated
122	Pliocene?	331	Late Devonian
123	Miocene	332	Late Devonian?
124	Miocene?	334	Middle Devonian
125	Oligocene	335	Middle Devonian?
126	Oligocene?	337	Early Devonian
127	Eocene	338	Early Devonian?
127	Eocene?	339	Devonian, undifferentiated?
129	Palaeocene	340	Silurian, undifferentiated
130	Palaeocene?	341	Late Silurian
131	Tertiary, undifferentiated?	342	Late Silurian?
200	Mesozoic, undifferentiated	344	Middle Silurian
209	Mesozoic, undifferentiated?	345	Middle Silurian?
210	Cretaceous, undifferentiated	347	Early Silurian
211	Late Cretaceous	348	Early Silurian?
212	Late Cretaceous?	349	Silurian, undifferentiated?
217	Early Cretaceous	350	Ordovician, undifferentiated
218	Early Cretaceous?	351	Late Ordovician
219	Cretaceous, undifferentiated?	352	Late Ordovician?
220	Jurassic, undifferentiated	357	Early Ordovician
221	Late Jurassic	358	Early Ordovician?
222	Late Jurassic?	359	Ordovician, undifferentiated?

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Table C.11: *continued*

Age code	Description	Age code	Description
224	Middle Jurassic	360	Cambrian, undifferentiated
225	Middle Jurassic?	361	Late Cambrian
226	Early Jurassic	362	Late Cambrian?
227	Early Jurassic?	364	Middle Cambrian
229	Jurassic, undifferentiated?	365	Middle Cambrian?
230	Triassic, undifferentiated	367	Early Cambrian
231	Late Triassic	368	Early Cambrian?
232	Late Triassic?	369	Cambrian, undifferentiated?
234	Middle Triassic	400	Precambrian, undifferentiated
235	Middle Triassic?	409	Precambrian, undifferentiated?
237	Early Triassic	500	Proterozoic, undifferentiated
238	Early Triassic?	510	Late Proterozoic
239	Triassic, undifferentiated?	511	Late Proterozoic?
300	Paleozoic, undifferentiated	540	Middle Proterozoic
309	Paleozoic, undifferentiated?	541	Middle Proterozoic?
310	Permian, undifferentiated	570	Early Proterozoic
311	Late Permian	571	Early Proterozoic?
312	Late Permian?	579	Proterozoic, undifferentiated?
314	Middle Permian	600	Archaean
315	Middle Permian?	610	Late Archaean

C.4.8 Data Dictionary for Tenterfield Geological System Table

Table C.7 shows the data dictionary for the Tenterfield geological system table, *geolsys*.

Table C.12: Data dictionary for database table, *geolsys*

Table name: <i>geolsys</i>		
Item names	Type	Item description
geolsystem	C	Tectonostratigraphic group; e.g. Accretionary Complex.
symbol	I	Number code for colour of unit using the <i>AGSOSHD</i> shade set obtained from the Australian Geological Survey Organisation. This field is used as a foreign key to link this table to the main Tenterfield geology table, <i>t_geol</i> .

C.5 Geophysical Data

C.5.1 Core Metadata Elements for Geophysical Data

The geophysical data used in the Tenterfield pilot study consists of an aeromagnetic and gamma-ray survey, which were flown simultaneously. The core metadata items (Page 0) described in the Australia New Zealand Land Information Council (ANZLIC) metadata guidelines (ANZLIC, 1996) are given in Table C.13 below.

Table C.13: ANZLIC core metadata elements for Tenterfield geophysical data

Dataset	Title	imag, igu, igth, igk, igtc —ARC/INFO BIL images of the Inverell and Grafton 1:250000 map sheet areas
	Custodian	NSW Department of Mineral Resources
	Jurisdiction	New South Wales
Description	Abstract	Airborne magnetic and gamma-ray survey of the Inverell and Grafton 1:250000 sheet areas as gridded grey scale (0–255 levels) images in IDRISI BIL format (file suffix: .img). Each file is accompanied by a Word 97 file containing header information.
	Search Words	GEOSCIENCES, GEOSCIENCES Geophysics
	Geographic Extent Name(s)	Inverell and Grafton 1:250000 Map Sheets
Data Currency	Beginning Date	01FEB1982
	Ending Date	01APR1982
Dataset Status	Progress	Complete
	Maintenance and Update Frequency	Not Known
Access	Stored Data Format	IDRISI image format. This is a single channel BIL file (file suffix: .img) with an 8-bit per value binary coding. Accompanying each file is a Word 97 file (file suffix: .doc) that provides header information
	Available Format Type	ARC/INFO image format
	Access Constraint	Available for research, subject to license agreement.

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Table C.13: *continued*

Data Quality	Lineage	<p>The magnetic and gamma-ray data were collected simultaneously by EG & G Geometrics International Corporation. These data were originally presented to the NSW Department of Mineral Resources as a series of coloured contour maps. The data were later re-gridded and contoured by Ross Spencer, Geophysics Section, NSW Geological Survey. The floating point digital data were converted by Ross Spencer to a series of 8-bit single channel BIL files.</p> <p>A UTM projection giving AMG 66 coordinates was used (Barnes, 1993). Barnes (1993) has pointed out that because the highly fractionated, K-, Th- and U-rich Mole granite was included in the data set prior to classification, the variability of the data set in the adjacent Tenterfield area was significantly reduced.</p>
	Positional Accuracy	A rough estimate based on the equipment used is in the range ± 10 to ± 50 m.
	Attribute Accuracy	<p>Magnetic data were collected with a Geometrics G-803 proton precession magnetometer with a nominal sensitivity of 0.5 nanoteslas.</p> <p>Radiometric data were collected with a Geometrics GR-800 spectrometer with a 2048 cu. in. crystal. The accuracy of the radiometric data are not known, however it is likely to be approximately $\pm 10\%$.</p>
	Logical Accuracy	Unknown.
	Completeness	Coverage is complete over the Inverell and Grafton 1:250000 map sheet areas.
Contact Information	Contact Organization	Geological Survey of NSW
	Contact Position	Senior Geophysicist
	Mail Address 1	P.O. Box 536
	Mail Address 2	
	Suburb/Locality	St Leonards
	State/Locality 2	NSW
	Country	Australia
	Postcode	1590
	Telephone	Australia Fixed Network Number 08 9901 8364

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Table C.13: *continued*

	Facsimile	08 9901 8777
	Email	spencerr@minerals.nsw.gov.au
Metadata Date	Metadata Date	01NOV1993
Additional Metadata		See Barnes (1993)

Table C.14: Survey specifications for the Tenterfield geophysical data set

Magnetometer	Geometrics G-803 proton procession
Sensitivity	0.5 nanoteslas
Spectrometer	Geometrics GR-800 (2048 cu. in.)
Digital acquisition system	Geometrics G-714
Flight path record	Geocam 35mm continuous strip film
Time base	0.8 seconds
Average sample interval	50 metres
Flight line direction	East-west
Tie line direction	North-south
Nominal flight line spacing	1.5 kilometres
Survey altitude	150 metres terrain clearance

C.6 Geochemical Data

C.6.1 Core Metadata Elements for Geochemical Data

The most important geochemical data set covering the Tenterfield area is the stream sediment geochemical survey carried out for the NRAC survey (referred to as the NRAC S1(A) Geochemical Atlas project). No metadata are available for the other geochemical data, which include a small amount of stream sediment sampling over the eastern portion of the Tenterfield 1:100,000 map sheet area (file: *t_stmgc*) and whole-rock geochemistry (file: *t_whrkgc*).

The core metadata items (Page 0) described in the Australia New Zealand Land Information Council (ANZLIC) metadata guidelines (ANZLIC, 1996) given for the NRAC stream sediment geochemical data in Table C.15 below was obtained from Barnes & Suppel (1995).

Table C.15: ANZLIC core metadata elements for Tenterfield Geochemical Data

Dataset	Title	t_nracstrmgc — NRAC Stream Sediment Geochemistry, Upper North East Region, NSW
	Custodian	NSW Department of Mineral Resources
	Jurisdiction	New South Wales
Description	Abstract	NRAC geochemistry for the Upper North East Region. The area comprises portions of the Warwick, Tweed Heads, Grafton, Maclean, Dorrigo, and Coffs Harbour 1:250000 sheet areas in NSW. The data comprise drainage basin polygons, sample points, and attributes. There is one sample analysis for each polygon. Active stream channels were sampled with 3 to 5 kg of material which was analysed for 39 elements. Each sample locality represents a drainage basin of 8 to 12 square kilometres.
	Search Words	GEOSCIENCES, GEOSCIENCES Geochemistry
	Geographic Extent Name(s)	Warwick 1:250000 Map Sheet, Tweed Heads 1:250,000 Map Sheet, Grafton 1:250000 Map Sheet, Maclean 1:250000 Map Sheet, Dorrigo 1:250000 Map Sheet, Coffs Harbour 1:250000 Map Sheet
Data Currency	Beginning Date	01JAN1995
	Ending Date	
Dataset Status	Progress	Complete
	Maintenance and Update Frequency	Not Planned
Access	Stored Data Format	DIGITAL ARC/INFO 7.0.3 under SunOS, vector coverage, AMG 88, records
	Available Format Type	ARC/INFO coverage, ARCVIEW shape file
	Access Constraint	Available for research, subject to license agreement.
Data Quality	Lineage	The data were compiled by Dr David Cohen, Dr Neil Rutherford, and David Garnett (Cohen <i>et al.</i> , 1995; Barnes & Suppel, 1995). Drainage polygons were marked on topographic sheets and digitized using Autocad. Autocad vectors were converted to a ARC/INFO polygon coverage using the sample points as polygon label points and the sample ID to identify each polygon. The regional coverage was clipped to the Tenterfield 1:100000 map sheet area in ARC/INFO.

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Table C.15: *continued*

	Positional Accuracy	Most sample sites located to an accuracy of 50 m. All sites are located to an accuracy of better than 100 m, which corresponds to the accuracy with which localities can be plotted on a 1:25,000 scale topographic map. Some sites were located with GPS.
	Attribute Accuracy	For concentrations below the detection limit, a value of half the detection is shown. This method avoids apparent gaps in the data and statistical distortions associated with using negative values to represent values below the detection limit (Cruikshank, 1994). Checking for errors was done by duplicating: 1) samples at one in fifty sites and analyzing those samples separately, 2) duplicating approximately one in fifty analyses by re-analyzing a separate split, and 3) performing analyses on up to four size fractions on some samples to check for possible sampling problems.
	Logical Accuracy	A high degree of internal consistency is expected as all samples were collected and analysed using the same laboratories in a short period of time. The data set was visually and statistically checked.
	Completeness	Approximately two percent of the planned sample sites were not sampled due to access problems. All samples were analysed for the full range of elements. Sites were logged using electronic notebooks with pre-programmed question-and-answer prompts.
Contact Information	Contact Organization	Geological Survey of NSW
	Contact Position	Senior Geologist
	Mail Address 1	P.O. Box 65
	Mail Address 2	
	Suburb/Locality	Armidale
	State/Locality 2	NSW
	Country	Australia
	Postcode	2350
	Telephone	Australia Fixed Network Number 02 6770 2118 (Armidale) 02 9901 8888 (St Leonards, Sydney)
	Facsimile	02 6770 2121

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Table C.15: *continued*

	Email	barnesr@minerals.nsw.gov.au
Metadata Date	Metadata Date	01MAY1995
Additional Metadata		See Barnes & Suppel (1995); Cohen <i>et al.</i> (1995)

C.6.2 Data Dictionary for Regional Geochemistry Layer

The data dictionary for the NRAC regional stream sediment geochemistry layer, *t_nracstrmgc* is shown in Table C.16 below.

Table C.16: Data dictionary for the regional stream sediment geochemistry layer, Upper North East region, NSW, *t_nracstrmgc*

Coverage name: <i>t_nracstrmgc</i>		
Coverage type: Point		
Item names	Type	Item description
X_coord	F	GPS location in AMG Easting
Y_coord	F	GPS location in AMG Northing
Major	I	Not used (set to constant value of 1)
Minor	I	unique identifier for point (same as ARCVIEW <i>_id</i> attribute)
East	F	Planned AMG Easting
North	F	Planned AMG Northing
X_log	F	Logarithm to the base 10 of the element <i>X</i> concentration in ppm. This current item and the one below are repeated for 36 elements; Ag, Au, Ba, Br, Cd, Ce, Co, Cr, Cu, Eu, Fe, Ga, Hf, K, La, Lu, Mo, Na, Nb, Ni, Pb, Rb, Sb, Sc, Sm, Sn, Sr, Ta, Th, U, W, Y, Yb, Z, Zn, and Zr.
X_1	F	Element <i>X</i> concentration in ppm
Site_no	I	Site number (same as <i>minor1</i> and ARCVIEW <i>_id</i> attributes)
Geol	I	Geology code
Majbld	I	Usage unknown
Minbld	I	Usage unknown
Size	I	Usage unknown
Geogrp	I	Usage unknown
Bldgp	I	Usage unknown
Slope	C	Slope of stream banks: F = flat, M = moderate, S = steep, N/R = not recorded

continued on next page

Table C.16: *continued*

Item names	Type	Item description
Landu	C	Land use code
Ckwid	F	Creek width (m), -999 = no data
Ckdpth	F	Creek depth (m)
Treecov	C	Density of tree cover: S = sparse, M = moderate, H = heavy, N/R = not recorded
Treesamp	C	Species of trees; e.g. Casuarina, Acacia, Eucalypt, N/R = not recorded
Ckflow	C	Creek flow: S = small, M = moderate, N = normal, N/R = not recorded
Waterq	C	Water quality: C = clear, M = muddy, N/R = not recorded
Weather	C	Weather: S = sunny, O = overcast
Ph	C	Ph value or N/R = not recorded
Cond	F	Usage unknown

C.7 Deposit Data

C.7.1 Core Metadata Elements for Tenterfield Deposit Location Data

Core metadata elements (Page 0) described in the Australia New Zealand Land Information Council (ANZLIC) metadata guidelines (ANZLIC, 1996) for the deposit locations used in the Tenterfield GIS database are listed in Table C.17 below. The information summarizes that given in Barnes (1997a)

Table C.17: ANZLIC core metadata elements for Tenterfield Deposit Location Data

Dataset	Title	t_deps — Mineral deposit locations for New England and North East Region, NSW
	Custodian	NSW Department of Mineral Resources
	Jurisdiction	New South Wales
Description	Abstract	The mineral deposit locations data set covers the NSW portions of the Warwick, Tweed Heads, Inverell, Grafton, Maclean, Manilla, Dorrigo, Coffs Harbour, Tamworth, Hastings, Singleton, and Newcastle 1:250000 sheet areas. The data set includes metallic and non-metallic industrial minerals.

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Table C.17: *continued*

	Search Words	MINERALS, GEOSCIENCES, GEOSCIENCES Geology
	Geographic Extent Name(s)	NSW portions of the Warwick, Tweed Heads, Inverell, Grafton, Maclean, Manilla, Dorrigo, Coffs Harbour, Tamworth, Hastings, Singleton, and Newcastle 1:250000 sheet areas.
Data Currency	Beginning Date	Not Known
	Ending Date	Current
Dataset Status	Progress	In Progress
	Maintenance and Update Frequency	Not Known
Access	Stored Data Format	DIGITAL ARC/INFO 7.0.3 under SunOS, vector coverage, AMG 88, records
	Available Format Type	ARC/INFO coverage, ARCVIEW shape file
	Access Constraint	Available for research, subject to license agreement.
Data Quality	Lineage	<p>The data were compiled from published and unpublished reports of the Geological Survey of NSW (GSNSW), mining company reports, annual reports and prospectuses, and field observations by GSNSW geologists.</p> <p>The regional coverage covering the Upper North East region was clipped to the Tenterfield 1:100000 map sheet area in ARC/INFO. Attribute were added to the ARCVIEW deposits table (<i>t_deps</i>) by creating a relational join with the <i>dep_size</i> table (file: <i>depsize.dbf</i>) using the common <i>code</i> field.</p>
	Positional Accuracy	The positional accuracy of deposit locations varies between 0 to 500 m with most deposits located with an accuracy of 100-200 m to their actual positions. Although some placer deposits extend for kilometres, they are represented as point locations. One to two percent of locations may be in error due to incorrect grid coordinates.
	Attribute Accuracy	Some rock hosts and minerals may be incorrectly identified. Some attributes are subject to interpretation and may vary according to the geologist who described them; e.g. ore genesis.

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Table C.17: *continued*

	Logical Accuracy	There may be a slight mismatch between the actual host rock for a mineral deposit and the host rock recorded in the data set due to the amount of detail recorded for a particular locality.
	Completeness	Coverage: Barnes (1997a) estimates that over 95% of the deposits in the Tenterfield 1:100000 map sheet area have been identified and that 95% of the identified deposits have been checked in the field. Classification: Over 75% of the attributes for each deposit are complete.
Contact Information	Contact Organization	Geological Survey of NSW
	Contact Position	Senior Geologist
	Mail Address 1	P.O. Box 65
	Mail Address 2	
	Suburb/Locality	Armidale
	State/Locality 2	NSW
	Country	Australia
	Postcode	2350
	Telephone	Australia Fixed Network Number 02 6770 2118 (Armidale) 02 9901 8888 (St Leonards, Sydney)
	Facsimile	02 6770 2121
	Email	barnesr@minerals.nsw.gov.au
Metadata Date	Metadata Date	01JUL1997
Additional Metadata		See Barnes (1997a)

C.7.2 Data Dictionary for Tenterfield Mineral Deposits Layer

Table C.18 shows the data dictionary for the Tenterfield geology, corresponding to the layer; *t_deps*.

Table C.18: Data dictionary for the Tenterfield mineral deposits layer

Coverage name: <i>t_deps</i>		
Coverage type: Point		
Item names	Type	Item description
pubno	C	Cross-reference to Geological Survey of NSW reports and publications.
fieldno	C	Cross-reference to geologist's field notes.
code	C	Code for deposit style (GSNSW nomenclature). Item is used to link descriptions of deposit types from the table <i>depcode</i> to the main table <i>t_deps</i> .
order	C	Use unknown
refno	C	Field is composed of the previous two items concatenated; <i><code><order></i> .
cl	C	Commodity class; M = metallic and I = industrial.
abbrevname	C	Abbreviated name of deposit.
names	C	Name of deposit.
map100k	C	Number of 1:100000 map sheet in which deposit is located.
map250k	C	Number of 1:250000 map sheet in which deposit is located.
amge	C	AMG easting for deposit location.
amgn	C	AMG northing for deposit location.
majcom	C	Major commodities.
mincom	C	Minor commodities.
size	C	Size of deposit expressed in classes; occ, sml, med, lge, vlge, and N/A.
size2	I	Size expressed in terms of numbers in the range [0–5].
N16	I	tonnages and grades or total metal produced.
1967a	I	Dollar value of total contained metal in 1967 Australian dollars.

The *genesis* attribute has the following values and meanings:

MAGVEIN	=	magmatic vein in granitoid host,
PIPE	=	granite-hosted breccia pipes e.g. Bungulla Si pipe,
GREISEN	=	greisen,
METAHYDRO	=	structurally controlled Au-Sb veins occurring along granite; contacts e.g. Lionsville-Solferino,
MAGDIS	=	disseminated Au in granite; e.g. Timbarra-Poverty Point,
APLITE	=	mineralization spatially associated with aplite dykes,
ALLUVIAL	=	Au placer; e.g. Timbarra,
COLLUVIAL	=	residual Au deposits,
VOLOTHER	=	epithermal Au-(Ag-Te) in volcanic complex; e.g. Drake.

C.7.3 Data Dictionary for Deposit Size Database Table

Deposits are classed into categories according to the value of the total contained metal expressed in 1967 Australian dollars (attribute: *value1967a*). The attributes, *size* and *size2*, are alternative names for the same deposit sizes. The equivalence between values of these three attributes is given by the GIS database table, *depsize.dbf*, shown in Table C.19 below.

Table C.19: Data dictionary for database table, *depsize*

Table name: <i>t_depsize</i>		
Item names	Type	Item description
size	C	Size of the deposit in classes; Occ, Sml, Med, Lge, and Vlge.
size2	I	Size of deposit in five classes labelled 1 to 5.
value1967a	C	Size of deposit in value of contained metal (1967 Australian dollars).

The equivalence between the attributes *size*, *size2* and *value1967a* in table *depsize* is described in table C.20 below.

Table C.20: Explanation of deposit size attributes used in Tenterfield *depsize* table

size	size2	value1967a
NA	0	Not applicable
Occ	1	<\$10,000 ^a
Sml	2	\$10,000–\$1,000,000
Med	3	\$1,000,000–\$10,000,000
Lge	4	\$10,000,000–\$100,000,000
Vlge	5	>\$100,000,000

^aValue of total contained metal in 1967 Australian dollars

C.7.4 Data Dictionary for Tenterfield Deposit Code Table

Table C.21 shows the data dictionary for the dominant lithology table, *depcode*.

Table C.21: Data dictionary for database table, *decode*

Table name: <i>decode</i>		
Item names	Type	Item description
code	I	Deposit code used as a foreign key to link this table to the deposit table, <i>t_deps</i> .
symbol	I	Code for colour of the symbol representing the unit using an ARC/INFO shade set.
label	C	Name for the deposit type.
desc	C	Description of deposit.
add_commod	C	A list of commodities in order of significance (for metallic deposits only).
examples	C	Name of a representative example for the deposit type.

C.8 Derived Thematic Layers

The primary thematic layers shown in Table C.22 below were derived from the data sets originally supplied by the Geological Survey of New South Wales.

Table C.22: Primary thematic layers in the Tenterfield GIS database

Coverage Name	Description
trglmap	Simplified solid geology for Tenterfield 1:100000 map sheet area (Map 9339).
trstruct	Regional scale faults and shear zones with post-mineralization faults removed.
trminocc	All mineral deposits and occurrences in the Tenterfield 1:100000 sheet area.
magslc	Classed total magnetic intensity (RTP). Image data were converted to 10 classes.
uslc	Classed Uranium channel gamma-ray survey data. Converted to 10 classes.
thslc	Classed Thorium channel gamma-ray survey data. Converted to 10 classes.
kslc	Classed Potassium channel gamma-ray survey data. Converted to 10 classes.
tcslc	Classed total count gamma-ray survey data. Converted to 10 classes.

C.9 Derived Thematic Layers

The thematic layers shown in Table C.23 below were derived from the data sets originally supplied by the Geological Survey of New South Wales. The derived thematic layers were used as inputs for the neural network, fuzzy logic and weights of evidence prospectivity analysis methods.

Table C.23: Derived thematic layers in the Tenterfield GIS database

Coverage Name	Description
dauplgru	Granite-related, placer, & unknown-type gold deposits (probably granite-hosted) in Tenterfield area.
dauplace	Placer gold deposits and occurrences in the Tenterfield 1:100000 sheet area.
daugran	Granite-related mineral deposits and occurrences in the Tenterfield 1:100000 sheet area.
d_unkn	Gold deposits and occurrences of unknown type in the Tenterfield 1:100000 sheet area.
buf_ftt	Distance to nearest major fault (post-mineralization faults removed).
uplusth	Index equal to unclassified U plus Th gamma-ray channel values derived from image containing 256 discrete grey-scale levels.
k_dv_mag	Index equal to unclassified K gamma-ray channel values divided by classed magnetic value.
th_dv_mag	Index equal to unclassified Th gamma-ray channel values divided by classed magnetic value.
u_dv_mag	Index equal to unclassified U gamma-ray channel values divided by classed magnetic value.
u_x_th	Index equal to product of unclassified $U \times Th$ gamma-ray channel values.
u_xth_xk	Index equal to product of unclassified $U \times Th \times K$ gamma-ray channel values.
uth_d_m	Index equal to unclassified $U \times Th$ gamma-ray channel values divided by classed magnetic value.
uthk_d_m	Index equal to unclassified $U \times Th \times K$ gamma-ray channel values divided by classed magnetic value.
uplusth	Index equal to unclassified $U + Th$ gamma-ray channel.

Appendix D

Metadata for Kalgoorlie GIS Database

D.1 Location of the Kalgoorlie Data Set

This appendix describes the data sets used in Chapter 5 for the case study on Archaean orogenic lode-gold deposits from the Kalgoorlie district in the Norseman-Wiluna Belt of the Yilgarn block, Western Australia. The data were collected and compiled by Dr Scott Halley, Dr Paul Kitto and other geologists at Goldfields Exploration Pty Ltd as part of a large gold exploration program.

The data set covers an approximately 110×110 km area near Kalgoorlie, Western Australia. The northern margin of the area is about 25 km north of Bardoc and the southern margin is located approximately 12 km south of Coolgardie. The data set covers the eastern half of the Kalgoorlie 1:250000 geological map sheet (SH51-9), with a small proportion of the data set extending into the Kurnalpi, Boorabbin and Widgiemooltha 1:250000 sheet areas (SH51-10, SH51-13, & SH51-14). The location of the case study area is shown in Figure 5.1 on page 139.

Coordinates of the corners of the Kalgoorlie data set together with parameters values used to convert the Australian Map Grid (AMG84) coordinates to geodetic coordinates, are shown in Table D.1 below.

Table D.1: Location of the Kalgoorlie study area in relation to the 1:250000 geological map sheets of the Geological Survey of Western Australia

Corner	Longitude	Latitude	Easting	Northing	Zone
	Deg. Min.	Deg. Min.	Metres	Metres	
Eastern Kalgoorlie 1:250000 sheet area					
Northwest	120° 43' 3" E	30° 4' 53" S	280,000.00	6,670,000.00	51
Northeast	121° 51' 30" E	30° 5' 46" S	390,000.00	6,670,000.00	51
Southeast	121° 50' 47" E	31° 7' 29" S	390,000.00	6,556,000.00	51
Southwest	120° 41' 35" E	31° 6' 33" S	280,000.00	6,556,000.00	51
Standards	Ellipsoid Datum Geographic coordinate set Grid coordinates (UTM)		Aust. National Spheroid (ANS) Aust. Geodetic Datum (AGD) AGD84 Australian Map Grid (AMG84)		
Ellipsoid parameters	Semi-major axis Inverse flattening		a = 6,378,160.0 m 1/f = 298.25		
AGD parameters	Initial zone number Initial central meridian longitude Zone width Central scale factor False easting False northing		31 3 degrees 6 degrees 0.9996 500,000 m 10,000,000 m		

D.2 Overview of Primary Thematic Layers

Table D.2 lists all the GIS layers in the Kalgoorlie data set that were supplied by Goldfields Exploration. The area that forms the basis of the Kalgoorlie case study described in Chapters 5, 6, and 7 is a subset of Goldfields Exploration Pty Ltd's Bardoc Tectonic Zone (BTZ) data set (completed November 2000). Data for the Kalgoorlie area was extracted by Sean Centa, cartographer, Goldfields Exploration Pty Ltd. The solid geology and structural layers layer were prepared by Dr Scott Halley, Chief Geologist by; 1) combining an interpretation of aeromagnetic survey data with geological maps and 2) re-interpreting company mapping and drill cores. Derived GIS layers are described in a separate section below and in Chapter 5.

Table D.2: Primary thematic layers in the Kalgoorlie GIS database

Coverage	Description
geol.btz	Solid geology along part of the Bardoc Tectonic Zone; new interpretation current in mid 2000
geol.kal	Solid geology over the eastern part of the Kalgoorlie 1:250000 map sheet; old interpretation based on pre-2000 work
struct.btz	Structural geology along part of the Bardoc Tectonic Zone; new interpretation current in mid 2000
struct.kal	Structural geology over the eastern part of the Kalgoorlie 1:250000 map sheet; old interpretation based on pre-2000 work
mag.trend	Trend lines interpreted from airborne magnetic images, Kalgoorlie area
au.as	Location of drill holes with gold and arsenic assays (ppb), Kalgoorlie area
reglth.au	Location of auger holes; max. gold assay in regolith (ppb), Kalgoorlie area
grav.locn	Location of gravity stations for AGSO gravity survey, Kalgoorlie area
Grid	Description
magnetic	World Geoscience, airborne magnetic survey data; TMI, RTP, Kalgoorlie area
gravity	AGSO Bouguer gravity anomaly grid, Kalgoorlie area
maj.deps	Location of mineral deposits, MINDEX 2000, Geological Survey of Western Australia

D.3 Core metadata elements for Kalgoorlie GIS data set

Core metadata is presented for the Kalgoorlie GIS data set as a whole since all layers have been obtained from Goldfields Exploration Pty Ltd. The Australia New Zealand Land Information Council (ANZLIC) core metadata items (ANZLIC, 1996) for the Kalgoorlie data are given in Table D.3 below.

Table D.3: ANZLIC core metadata elements for the Kalgoorlie GIS database

Data set	Title	Goldfields Exploration regional gold exploration in the Kalgoorlie district, W.A.
	Custodian	Goldfields Exploration Pty Ltd
	Jurisdiction	Western Australia

continued on next page

Table D.3: *continued*

Description	Abstract	Regional exploration data set used by Goldfields Exploration Pty Ltd in the search for Archaean lode-gold deposits in the Kalgoorlie area, Western Australia. The GIS database includes the following layers; solid geology and structural geology for each of the Kalgoorlie and Bardoc Tectonic Zone areas, magnetic trend lines, maximum gold in regolith, maximum gold and arsenic in drill holes, gravity, total magnetic intensity, major deposits, minor deposits, and deposit outlines.
	Search Words	GEOSCIENCES, GEOSCIENCES Geology, GEOSCIENCES Geochemistry, GEOSCIENCES Geophysics
	Geographic Extent Name(s)	Kalgoorlie (SH51-9), Kurnalpi (SH51-10), Boorabbin (SH51-13), Widgiemooltha (SH51-14) 1:250000 map sheets
Data Currency	Beginning Date	02FEB1998
	Ending Date	CURRENT
Data set Status	Progress	IN PROGRESS
	Maintenance and Update Frequency	Not Planned
Access	Stored Data Format	DIGITAL MAPINFO 5.0 and ARCVIEW under Windows 98, raster & vector, AMG 84
	Available Format Type	MAPINFO tables and ARCVIEW shape files and grids
	Access Constraint	Access may be granted for research. Publication of research based on data requires the approval of Goldfields Exploration Pty Ltd
Data Quality	Lineage	<p>The data were obtained from Goldfields Exploration Pty Ltd. The maps were compiled from published maps, and company maps.</p> <p>Geological and geochemical data were compiled in the MAPINFO GIS package. Data in MAPINFO format were exported from MAPINFO in <i>Mapinfo Interchange Format (MIF)</i> and converted to ARCVIEW shape files (vector format) using a DOS program, supplied with ARCVIEW, called <i>miftoshape</i>.</p> <p>Geophysical data were stored as ASCII files and re-gridded by Dr Mike House, using 100 metre cell size in the ERMAPPER data analysis package.</p>

continued on next page

Table D.3: *continued*

Data Quality	Positional Accuracy	No estimate of positional accuracy is given by Goldfields Exploration Pty Ltd. GPS devices were used; therefore, the positional accuracy of geological boundaries in layer, <i>geology</i> , is likely to be in the range ± 50 m. The accuracy of older mapping is probably in the range ± 100 m.
	Attribute Accuracy	The attribute values are the result of several phases of work by different geologists and are therefore likely to contain some errors in terms of identification and naming of some rock units and currency of data.
	Logical Accuracy	Unknown.
	Completeness	Attribute data available for entire area of the Kalgoorlie data set.
Contact Information	Contact Organization	Goldfields Exploration Pty Ltd.
	Contact Position	Chief Geologist
	Mail Address 1	89 Burswood Road
	Mail Address 2	Victoria Park
	Suburb/Locality	Perth
	State/Locality 2	WA
	Country	Australia
	Postcode	6100
	Telephone	Australia Fixed Network Number 08 9442 8110
	Facsimile	08 9442 8181
	Email	shalley@goldfields.com.au
Metadata Date	Metadata Date	22MAY2000
Additional Metadata		none

D.4 Geological Data

D.4.1 Data Dictionary for Solid Geology Layer, *geology.shp*

The Kalgoorlie solid geology layer (vector format, ArcView shape file, *geology.shp*), is the result of combining a maps produced by Goldfields Exploration Pty Ltd for the Kalgoorlie area prior to mid-1999 with a more recent interpretation of the Bardoc Tectonic Zone

(produced in the period, 2000-2001). Where the two areas overlap, the Bardoc Tectonic Zone map has been used to update the Kalgoorlie map. The work of combining the two maps was carried out by Sean Centa at Goldfields Exploration Pty Ltd. Table D.4 shows the data dictionary for the layer; *geology.shp*

A subset of the solid geology map of the Bardoc Tectonic Zone was selected for the study and all other GIS layers have these same boundaries (shown in Table D.1).

Lineage

The earlier solid geology map around the Kalgoorlie area is a compilation of published Geological Survey of Western Australia maps, mapping by Goldfields Exploration Pty Ltd, and information obtained from drilling and interpretation of aeromagnetic images. A geological interpretation at 1:100000 scale by Etheridge, Henley and Williams (now SRK Consulting, Australasia) forms the south-eastern part of the layer. All the layers for the Kalgoorlie area are subsets of more extensive data sets compiled at Goldfields Exploration Pty Ltd. GIS layers in MAPINFO version 4.5 format were initially clipped to the boundaries shown in Table D.1.

Much of the geology in the original Kalgoorlie area map had been updated resulting in many overlapping polygons, sliver polygons, and small holes in the coverage. Since the MAPINFO program is primarily used for map production and presentation, rather than spatial analysis, the topological correctness of GIS layers is not an issue, however it did present problems when importing data into ARCVIEW. All overlap areas are interpreted as new polygons in ARCVIEW. Consequently, these problems were corrected in MAPINFO prior to converting to ARCVIEW format. The layer was then exported from MAPINFO as MAPINFO *Interchange Format (MIF)* files and converted to ARCVIEW shape files (vector format) using a DOS program, supplied with ARCVIEW, called *miftoshape*.

The Geological mapping for Bardoc Tectonic Zone map was carried out at a 1:5000 scale by John Crossing (Principal Geologist, Goldfields Exploration Pty Ltd). Aerial photographs, which were registered using the surveyed positions of drill hole collars, were used as base maps. Drill collar positions were determined with differential GPS and are therefore accurate to within ± 10 m. A significant proportion of this layer is the result of a geological interpretation of high-resolution aeromagnetic images by Dr Scott Halley and John Bayson. The layer also incorporates information from maps published by the Geological Survey of Western Australia, and drilling and mapping by Goldfields Exploration Pty Ltd. The layer was exported from MAPINFO as *Mapinfo Interchange Format (MIF)* files and converted

to ARCVIEW shape files (vector format) using a DOS program, supplied with ARCVIEW, called *miftoshape*.

Logical Accuracy

The original map of the Kalgoorlie area was compiled from multiple sources and was updated by different geologists. Consequently, the number of logical errors are likely to be relatively high. All of the topological errors were corrected prior to importing the data into ARCVIEW, as explained above.

The Bardoc Tectonic Zone map was prepared over a period of approximately six months, primarily by Dr Scott Halley and John Bayson, and is therefore likely to be significantly more accurate and consistent than the older Kalgoorlie map.

Table D.4: Data dictionary for the Kalgoorlie geology coverage

Coverage name: <i>geology.shp</i>		
Coverage type: Polygon		
Item names	Type	Item description
feature_id	I	One to three digit code for rock type
feature	C	Lithological code for use in a stratigraphic legend (2-3 characters)
description	C	Short description of lithology and textural features
feature_na	C	Usage unknown - not used
source_id	F	Usage unknown - not used

D.5 Rock Strength Data and Rheological Contrast Calculations

D.5.1 Data for Rheological Contrast Calculations, *geology.shp*

Rock strength and deformational property data provided by Mark Lee (unpublished data, Australian Mining Consultants Pty Ltd, AMC). These data were used to calculate the rheological contrast at lithological boundaries. Data supplied by AMC consisted of Young's Modulus, uniaxial compressive and tensile strength and fracture toughness. Some of the data supplied by AMC originated from Szwedzicki & Jiang (1994). In cases where the

original compressive strength data were measured on 35 mm core, the following conversion was applied to give the values for a 50 mm diameter core size;

$$\frac{UCS_x}{UCS_{50}} = \left(\frac{50}{x}\right)^{0.18}, \quad (\text{D.1})$$

where x is the diameter of the core in millimetres. Data for rheological properties are contained as attributes in the database table associated with the solid geology GIS layer (refer to Table D.4 above). Rock strength values shown in Table 5.5 in Chapter 5 represent the averages of rock types from different localities in the AMC data that are of the same type or are used to approximate those in the Kalgoorlie solid geology coverage. The AMC data for a given rock type represent the average of many tests (generally >10) at particular mine site.

Although many rock engineering measurements are routinely made, published data for specific areas and rock types are scarce. This, combined with the fact that the solid geology attribute table contains 108 rock types meant it was often necessary to use data for a generic rock type to approximate the more specific types appearing in the solid geology attribute table (e.g. granite data used for tonalite). The correspondence between the rock types for which engineering data were available and the rock types shown in the Kalgoorlie solid geology coverage (i.e. rock types in the detailed Goldfields Exploration geology legend) is shown in Table D.5 below.

Table D.5: Calculation of average rock strength and deformational properties for rocks in the Kalgoorlie study area. Unpublished data provided by M. Lee, Australian Mining Consultants Pty Ltd, 2000. Left rock type column shows rock types in legend of solid geology GIS layer (108 rock types). The second rock type column shows closest equivalent rock types from the AMC data set that were used to estimate rock strength properties. Abbreviations: Fract. Tough. = fracture toughness, UCS & UTS = Uniaxial compressive & tensile strength, respectively,

Rock Type (GIS layer)	Rock Type (AMC data)	Location or mine	Young's Modulus GPa	UCS MPa	UTS MPa	Fract. Tough. MPa m ^{1/2}
Chert Quartzite	Vein quartz	Zarmitain, USSR	85.0	156	8	— ³
Si-rich Hornfels Fe-rich Ortho Hornfels Mg-rich Ortho Hornfels	Metasediments (h.w.) Metasiltstone Ave.	Perseverance Big Bell	74.9 77.1 76.0	166 268 217	19.4 21.8 20.6	— 3.12 3.12
Banded Iron Formation Iron Formation	Banded Iron Formation	Bounty	64.0	152	13.6	1.76
Felds+Qtz Porphyry ¹⁵ Felds+Qtz+Hbl Porph. Felds+Qtz+Bio Porph. Felds Porphyry	Qtz felds. porphyry Porphyry Porphyry Porphyry	Bounty Junction Mount Charlotte Macassa	65.7 56.8 66.7 60.0	258 216 118 233	12.2 19.3 15.3 20.6	2.50 ⁴ 2.66 2.10 —

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Table D.5: *continued*

Plag±Hbl Porph. Felds+Hbl+Bio Porph.	Porphyry Porphyry Porphyry Ave.	Kanowna Belle Kambalda-St Ives Long Shaft	69.7 61.7 62.7 63.3	67 266 277 250	18.1 17.6 17.5 17.2	— 2.3 2.31 2.37
Granite Quartz Monzonite Granodiorite Weebo Granodiorite Tonalite Monzonite Syenodiorite Granitoid	Granite	Zarmitain, USSR	48.2	141	10.8	1.61
Syenite	Basic syenite Basic syenite (siliceous) Ave.	Macassa Macassa	44.8 57.2 51.0	135 208 172	18.8 14.5 16.7	— ⁵ — 1.61
Dolerite Porphyritic Dolerite Leucocratic Dolerite Porphyritic Andesite Dacite Andesite Magnetic Basalt	Dolerite Altered Dolerite Junction Dolerite Golden Mile Dolerite (unit 6) Golden Mile Dolerite (unit 7) Golden Mile Dolerite (unit 8) carbonated Golden Mile Dolerite (unit 9) carbonated Williamstown Dolerite (fuxchite alt.) Ave.	Bounty Bounty Junction Mount Charlotte Mount Charlotte Mount Charlotte Mount Charlotte Mount Charlotte Mount Charlotte Ave.	75.4 71.7 92.6 87.6 83.9 64.8 69.4 88.5 80.3	245 217 335 — 153 177 167 331 215	13.2 12.1 21.8 — — 14.1 17.3 16.0 16.7	2.63 2.71 3.81 — — 2.97 2.70 3.20 2.96
Quartz Dolerite	Ore (quartz dolerite)	Centenary Lode, Darlot	76.5	223	17.9	2.96 ⁶
Felsic Volc. Rock M/m Felsic Tuff & Lava Felsic P/clastic Breccia Felsic Tuff (crystal,lithic) Undiv. Felsic A/clastic Undiv. Felsic P/clastic Volc. Feldspathic Wacke Fragmental (m.g.) Fragmental (c.g.)	Felsics Tuff Felsic (clastic) Felsic (volcanic) Felsic Volcanic Felsic Volcanic Ave.	Perseverance Macassa Black Swan Black Swan Kanowna Belle Centenary Lode, Darlot Ave.	80.5 64.1 54.0 57.1 68.2 81.5 64.3	142 218 84 99 213 169 152	13.3 16.2 17.2 15.1 16.3 19.1 19.0	— — 1.40 — 1.43 — 1.42
Undiv. Int. Volc. Rock Undiv. Int. A/clastic Int. P/clastic Breccia	Int. Volcanics (IMVT) Int. Volcanics (IMVT) Int. Volcanics (IMVT) Tuff (IVT) FW Tuff (IVT) FW Tuff (IVT) FW Tuff (IVT) FW Tuff (IVT) FW Tuff (IVT) FW Tuff (IVT) FW Tuff (IVT) FW Tuff (IVT) FW Tuff (IVT) FW Tuff (IVT) FW Tuff (IVT) FW Tuff (IVT) FW Tuff (IVT) FW	Kundana KD28 ¹ Kundana KD29 Kundana KD21 Kundana CD6-1 Kundana CD4-14 Kundana CD4-15 Kundana CD6-2 Kundana KC2D-14 Kundana CD6-3 Kundana CD5-11 Kundana KC2D-16A Kundana KC2D-16B Kundana CD5-12	— — — — — — — 59.7 — — — 62.5 51.2 —	150 105 171 — — — — — — — — — 136 —	— — — 10.6 17.5 25.1 20.0 — 23.9 13.9 — — 28.9	— ⁷ — — — — — — — — — — — — — — — —

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Table D.5: *continued*[illegible]

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Table D.5: *continued*

Fe-Ortho Amphib. f.g. Fe-Ortho Amphib. c.g. Calcic Para Amphibolite Para-Amphibolite, mafic Mg-rich Ortho Amphib. Mafic Amphibolite	Metasiltstone (amphib.) Ave.	Big Bell 	77.1 79.0	268 216	21.8 14.6	3.12 2.67
Undivided Arenite	Black Flag Beds (sed. rock) Sandstone Ave.	Junction Kanowna Belle 	69.2 79.2 74.2	219 — 219	21.7 — 21.7	2.92 — 2.92
Conglomerate Monomict Conglomerate Polymict Congl. (Kur- rawang) Jones Ck Conglomerate Volc.-derived Conglom. (mafic-u/m)	Cemetery Conglomerate Felsic conglomerate Footwall conglomerate Golden Valley Conglom. Ave.	Kanowna Belle Kanowna Belle Kanowna Belle Kanowna Belle 	79.1 78.0 70.9 72.2 75.1	144 94 — 105 114	12.9 — — 15.9 14.4	2.05 — — 3.68 2.87
Int. Volcanogenic Sed. Volcanogenic Sed. Rock Feldspathic Wacke Fine-grained Fragmental Undivided Wacke Volcanic Wacke	Arkosic grit Felsic grit Felsic clastic Ave.	Kanowna Belle Kanowna Belle Black Swan 	61.4 69.3 54.0 61.6	161 — 84 123	15.2 — 17.2 16.2	0.80 — 1.40 1.1
Siltstone Interbedded Slst-Shale	Black Flag Beds (sed. rock), carbonated Black Flag Beds (sed. rock) Ave.	Mount Charlotte Junction 	53.0 69.2 61.1	116 219 168	15.2 21.7 18.5	2.30 2.92 2.61
Undiv. Sed. Rocks	Contact sediments Sediments Contact sediments Grit Black Flag Beds (sed. rock) Arkosic grit Felsic grit Felsic clastic Ave.	Kambalda Zamitain, USSR Long, Kambalda Kanowna Belle Junction Kanowna Belle Kanowna Belle Black Swan 	48.5 53.9 48.5 77.1 69.2 61.4 69.3 54.0 60.2	141 166 144 162 219 161 — 84 154	— 12.2 — 18.0 21.7 15.2 — 17.2 16.9	— — — 1.33 2.92 0.80 — 1.40 1.28
Komatiite Ultramafic Autobreccia	Komatiitic Basalt Altered komatiitic basalt F.w. komatiitic basalt Ave.	Bounty Bounty Lancefield 	82.2 70.2 93.6 82.0	169 180 273 207	15.6 16.4 19.4 17.1	4.73 3.07 — 3.90
Peridotite Pyroxenite	Peridotite, not serp./ized	Bounty 	70.8 	118 	19.3 	2.61
Serpentinised Komatiite Serpentinised Peridotite Serpentinite	U/mafic (serp.-talc) U/mafic (ol.-serp.) Hannans Lake Serpenti- nite Ave.	Perseverance Perseverance Mount Charlotte 	36.8 79.7 26.8 47.8	90 128 68 95	7.1 12.1 5.7 8.3	— 1.76 — 1.76
Ultramafic Rock Amph-Chl u/mafic Rock	U/mafic (talc-carb.) U/mafic (antigorite) U/mafic (talc-chl.) U/mafic (serp.-talc)	Long Shaft Long Shaft Perseverance Perseverance	49.3 66.4 33.7 36.8	64 212 46 90	7 25.3 4.3 7.1	1.22 — — —

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Table D.5: *continued*

	U/mafic (ol.-serp.) Talc-carbonate (soft/weak) TA 1 Talc-carbonate (stiff/strong) TA 2 U/mafic (talc-chl.) serpentinized U/mafic (talc-carb.) serpentinized U/mafic (antigorite) serpentinized U/mafic (talc-chl.) f.w. Ave.	Perseverance Black Swan Black Swan Kambalda-St Ives Kambalda-St Ives Kambalda-St Ives Lancefield	79.7 47.1 87.2 16.3 44.0 67.3 17.0 49.5	128 56 177 27 44 209 28 98	12.1 9.0 18.3 4.4 6.3 25.3 5.2 11.3	1.76 — — — 1.4 — — 1.46
Ultramafic Schist	U/mafic (talc-chlorite) U/mafic (serp.-talc) Talc-carbonate (soft/weak) TA 1 U/mafic (talc-chl.) serpentinized U/mafic (talc-carb.) serpentinized U/mafic (talc-chl.) f.w. Ave.	Perseverance Perseverance Black Swan Kambalda-St Ives Kambalda-St Ives Lancefield	33.7 36.8 47.1 16.3 44.0 17.0 32.5	46 90 56 27 44 28 49	4.3 7.1 9.0 4.4 6.3 5.2 6.1	— ¹⁰ — — — 1.4 — 1.31
Shale	Shale	Kundana KD37 (SHAB) FW ¹	—	31	—	— ¹¹
Shale (altered)		Kundana KD34 (SHAB) FW	—	34	—	—
Carbonaceous Shale		Kundana SD54 272.6 m (SHAB) FW	—	35	—	—
Actinolite Schist		Kundana SD54 273.8 m (SHAB) FW	—	60	—	—
Fuchsite Schist		Kundana KD34 177.3 m (SHAB) FW	—	98	—	—
Undiff. Felsic Schists		Kundana KD34 178.4 m (SHAB) FW	—	154	—	—
Sericite Schist		Kundana KD34 177.3 m (SHAB) FW	—	115	—	—
Muscovite Schist		Kundana KD34 182.5 m (SHAB) FW	—	134	—	—
		Kundana KD34 194.6 m (SHAB) FW	—	118	—	—
		Kundana KD34 196.1 m (SHAB) FW	—	117	—	—
		Kundana KD34 199.5 m (SHAB) FW	—	138	—	—
		Kundana CD3-9 (SHCC,ORE)	72.3	—	—	—
		Kundana CD3-17A (SHCC,ORE)	—	—	29.0	—
		Kundana CD3-17C (SHCC,ORE)	—	—	17.0	—
		Kundana CD5-9B (SHCC,ORE)	—	—	14.0	—
		Kundana CD5-9A (SHCC,ORE)	—	—	10.0	—
		Kundana CD5-10 (SHCC,ORE)	—	—	7.0	—
		Kundana CD5-6 (SHCC,ORE)	75.8	113	—	—
		Kundana CD5-7 (SHCC,ORE)	69.3	—	—	—
	Ave.		72.5	96	15.4	1.1 ¹²
Talc-Chl. U/mafic Rock	U/mafic (talc-chl.) U/mafic (talc-chl.)	Perseverance Kambalda-St Ives	33.7 16.3	46 27	4.3 4.4	— ¹³ —

continued on next page

Table D.5: *continued*

	serpentinized U/mafic (talc-chl.), f.w. Ave.	Lancefield	17.0 28.5	28 39	5.2 5.7	— 1.22
Unknown/Unclassified ² Mylonite ²	Ave. all rock types used Ave. all rock types used		66.0 66.0	166 166	15.6 15.6	2.33 ¹⁴ 2.33 ¹⁴

¹Lee:2000 cites source of Kundana rock property database as Szwedzicki & Jiang, 1994.²Cells in the solid geology raster GIS layer, which are classified as “unknown” or as mylonite were assigned average values calculated using all available data.³Fracture toughness set to granite value.⁴Two very low UCS values were omitted from the average calculation.⁵Fracture toughness = granite value.⁶Fracture toughness = ave. of dolerite.⁷Fracture toughness = ave. of granite & dolerite.⁸Lower 50 percentile of basalts, incl. altered & amygdaloidal rocks.⁹Brittle quartz-rich unit; used highest values of Young's Modulus & UTS available.¹⁰Used lower 50 percentile of ultramafic samples above.¹¹Omitted one sample from AMC data with extremely high Young's Modulus¹²Fracture toughness = average of arkosic grit (0.8) & felsic clastic (1.4).¹³Omitted extremely strong sample from average. Fracture toughness value from talc-carb. rock, Long shaft, Kambalda.¹⁴Average for all rock types used.¹⁵Abbreviations: alt. = altered, amphib. = amphibolite, a/clastic = autoclastic, bio. = biotite, carb. = carbonated, chlorite, felds. = feldspar, f.w. = footwall, hbl = hornblende, h.w. = hanging wall, int. = intermediate, m/m = metamorphosed, ol = olivine, plag = plagioclase, porph. = porphyry, serp = serpentinite, undiv. = undivided, u/mafic = ultramafic.

D.5.2 Data Dictionary for Structural Geology Layer

The layer shows the structural geology for the Bardoc Tectonic Zone. The shears correspond to D_2 structures and the faults are late brittle D_3 structures. The data dictionary for the layer, *faults*, is shown in Table D.6 below. Lineage details are given in Section D.4.1 on page 548 above.

Table D.6: Data dictionary for the Kalgoorlie structural geology layer

Coverage name: <i>faults</i>		
Coverage type: Polygon		
Item names	Type	Item description
feature_id	I	Code; 323 = fault, 365 = shear, 671 = magnetic trend line
feature	C	Name of feature; i.e., fault or trend
description	C	Description of feature; i.e., shear zone, fault inferred, trend line
feature_na	C	Usage unknown - not used
source_id	F	Usage unknown - not used

D.5.3 Data Dictionary for Fold Axis Layer

A GIS layer, which shows the location of major anticlinal and synclinal axes were obtained from Yun (2000). Both maps are based on interpretations of the geology and structural maps of the Kalgoorlie area (Swager & Griffin, 1990; Swager *et al.*, 1990) by Prof. David Groves. The data dictionary for the anticlinal-fold axis layer, *faults*, is shown in Table D.7 below.

Table D.7: Data dictionary for the anticlinal-fold axis; layer *l45_dist_anti*.

Coverage name:		
Coverage type: Polygon		
Item names	Type	Item description
syncline_i	I	Code; 1 = anticline, 2 = syncline
Typefeature	C	Name of feature; i.e., fault or trend
description	C	Description of feature; i.e., shear zone, fault inferred, trend line
feature_na	C	Usage unknown - not used
source_id	F	Usage unknown - not used

D.6 Geochemical Data

D.6.1 Data for Chemical Contrast Calculations

This section documents the whole-rock geochemical data used to calculate the chemical ratios as the first step in creating GIS layers, which depict the chemical contrast at lithological boundaries (refer to Section 5.5.12 in Chapter 5). The data used to calculate

the chemical ratios represents a subset of the Australian Government Survey Organization's (AGSO) OZCHEM database for the Yilgarn Block. It contains 4473 analyses. The OZCHEM database was imported into ArcView as an ASCII text file and converted to a shape file (point coverage). ArcViews polygon tool was used select the sample points corresponding to the Kalgoorlie Terrane as defined by Swager *et al.* (1990). This reduced the total number of analyses to 2476.

In Table D.8, the first set of rows show the rock code and rock type from the ArcView solid geology shape file (vector format) together with the calculated chemical ratios; $\text{Fe}_2\text{O}_3(\text{total wt\%}) \times \text{Fe}_{tot}/(\text{Fe}_{tot} + \text{Mg} + \text{Ca})$, $\text{Fe}_{tot}/(\text{Fe}_{tot} + \text{Mg} + \text{Ca})$, $\text{Fe}_2\text{O}_3/(\text{Fe}_2\text{O}_3 + \text{FeO})$, $\text{Fe}_2\text{O}_3/\text{FeO}$, and $\text{Fe}^{3+}/\text{Fe}^{2+}$. The next set of rows in each group show selected fields from the corresponding OZCHEM database record; Rock Number, Total Decsription, Fe_2O_3 , total iron as Fe_2O_3 , FeO, MgO, CaO, Easting, and Northing.

Table D.8: Calculation of average chemical reactivity ratios for the Kalgoorlie study area

Rock Code	Rock Type in solid geology GIS layer	$\frac{Fe_{wt\%} \times Fe}{(Fe+Mg+Ca)}$ l3.1.ch2	$\frac{Fe}{(Fe+Mg+Ca)}$ l3.1.ch1	$\frac{Fe_2O_3}{(Fe_2O_3+FeO)}$ l3.1.ch3	$\frac{Fe_2O_3}{FeO}$ l3.1.ch4	$\frac{Fe^{3+}}{Fe^{2+}}$ l3.1.ch5	Location
Bif	Banded Iron Formation ³	22.65	0.78	0.54	1.15	1.04	
Sif	Iron Formation	22.65	0.78	0.54	1.15	1.04	
OZCHEM data							
Rock No.	Total Description ⁴	Fe ₂ O ₃	Fe ₂ O ₃ total	FeO	MgO	CaO	Location
5	Banded Iron Formation	3.76		27.86	3.82	2.99	Southern Cross
6	Banded Iron Formation	5.89		28.96	2.29	2.84	Southern Cross
7	Banded Iron Formation	11.88		18.61	1.11	3.62	Southern Cross
8	Banded Iron Formation	13.00		26.77	6.50	1.34	Southern Cross
9	Banded Iron Formation	19.47		20.52	3.12	0.78	Southern Cross
10	Banded Iron Formation	18.07		18.23	4.38	1.09	Southern Cross
11	Banded Iron Formation	22.93		20.16	2.19	4.89	Southern Cross
12	Banded Iron Formation	36.73		17.17	2.22	1.27	Southern Cross
13	Banded Iron Formation	36.57		16.31	3.05	1.65	Southern Cross
14	Banded Iron Formation	3.73		48.58	3.70	1.27	Southern Cross
15	Banded Iron Formation	3.10		34.31	3.86	4.48	Southern Cross
16	Banded Iron Formation	5.69		23.03	2.86	1.88	Southern Cross
17	Banded Iron Formation	4.38		20.19	4.70	6.74	Southern Cross
18	Banded Iron Formation	2.31		18.45	4.66	7.51	Southern Cross
19	Banded Iron Formation	6.74		24.61	4.66	3.79	Southern Cross
20	Banded Iron Formation	9.49		22.38	5.84	4.67	Southern Cross
21	Banded Iron Formation	8.82		23.38	3.84	4.09	Southern Cross
22	Banded Iron Formation	9.78		16.08	2.63	1.52	Norseman-Wiluna
23	Banded Iron Formation	19.14		22.96	3.64	5.65	Norseman-Wiluna
24	Banded Iron Formation	18.28		21.09	5.39	0.50	Norseman-Wiluna
25	Banded Iron Formation	21.25		19.31	2.49	4.17	Norseman-Wiluna
26	Banded Iron Formation	16.61		14.68	0.99	3.63	Norseman-Wiluna
27	Banded Iron Formation	25.45		20.68	2.57	0.95	Norseman-Wiluna
29	Banded Iron Formation	33.22		20.84	2.46	1.22	Norseman-Wiluna
34	Banded Iron Formation	36.07		14.95	2.16	1.39	Norseman-Wiluna
Rock Code	Rock Type in solid geology GIS layer	$\frac{Fe_{wt\%} \times Fe}{(Fe+Mg+Ca)}$ l3.1.ch2	$\frac{Fe}{(Fe+Mg+Ca)}$ l3.1.ch1	$\frac{Fe_2O_3}{(Fe_2O_3+FeO)}$ l3.1.ch3	$\frac{Fe_2O_3}{FeO}$ l3.1.ch4	$\frac{Fe^{3+}}{Fe^{2+}}$ l3.1.ch5	

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Table D.8: *continued*

Md	Dolerite	4.75	0.44	0.25	0.62	0.56	
Mdl	Leucocratic Dolerite	4.75	0.44	0.25	0.62	0.56	
Mb-m	Magnetic Basalt	4.75	0.44	0.25	0.62	0.56	
Mdp	Porphyritic Dolerite	4.75	0.44	0.25	0.62	0.56	
OZCHEM data							
Rock No.	Total Description ⁴	Fe ₂ O ₃	Fe ₂ O ₃ total	FeO	MgO	CaO	Location
47723	dolerite 52984N 19755E 29 Level	5.92	20.60	13.21	1.77	4.35	354472.14 E 6597459.4 N
47722	dolerite 52984N 19755E 29 Level	5.46	19.92	13.01	1.80	4.65	354472.14 E 6597459.4 N
47721	dolerite 52984N 19755E 29 Level	4.99	20.41	13.88	1.88	4.33	354472.14 E 6597459.4 N
47720	dolerite 52984N 19755E 29 Level	6.41	20.13	12.35	1.93	4.56	354472.14 E 6597459.4 N
47719	dolerite 52984N 19755E 29 Level	4.29	19.94	14.08	1.99	4.15	354472.14 E 6597459.4 N
47718	dolerite 52984N 19755E 29 Level	3.50	19.54	14.43	1.91	4.27	354472.14 E 6597459.4 N
47717	dolerite 52984N 19755E 29 Level	3.17	19.95	15.10	2.03	4.69	354472.14 E 6597459.4 N
47716	dolerite 52984N 19755E 29 Level	6.32	18.93	11.35	1.81	5.87	354472.14 E 6597459.4 N
47715	dolerite 52984N 19755E 29 Level	10.73	18.84	7.30	1.86	6.06	354472.14 E 6597459.4 N
47714	dolerite 52984N 19755E 29 Level	13.14	18.09	4.45	2.01	6.94	354472.14 E 6597459.4 N
47713	dolerite 52984N 19755E 29 Level	12.59	17.29	4.23	1.71	6.92	354472.14 E 6597459.4 N
47712	dolerite 52984N 19755E 29 Level	11.82	16.00	3.76	1.94	7.25	354472.14 E 6597459.4 N
47689	dolerite 52997N 19779E 29 Level	0.22	11.80	10.42	1.04	6.74	354472.14 E 6597459.4 N
47688	dolerite 52997N 19779E 29 Level	0.26	11.42	10.04	0.90	6.06	354472.14 E 6597459.4 N
47687	dolerite 52997N 19779E 29 Level	0.16	11.22	9.95	0.83	5.52	354472.14 E 6597459.4 N
47686	dolerite 52997N 19779E 29 Level	0.44	11.71	10.14	0.93	6.39	354472.14 E 6597459.4 N
47685	dolerite 52997N 19779E 29 Level		12.85	11.56	0.96	7.06	354472.14 E 6597459.4 N
47684	dolerite 52997N 19779E 29 Level		12.87	11.58	0.99	7.53	354472.14 E 6597459.4 N
47683	dolerite 52997N 19779E 29 Level	0.03	10.43	9.36	0.87	7.34	354472.14 E 6597459.4 N
47681	dolerite 52997N 19779E 29 Level	9.11	11.37	2.03	0.78	5.58	354472.14 E 6597459.4 N
47703	dolerite 52997N 19779E 29 Level	9.92	12.86	2.65	0.83	5.93	354472.14 E 6597459.4 N
47702	dolerite 52997N 19779E 29 Level	4.42	15.50	9.97	0.88	4.89	354472.14 E 6597459.4 N
47701	dolerite 52997N 19779E 29 Level	5.08	17.73	11.38	1.20	5.23	354472.14 E 6597459.4 N
47700	dolerite 52997N 19779E 29 Level	3.19	15.53	11.10	1.01	5.76	354472.14 E 6597459.4 N
47699	dolerite 52997N 19779E 29 Level	3.07	15.69	11.36	1.02	5.90	354472.14 E 6597459.4 N
47698	dolerite 52997N 19779E 29 Level	3.05	16.29	11.91	1.09	6.07	354472.14 E 6597459.4 N
47697	dolerite 52997N 19779E 29 Level	4.03	17.51	12.13	1.26	5.87	354472.14 E 6597459.4 N
47696	dolerite 52997N 19779E 29 Level	2.29	13.66	10.23	0.92	5.58	354472.14 E 6597459.4 N

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Table D.8: *continued*

47695	dolerite 52997N 19779E 29 Level	2.39	13.86	10.32	0.93	5.54	354472.14 E 6597459.4 N
47694	dolerite 52997N 19779E 29 Level	1.75	13.36	10.45	0.93	5.47	354472.14 E 6597459.4 N
47693	dolerite 52997N 19779E 29 Level	1.59	12.14	9.49	0.86	5.57	354472.14 E 6597459.4 N
47692	dolerite 52997N 19779E 29 Level	1.18	13.09	10.72	0.95	5.86	354472.14 E 6597459.4 N
47691	dolerite 52997N 19779E 29 Level	1.35	13.59	11.01	0.92	5.20	354472.14 E 6597459.4 N
47690	dolerite 52997N 19779E 29 Level	0.65	11.14	9.44	0.80	5.21	354472.14 E 6597459.4 N
47711	dolerite 53016N 19798E 29 Level	8.26	12.42	3.74	2.31	10.93	354472.14 E 6597459.4 N
47710	dolerite 53016N 19798E 29 Level	6.38	12.57	5.57	2.62	10.48	354472.14 E 6597459.4 N
47709	dolerite 53016N 19798E 29 Level	2.17	11.93	8.78	3.18	11.69	354472.14 E 6597459.4 N
47708	dolerite 53016N 19798E 29 Level	0.94	12.99	10.84	3.63	10.53	354472.14 E 6597459.4 N
47707	dolerite 53016N 19798E 29 Level	1.48	15.74	12.83	4.84	5.89	354472.14 E 6597459.4 N
47706	dolerite 53016N 19798E 29 Level	1.01	14.86	12.46	4.57	7.09	354472.14 E 6597459.4 N
47705	dolerite 53016N 19798E 29 Level	1.43	14.61	11.86	4.38	7.02	354472.14 E 6597459.4 N
47704	dolerite 53016N 19798E 29 Level	1.06	14.58	12.17	3.84	6.96	354472.14 E 6597459.4 N
75751	dolerite dolerite	2.34	11.15	7.93	5.02	12.20	258220.00 E 6771812.0 N
79087	dolerite medium grained dolerite	1.60	11.39	8.81	11.42	11.24	263000.00 E 6751060.0 N
76566	dolerite medium grained dolerite	2.07	10.99	8.03	6.11	12.79	263000.00 E 6751060.0 N
53947	dolerite meta- dolerite	1.80	10.31	7.66	15.04	9.45	256471.00 E 6772545.0 N
63391	dolerite metasomite	1.94	18.54	14.94	2.26	8.16	354472.14 E 6597459.4 N
63395	dolerite metasomite	2.46	16.12	12.29	1.77	6.40	354472.14 E 6597459.4 N
63376	dolerite metasomite	12.74	19.23	5.84	1.69	6.93	354472.14 E 6597459.4 N
63362	dolerite metasomite	12.15	14.36	1.99	1.14	2.75	354472.14 E 6597459.4 N
63396	dolerite metasomite	0.48	0.89	0.37	0.55	0.07	354472.14 E 6597459.4 N
63394	dolerite metasomite	2.40	16.72	12.89	1.84	7.18	354472.14 E 6597459.4 N
63393	dolerite metasomite	2.06	17.31	13.72	2.06	8.07	354472.14 E 6597459.4 N
63390	dolerite metasomite	2.02	18.33	14.68	2.43	7.70	354472.14 E 6597459.4 N
63389	dolerite metasomite	1.88	18.64	15.08	2.60	7.56	354472.14 E 6597459.4 N
63387	dolerite metasomite	1.47	18.02	14.89	2.64	7.55	354472.14 E 6597459.4 N
63386	dolerite metasomite	0.50	17.18	15.01	2.75	8.45	354472.14 E 6597459.4 N
63385	dolerite metasomite	9.71	17.58	7.08	2.25	7.25	354472.14 E 6597459.4 N
63384	dolerite metasomite	11.35	18.23	6.19	2.36	7.14	354472.14 E 6597459.4 N
63383	dolerite metasomite	11.96	18.01	5.44	2.38	6.91	354472.14 E 6597459.4 N
63382	dolerite metasomite	11.98	18.07	5.48	2.51	7.19	354472.14 E 6597459.4 N
63381	dolerite metasomite	11.56	18.02	5.81	2.59	7.59	354472.14 E 6597459.4 N
63380	dolerite metasomite	10.13	17.31	6.46	1.83	7.64	354472.14 E 6597459.4 N

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Table D.8: *continued*

63379	dolerite metasomite	12.45	18.40	5.35	2.42	7.15	354472.14 E 6597459.4 N
63378	dolerite metasomite	12.66	18.93	5.64	1.61	6.55	354472.14 E 6597459.4 N
63377	dolerite metasomite	12.53	19.08	5.89	1.73	6.96	354472.14 E 6597459.4 N
63375	dolerite metasomite	10.43	17.60	6.45	1.81	7.52	354472.14 E 6597459.4 N
63374	dolerite metasomite	8.57	16.59	7.22	1.71	8.14	354472.14 E 6597459.4 N
63373	dolerite metasomite	1.00	18.44	15.69	1.78	7.13	354472.14 E 6597459.4 N
63372	dolerite metasomite	0.83	18.48	15.88	1.74	7.45	354472.14 E 6597459.4 N
63371	dolerite metasomite	0.68	17.29	14.95	1.64	7.60	354472.14 E 6597459.4 N
63370	dolerite metasomite	0.63	17.66	15.32	1.64	8.10	354472.14 E 6597459.4 N
63369	dolerite metasomite	0.65	18.03	15.64	1.65	8.55	354472.14 E 6597459.4 N
63368	dolerite metasomite	1.24	16.31	13.56	1.48	8.25	354472.14 E 6597459.4 N
63367	dolerite metasomite	0.01	17.14	15.41	1.66	8.80	354472.14 E 6597459.4 N
63366	dolerite metasomite	0.66	17.31	14.98	1.56	8.21	354472.14 E 6597459.4 N
63365	dolerite metasomite	0.94	19.60	16.79	1.91	6.42	354472.14 E 6597459.4 N
63364	dolerite metasomite	5.67	21.45	14.20	2.38	5.66	354472.14 E 6597459.4 N
63363	dolerite metasomite	13.32	15.88	2.30	1.32	3.02	354472.14 E 6597459.4 N
63361	dolerite metasomite	11.29	13.85	2.30	1.20	3.06	354472.14 E 6597459.4 N
63360	dolerite metasomite	15.35	17.99	2.38	1.24	3.26	354472.14 E 6597459.4 N
63359	dolerite metasomite	13.63	16.83	2.88	1.23	3.26	354472.14 E 6597459.4 N
63358	dolerite metasomite	4.28	13.95	8.70	1.72	4.33	354472.14 E 6597459.4 N
63357	dolerite metasomite	2.11	12.13	9.02	1.52	4.29	354472.14 E 6597459.4 N
63356	dolerite metasomite	5.19	17.21	10.82	1.68	3.21	354472.14 E 6597459.4 N
63355	dolerite metasomite	4.82	18.32	12.15	1.88	2.86	354472.14 E 6597459.4 N
63354	dolerite metasomite	4.12	17.23	11.80	1.85	3.93	354472.14 E 6597459.4 N
63353	dolerite metasomite	7.78	22.89	13.60	1.97	2.91	354472.14 E 6597459.4 N
63352	dolerite metasomite	8.37	26.40	16.22	2.18	2.52	354472.14 E 6597459.4 N
63351	dolerite metasomite	6.85	22.09	13.71	2.07	2.89	354472.14 E 6597459.4 N
32322	dolerite recrystallised dolerite	0.90		9.40	7.90	9.60	385060.09 E 6437349.9 N
32350	dolerite recrystallised dolerite	5.10		5.50	3.10	5.20	363768.87 E 6521169.0 N
32349	dolerite recrystallised dolerite	5.40		5.50	3.10	4.90	363768.87 E 6521169.0 N
32348	dolerite recrystallised dolerite	2.70		9.50	6.60	8.10	363768.87 E 6521169.0 N
32346	dolerite recrystallised dolerite	1.90		9.30	5.70	9.50	363768.87 E 6521169.0 N
32345	dolerite recrystallised dolerite	2.00		9.30	5.90	9.50	363768.87 E 6521169.0 N
32344	dolerite recrystallised dolerite	2.40		9.90	5.80	9.60	363768.87 E 6521169.0 N
32343	dolerite recrystallised dolerite	2.30		10.00	6.40	9.30	363768.87 E 6521169.0 N

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Table D.8: *continued*

32342	dolerite recrystallised dolerite	1.90			10.10	6.40	8.90	363768.87 E 6521169.0 N
32269	dolerite recrystallised dolerite	1.20			10.10	7.10	10.80	383609.75 E 6436682.8 N
32682	dolerite recrystallised dolerite	1.30			11.70	7.60	9.40	382969.79 E 6436670.8 N
32680	dolerite recrystallised dolerite	1.20			11.10	6.60	8.00	382969.79 E 6436670.8 N
32644	dolerite recrystallised dolerite	1.40			11.90	7.20	10.60	387210.43 E 6429892.7 N
32641	dolerite recrystallised dolerite	1.10			11.80	8.30	10.10	387210.43 E 6429892.7 N
32631	dolerite recrystallised dolerite	1.40			10.00	7.80	7.60	388031.48 E 6429999.5 N
32630	dolerite recrystallised dolerite	1.60			10.90	7.90	9.60	388031.48 E 6429999.5 N
32629	dolerite recrystallised dolerite	3.20			9.90	5.50	10.60	388031.48 E 6429999.5 N
32624	dolerite recrystallised dolerite	2.10			9.90	5.70	9.50	387939.46 E 6429997.7 N
32623	dolerite recrystallised dolerite	2.50			10.90	7.10	10.00	387939.46 E 6429997.7 N
32616	dolerite recrystallised dolerite	2.60			13.40	4.30	8.20	387939.46 E 6429997.7 N
32603	dolerite recrystallised dolerite	2.10			10.20	7.00	9.80	387848.19 E 6429996.2 N
32600	dolerite recrystallised dolerite	1.80			10.40	5.50	8.20	387848.19 E 6429996.2 N
32589	dolerite recrystallised dolerite	1.40			8.50	3.10	5.70	387756.92 E 6429994.3 N
32584	dolerite recrystallised dolerite	1.60			9.20	6.10	9.40	388031.48 E 6429999.5 N
32583	dolerite recrystallised dolerite	1.80			9.00	7.50	8.70	388031.48 E 6429999.5 N
32582	dolerite recrystallised dolerite	1.50			8.50	6.90	10.00	388031.48 E 6429999.5 N
32347	dolerite recrystallised dolerite	2.70			9.10	5.90	9.00	363768.87 E 6521169.0 N
32681	dolerite recrystallised dolerite	1.30			10.80	7.30	10.10	382969.79 E 6436670.8 N
32642	dolerite recrystallised dolerite	1.00			11.20	7.80	11.10	387210.43 E 6429892.7 N
32622	dolerite recrystallised dolerite	2.60			13.20	4.90	9.70	387939.46 E 6429997.7 N
32590	dolerite recrystallised dolerite	1.50			12.00	3.90	6.30	387756.92 E 6429994.3 N
32341	dolerite recrystallised dolerite	2.30			7.20	3.90	8.40	363768.87 E 6521169.0 N
32235	dolerite uraltised dolerite	1.20			8.60	6.70	12.20	385151.43 E 6437351.8 N
32234	dolerite uraltised dolerite	1.90			8.50	8.20	10.70	385151.43 E 6437351.8 N
32233	dolerite uraltised dolerite	1.00			9.50	9.20	10.50	385060.09 E 6437349.9 N
32230	dolerite uraltised dolerite	1.00			10.40	8.90	10.60	385060.09 E 6437349.9 N
32229	dolerite uraltised dolerite	1.20			9.20	7.90	11.00	385060.09 E 6437349.9 N
32228	dolerite uraltised dolerite	1.20			9.70	8.50	11.10	385060.09 E 6437349.9 N
32177	dolerite uraltised dolerite	1.90			10.80	7.60	11.40	385517.43 E 6437358.5 N
32165	dolerite uraltised dolerite	1.60			10.50	7.80	11.10	385426.10 E 6437356.6 N
32164	dolerite uraltised dolerite	0.50			9.40	7.30	10.60	385426.10 E 6437356.6 N
32260	dolerite uraltised dolerite	0.80			10.20	8.60	10.90	383609.75 E 6436682.8 N
32256	dolerite uraltised dolerite	0.70			7.30	6.70	11.70	383609.75 E 6436682.8 N

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Table D.8: *continued*

32255	dolerite uraltitised dolerite	1.50			9.50	7.40	11.30	383609.75 E 6436682.8 N
32677	dolerite uraltitised dolerite	0.90			9.30	8.40	11.80	382969.79 E 6436670.8 N
32645	dolerite uraltitised dolerite	1.10			10.60	12.30	10.40	386899.60 E 6436744.3 N
32640	dolerite uraltitised dolerite	0.90			9.90	8.30	10.90	387210.43 E 6429892.7 N
32639	dolerite uraltitised dolerite	0.80			10.60	7.40	10.80	387210.43 E 6429892.7 N
32637	dolerite uraltitised dolerite	1.80			11.30	7.60	10.80	387210.43 E 6429892.7 N
32636	dolerite uraltitised dolerite	2.30			8.50	7.30	10.00	387210.43 E 6429892.7 N
33102	dolerite uraltitised dolerite	3.20			11.20	3.40	5.90	348865.72 E 6759474.7 N
32778	dolerite uraltitised dolerite	5.90			11.40	4.30	6.60	334411.19 E 6577151.0 N
32777	dolerite uraltitised dolerite	0.10			14.90	4.40	8.20	334411.19 E 6577151.0 N
32776	dolerite uraltitised dolerite	3.30			7.70	7.20	8.90	338481.55 E 6584723.0 N
32775	dolerite uraltitised dolerite	3.80			7.40	5.80	11.50	341968.66 E 6578932.5 N
32227	dolerite uraltitised dolerite	0.70			9.90	8.50	11.10	385060.09 E 6437349.9 N
32167	dolerite uraltitised dolerite	0.90			10.40	8.20	10.70	385517.43 E 6437358.5 N
32779	dolerite uraltitised dolerite	3.90			8.60	4.80	5.40	334411.19 E 6577151.0 N
32638	dolerite uraltitised dolerite	0.60			10.40	7.30	10.80	387210.43 E 6429892.7 N
32617	dolerite uraltitised dolerite	1.80			9.80	7.70	10.80	387939.46 E 6429997.7 N
32170	dolerite uraltitised dolerite	1.50			11.70	8.40	9.50	385517.43 E 6437358.5 N
32605	dolerite	2.70			8.50	7.30	10.40	386168.96 E 6436730.5 N
32559	dolerite	2.40			9.80	6.70	10.30	386168.96 E 6436730.5 N
32557	dolerite	1.50			8.70	6.90	10.50	386168.96 E 6436730.5 N
32555	dolerite	2.20			10.40	6.40	8.70	386168.96 E 6436730.5 N
32554	dolerite	2.40			12.70	5.40	12.10	386168.96 E 6436730.5 N
32606	dolerite	1.90			9.00	7.30	11.20	386168.96 E 6436730.5 N
32556	dolerite	1.20			7.80	3.90	11.50	386168.96 E 6436730.5 N
32558	dolerite	2.30			9.70	6.80	10.90	386168.96 E 6436730.5 N
32553	dolerite	2.30			8.60	7.10	11.00	386168.96 E 6436730.5 N
38829	dolerite	4.08			11.70	4.23	7.33	299500.00 E 6609600.0 N
38796	dolerite	1.93			8.73	29.30	2.72	299370.00 E 6724030.0 N
38775	dolerite	1.95			7.68	6.01	11.06	392697.00 E 6514499.0 N
38773	dolerite	1.36			7.30	9.42	4.46	391557.00 E 6514389.0 N
38772	dolerite	0.94			6.29	5.90	8.73	391557.00 E 6514389.0 N
38764	dolerite	0.99			5.15	6.90	7.77	381065.00 E 6531189.0 N
38755	dolerite	2.65			7.74	7.92	10.18	373630.00 E 6546179.0 N
38748	dolerite	1.70			7.73	8.83	9.70	373630.00 E 6546179.0 N

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Table D.8: continued

38737	dolerite	1.78			5.72	4.08	10.01	373748.00 E 6545680.0 N
38776	dolerite	2.11			8.61	6.31	10.30	392697.00 E 6514499.0 N
38770	dolerite	1.52			9.40	4.80	12.15	391557.00 E 6514389.0 N
Rock	Rock Type in solid	$\frac{Fe_{wt\%} \times Fe}{(Fe+Mg+Ca)}$	$\frac{Fe}{(Fe+Mg+Ca)}$	$\frac{Fe_2O_3}{(Fe_2O_3+FeO)}$	$\frac{Fe_2O_3}{(Fe_2O_3+FeO)}$	$\frac{Fe_2O_3}{FeO}$	$\frac{Fe^{3+}}{Fe^{2+}}$	
Code	geology GIS layer	l3_l_ch2	l3_l_ch1	l3_l_ch3	l3_l_ch4	l3_l_ch5		
Sslh	Interbedded Siltstone - Shale	4.11	0.68	0.37	0.78	0.70	No data for FeO.	
Ssl	Siltstone	4.11	0.68	0.37	0.78	0.70		
OZCHEM data								
Rock No.	Total Description ⁴	Fe ₂ O ₃	Fe ₂ O ₃ total	FeO	MgO	CaO	Location	
33690	siltstone	8.40			0.80	2.30	379995.67 E 6794566.8 N	
33689	siltstone	8.60			0.30	0.50	379995.67 E 6794566.8 N	
33688	siltstone	8.90			3.40	0.50	379995.67 E 6794566.8 N	
Rock	Rock Type in solid	$\frac{Fe_{wt\%} \times Fe}{(Fe+Mg+Ca)}$	$\frac{Fe}{(Fe+Mg+Ca)}$	$\frac{Fe_2O_3}{(Fe_2O_3+FeO)}$	$\frac{Fe_2O_3}{FeO}$	$\frac{Fe^{3+}}{Fe^{2+}}$		
Code	geology GIS layer	l3_l_ch2	l3_l_ch1	l3_l_ch3	l3_l_ch4	l3_l_ch5		
Zf	Fuchsite Schist	3.54	0.31	0.17	0.20	0.18		
Zm	Muscovite Schist	3.54	0.31	0.17	0.20	0.18		
Zs	Sericite Schist	3.54	0.31	0.17	0.20	0.18		
Zls	Undiff. Felsic Schists	3.54	0.31	0.17	0.20	0.18		
OZCHEM data								
Rock No.	Total Description ⁴	Fe ₂ O ₃	Fe ₂ O ₃ total	FeO	MgO	CaO	Location	
31579	schist amphibolite	1.59	10.02	7.59	7.09	11.66	247806.0 E 6770305.0 N	
31508	schist, actinolite, meta-high-Mg basalt	1.54	9.81	7.44	15.51	10.16	255910.0 E 6763039.0 N	
31393	schist hornblende schist	2.05	13.41	10.22	5.98	12.45	253949.0 E 6760035.0 N	
53941	schist actinolite-chl schist	1.58	10.55	8.07	19.96	9.43	256278.0 E 6761183.0 N	
31505	schist chl schist	3.08	19.76	15.01	23.08	0.11	253958.0 E 6776497.0 N	
Rock	Rock Type in solid	$\frac{Fe_{wt\%} \times Fe}{(Fe+Mg+Ca)}$	$\frac{Fe}{(Fe+Mg+Ca)}$	$\frac{Fe_2O_3}{(Fe_2O_3+FeO)}$	$\frac{Fe_2O_3}{FeO}$	$\frac{Fe^{3+}}{Fe^{2+}}$		
Code	geology GIS layer	l3_l_ch2	l3_l_ch1	l3_l_ch3	l3_l_ch4	l3_l_ch5		
Sc	Conglomerate	3.30	0.38	0.14	0.38	0.34		
Sxcm	Monomict Conglomerate	3.30	0.38	0.14	0.38	0.34		
S	Undivided Sedimentary Rocks	3.30	0.38	0.14	0.38	0.34		
OZCHEM data								

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Table D.8: *continued*

Rock No.	Total Description ⁴	Fe ₂ O ₃	Fe ₂ O ₃ total	FeO	MgO	CaO	Location
36980	metasediment, clay, m/sed. fragments?		20.87				371577.45 E 6629767.8 N
37223	metasediment felsic metasediment		3.67				317415.87 E 6620176.2 N
36970	metasediment greenish clay, foliated m/sed.		12.30				373975.16 E 6629695.3 N
36992	metasediment metasediment?		14.44				368699.91 E 6629855.3 N
36981	metasediment metasediment??		19.44				371337.58 E 6629775.0 N
37444	metasediment, clay, m/sed. + andalusite		0.33				276948.90 E 6616452.1 N
32612	sediment garnetiferous meta sediment	0.50		9.30	2.10	5.60	387939.46 E 6429997.7 N
32610	sediment garnetiferous meta sediment	0.60		12.10	4.30	5.50	387939.46 E 6429997.7 N
32611	sediment garnetiferous meta sediment	0.80		8.40	3.40	5.20	387939.46 E 6429997.7 N
32595	sediment garnetiferous meta sediment	2.40		17.00	5.60	8.20	387756.92 E 6429994.3 N
32368	sediment interpillow meta sediment	0.10		7.30	3.90	8.40	374585.86 E 6519628.8 N
32298	sediment meta sediment	9.30		1.70	11.60	0.40	357285.74 E 6586522.6 N
32625	sediment meta sediment	0.50		8.90	4.90	8.10	387939.46 E 6429997.7 N
32613	sediment meta sediment	1.60		10.20	5.20	7.90	387939.46 E 6429997.7 N
32609	sediment meta sediment	1.10		9.70	3.60	7.10	387939.46 E 6429997.7 N
32607	sediment meta sediment	2.20		13.30	5.70	5.30	387939.46 E 6429997.7 N
32604	sediment meta sediment	1.10		10.40	5.40	3.90	387848.19 E 6429996.2 N
32602	sediment meta sediment	2.70		13.40	3.50	12.50	387848.19 E 6429996.2 N
32599	sediment meta sediment	1.70		11.10	9.40	11.10	387756.92 E 6429994.3 N
32598	sediment meta sediment	0.60		6.30	2.10	6.20	387756.92 E 6429994.3 N
32597	sediment meta sediment	1.00		11.60	7.80	8.00	387756.92 E 6429994.3 N
32596	sediment meta sediment	0.80		5.70	2.30	9.90	387756.92 E 6429994.3 N
32591	sediment meta sediment	0.90		4.90	3.40	6.40	387756.92 E 6429994.3 N
32588	sediment meta sediment	1.80		9.20	8.60	11.00	388031.48 E 6429999.5 N
32306	sediment meta sediment	1.60		5.80	5.50	7.60	371957.14 E 6498368.0 N
32601	sediment meta sediment	1.00		7.60	1.90	5.70	387848.19 E 6429996.2 N
32594	sediment meta sediment	0.20		13.40	4.40	3.70	387756.92 E 6429994.3 N
37115	sediment meta sediment		15.67				342933.28 E 6622110.8 N
36971	sediment meta sediment		12.58				373735.39 E 6629702.6 N
36884	slate grey slate		5.15				393512.31 E 6630924.4 N
37105	slate grey slate		10.67				345219.89 E 6622818.5 N
37107	slate grey slate		9.22				344765.51 E 6622664.5 N
37106	slate grey slate		4.56				344992.74 E 6622741.6 N
37114	slate grey to black slate		6.22				343167.58 E 6622162.8 N

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Table D.8: *continued*

36888	slate slaty metasediment			12.58						392552.95 E 6630898.2 N
Rock Code	Rock Type in solid geology GIS layer	$\frac{Fe\ wt\% \times Fe}{(Fe+Mg+Ca)}$ l3.l.ch2	$\frac{Fe}{(Fe+Mg+Ca)}$ l3.l.ch1	$\frac{Fe_2O_3}{(Fe_2O_3+FeO)}$ l3.l.ch3	$\frac{Fe_2O_3}{FeO}$ l3.l.ch4	$\frac{Fe^{3+}}{Fe^{2+}}$ l3.l.ch5				
Shcc	Carbonaceous Shale	3.02	0.45	0.71	2.44	2.19				
OZCHEM data										
Rock No.	Total Description ⁴	Fe ₂ O ₃	Fe ₂ O ₃ total	FeO	MgO	CaO	Location			
93394	shale graphitic slate or phyllite	6.53	9.51	2.68	4.24	2.14	277550.30 E 7029826.8 N			
Rock Code	Rock Type in solid geology GIS layer	$\frac{Fe\ wt\% \times Fe}{(Fe+Mg+Ca)}$ l3.l.ch2	$\frac{Fe}{(Fe+Mg+Ca)}$ l3.l.ch1	$\frac{Fe_2O_3}{(Fe_2O_3+FeO)}$ l3.l.ch3	$\frac{Fe_2O_3}{FeO}$ l3.l.ch4	$\frac{Fe^{3+}}{Fe^{2+}}$ l3.l.ch5				
Mg	Gabbro	2.58	0.29	0.13	0.15	0.13				
Mg1	Gabbro - Kundana unit 1	2.58	0.29	0.13	0.15	0.13				
Mg2	Gabbro - Kundana unit 2	2.58	0.29	0.13	0.15	0.13				
Mg3	Gabbro - Kundana unit 3	2.58	0.29	0.13	0.15	0.13				
Mg5	Gabbro - Kundana unit 5	2.58	0.29	0.13	0.15	0.13				
Mg6	Gabbro - Kundana unit 6	2.58	0.29	0.13	0.15	0.13				
Mg6A	Gabbro - Kundana unit 6A	2.58	0.29	0.13	0.15	0.13				
Mg1	Leucocratic Gabbro	2.58	0.29	0.13	0.15	0.13				
Mgm	Melanocratic Gabbro	2.58	0.29	0.13	0.15	0.13				
Mgp	Porphyritic Gabbro	2.58	0.29	0.13	0.15	0.13				
OZCHEM data										
Rock No.	Total Description ⁴	Fe ₂ O ₃	Fe ₂ O ₃ total	FeO	MgO	CaO	Location			
76563	gabbro gabbro	1.84	10.59	7.87	24.20	5.62	262464.00 E 6754013.0			
37159	gabbro gabbro, fine-medium-grained		15.22				332507.63 E 6620846.2 N			
37157	gabbro gabbro, fine-medium-grained		13.11				332974.14 E 6620959.1 N			
37160	gabbro gabbro, medium-grained		14.67				332271.89 E 6620805.2 N			
37158	gabbro gabbro, medium-grained		11.89				332740.93 E 6620902.6 N			
37298	gabbro gabbro, medium-grained		10.33				299659.48 E 6617639.3 N			
37288	gabbro gabbro, pyroxenite		10.44				302038.69 E 6617955.5 N			
37155	gabbro leuco gabbro, medium-grained		6.11				333441.59 E 6621067.6 N			
32243	gabbro recrystallised gabbro	1.20		11.70	6.90	9.80	385151.43 E 6437351.8 N			
32241	gabbro recrystallised gabbro	2.20		12.90	4.40	11.00	385151.43 E 6437351.8 N			
32238	gabbro recrystallised gabbro	2.20		15.50	5.30	7.40	385151.43 E 6437351.8 N			

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Table D.8: *continued*

32237	gabbro recrystallised gabbro	1.80			11.80	6.10	9.90	385151.43 E 6437351.8 N
32184	gabbro recrystallised gabbro	1.30			10.00	7.50	11.40	385517.43 E 6437358.5 N
32160	gabbro recrystallised gabbro	1.40			9.80	6.20	9.40	385426.10 E 6437356.6 N
32365	gabbro recrystallised gabbro	0.70			5.70	6.90	8.10	374585.86 E 6519628.8 N
32363	gabbro recrystallised gabbro	1.10			7.20	7.30	5.50	374489.07 E 6519901.2 N
32362	gabbro recrystallised gabbro	1.10			6.70	7.70	9.30	374489.07 E 6519901.2 N
32361	gabbro recrystallised gabbro	1.30			8.20	7.30	9.90	374489.07 E 6519901.2 N
32244	gabbro recrystallised gabbro	1.20			10.00	6.00	9.60	385426.10 E 6437356.6 N
32240	gabbro recrystallised gabbro	1.50			14.30	5.80	10.50	385151.43 E 6437351.8 N
32236	gabbro recrystallised gabbro	1.60			10.20	4.00	8.00	385151.43 E 6437351.8 N
32626	gabbro recrystallised gabbro	1.70			6.70	9.20	10.50	387939.46 E 6429997.7 N
32364	gabbro recrystallised gabbro	1.00			5.60	6.20	8.60	374585.86 E 6519628.8 N
32188	gabbro recrystallised gabbro sill	1.60			8.90	11.90	10.90	371957.14 E 6498368.0 N
32162	gabbro uraltised gabbro	1.60			10.60	6.60	10.50	385426.10 E 6437356.6 N
32161	gabbro uraltised gabbro	1.00			8.60	6.30	10.70	385426.10 E 6437356.6 N
32250	gabbro uraltised gabbro	1.30			9.30	6.60	11.10	383609.75 E 6436682.8 N
32249	gabbro uraltised gabbro	1.40			9.90	6.50	11.20	383609.75 E 6436682.8 N
32665	gabbro uraltised gabbro	1.20			9.30	6.90	11.30	382969.79 E 6436670.8 N
32663	gabbro uraltised gabbro	0.80			8.10	6.80	11.70	382969.79 E 6436670.8 N
32608	gabbro uraltised gabbro	2.70			11.20	3.90	5.50	387939.46 E 6429997.7 N
32248	gabbro uraltised gabbro	1.40			9.40	6.20	10.10	383609.75 E 6436682.8 N
32664	gabbro uraltised gabbro	1.60			11.20	6.60	10.30	382969.79 E 6436670.8 N
37156	gabbro			8.22				333207.77 E 6621013.6 N
38833	gabbro	2.31			9.27	9.47	8.62	295300.00 E 6610500.0 N
38794	gabbro	1.17			7.46	14.40	13.20	295020.00 E 6730850.0 N
32187	gabbro norite, recrystal'd gabbro norite sill	1.20			9.90	14.80	9.80	371957.14 E 6498368.0 N
32581	gabbro norite, recrystal'd gabbro norite sill	1.50			9.10	13.70	9.90	371957.14 E 6498368.0 N
32580	norite recrystallised norite sill	0.80			11.60	20.30	7.30	371957.14 E 6498368.0 N
32649	norite uraltised norite	0.50			9.50	17.60	9.30	386899.60 E 6436744.3 N
Rock Code	Rock Type in solid geology GIS layer	$\frac{Fe_{wt\%} \times Fe}{(Fe+Mg+Ca)}$ l3_l.ch2	$\frac{Fe}{(Fe+Mg+Ca)}$ l3_l.ch1	$\frac{Fe_2O_3}{(Fe_2O_3+FeO)}$ l3_l.ch3	$\frac{Fe_2O_3}{FeO}$ l3_l.ch4	$\frac{Fe^{3+}}{Fe^{2+}}$ l3_l.ch5		
Hof	Alkali-rich Ortho Amphibolite	2.52	0.29	0.17	0.21	0.19		
Hpc	Calcic Para Amphibolite	2.52	0.29	0.17	0.21	0.19		
Hm	Mafic Amphibolite (undivided)	2.52	0.29	0.17	0.21	0.19		

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Table D.8: continued

OZCHEM data									
Rock No.	Total Description ⁴	Fe ₂ O ₃	Fe ₂ O ₃ total	FeO	MgO	CaO	Location		
53353	amphibolite amphibolite - mica bearing	1.87	14.58	11.44	3.29	10.83	252905.00 E 6777858.0 N		
31476	amphibolite amphibolite (metabasalt)	0.76	8.96	7.38	8.28	14.95	253904.00 E 6757670.0 N		
31389	amphibolite amphibolite (metabasalt)	1.87	11.46	8.63	4.71	10.90	254903.00 E 6759088.0 N		
31478	amphibolite amphibolite (metadolerite)	2.13	11.32	8.27	7.41	11.25	251622.00 E 6757336.0 N		
31427	amphibolite amphibolite (metadolerite)	1.14	10.75	8.65	8.74	10.53	248517.00 E 6761495.0 N		
31434	amphibolite amphibolite (metadolerite)	2.18	12.88	9.63	7.06	10.56	253509.00 E 6758378.0 N		
31485	amphibolite amphibolite (meta gabbro)	1.74	11.93	9.17	7.75	11.88	256914.00 E 6760549.0 N		
31507	amphibolite amphibolite (meta gabbro)	0.93	10.72	8.81	14.68	11.36	254532.00 E 6772344.0 N		
31436	amphibolite amphibolite (metagabbro)	1.72	11.60	8.89	7.09	12.25	252160.00 E 6757911.0 N		
31504	amphibolite amphibolite (metagabbro)	2.48	14.82	11.10	6.07	9.63	253705.00 E 6776393.0 N		
37414	amphibolite amphibolite, doleritic		8.44				281988.72 E 6616530.6 N		
37412	amphibolite amphibolite, doleritic		10.00				282468.77 E 6616535.5 N		
37413	amphibolite amphibolite?		11.00				282228.79 E 6616533.1 N		
37419	amphibolite banded amphibolite, doleritic		11.89				280788.62 E 6616518.0 N		
37428	amphibolite banded amphibolite, epidote		16.89				278628.76 E 6616490.7 N		
31475	amphibolite epidote amphib.(metabasalt)	2.80	10.56	6.98	5.20	16.55	253410.00 E 6757363.0 N		
37429	amphibolite foliated epidote amphibolite		11.89				278388.72 E 6616486.2 N		
53944	amphibolite	2.26	14.16	10.71	5.65	10.66	256472.00 E 6761239.0 N		
53948	amphibolite	2.64	13.31	9.60	6.41	8.64	257846.00 E 6776000.0 N		
33751	amphibolite	12.30			12.20	11.50	333367.82 E 6656511.6 N		
37426	amphibolite		9.56				279108.57 E 6616498.7 N		
Rock Code	Rock Type in solid geology GIS layer	$\frac{Fe_{wt\%} \times Fe}{(Fe+Mg+Ca)}$ l3.l.ch2	$\frac{Fe}{(Fe+Mg+Ca)}$ l3.l.ch1	$\frac{Fe_2O_3}{(Fe_2O_3+FeO)}$ l3.l.ch3	$\frac{Fe_2O_3}{FeO}$ l3.l.ch4	$\frac{Fe^{3+}}{Fe^{2+}}$ l3.l.ch5			
Mb	Basalt	2.38	0.29	0.18	0.24	0.22			
Mbbx	Mafic Pyroclastic Breccia	2.38	0.29	0.18	0.24	0.22			
Mb-mg	Mount Goode Basalt	2.38	0.29	0.18	0.24	0.22			
Mbp	Porphyritic Basalt	2.38	0.29	0.18	0.24	0.22			
Mbx	Undiv. Basalt, Autoclastic Rock	2.38	0.29	0.18	0.24	0.22			
Mby	Undiv. Mafic Pyroclastic Rock	2.38	0.29	0.18	0.24	0.22			
M	Undivided Mafic Rocks	2.38	0.29	0.18	0.24	0.22			
OZCHEM data									

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Table D.8: *continued*

Rock No.	Total Description ⁴	Fe ₂ O ₃	Fe ₂ O ₃ total	FeO	MgO	CaO	Location
32672	basalt altered basalt	1.40		8.20	5.20	11.00	382969.79 E 6436670.8 N
32666	basalt altered basalt	1.40		9.30	7.50	9.50	382969.79 E 6436670.8 N
53946	basalt amphibolite	1.97	9.60	6.87	6.41	11.39	247342.00 E 6771180.0 N
37372	basalt amphibolitic basalt		11.67				292068.29 E 6616646.4 N
37364	basalt amphibolitic basalt		11.56				292788.59 E 6616652.5 N
37352	basalt amphibolitic basalt		10.56				293268.83 E 6616656.5 N
37340	basalt amphibolitic basalt		10.22				293729.03 E 6616774.5 N
37411	basalt amphibolitic basalt		9.56				282708.75 E 6616538.0 N
37346	basalt amphibolitic basalt		11.56				293502.34 E 6616695.2 N
37334	basalt amphibolitic basalt		10.67				293955.44 E 6616853.8 N
37410	basalt amphibolitic basalt, f.g. doleritic		10.67				282948.73 E 6616540.4 N
37358	basalt amphibibic basalt, qtz-phyrlic felsic		13.33				293028.86 E 6616654.4 N
53940	basalt basalt - very fine-grained	2.49	11.59	8.19	6.22	9.64	253189.00 E 6761129.0 N
32821	basalt basalt breccia	0.50		8.20	4.90	9.70	359764.66 E 6545327.8 N
32820	basalt basalt breccia	1.10		7.80	4.90	9.40	359673.12 E 6545326.1 N
32819	basalt basalt breccia	1.10		3.70	6.80	10.10	359949.06 E 6545239.6 N
32818	basalt basalt breccia	2.10		10.20	7.00	9.40	359949.06 E 6545239.6 N
32305	basalt basalt tuff	1.30		17.90	4.70	7.90	371957.14 E 6498368.0 N
36952	basalt basalt, feldspar-phyrlic		13.73				377967.24 E 6629457.8 N
37271	basalt basalt, feldspar-phyrlic?		10.67				306087.63 E 6618456.2 N
37405	basalt basalt, fine elongate hornblende		9.33				284148.92 E 6616552.6 N
36956	basalt basalt, fine-grained		13.15				377089.14 E 6629513.9 N
36954	basalt basalt, fine-grained		14.44				377567.97 E 6629483.3 N
36946	basalt basalt, fine-grained		16.87				379001.98 E 6629544.0 N
37171	basalt basalt, fine-grained		10.11				329648.24 E 6620549.5 N
37165	basalt basalt, fine-grained		12.11				331077.56 E 6620690.7 N
37148	basalt basalt, fine-grained		12.33				335077.84 E 6621446.4 N
37144	basalt basalt, fine-grained		12.33				336018.53 E 6621634.7 N
37142	basalt basalt, fine-grained		8.22				336486.65 E 6621740.1 N
37396	basalt basalt, hornblende needles		5.56				286309.05 E 6616571.5 N
37406	basalt basalt, leucocratic, feldspar-phyrlic		8.67				283908.84 E 6616550.2 N
37273	basalt basalt, slightly weathered		10.44				305611.43 E 6618396.8 N
36936	basalt basalt, very fine-grained		15.44				381401.18 E 6629571.9 N
36934	basalt basalt, very fine-grained		14.15				381881.14 E 6629577.2 N

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Table D.8: *continued*

37018	basalt basalt, very fine-grained		12.58				363163.08 E 6629883.2 N
37017	basalt basalt, very fine-grained		13.73				363201.94 E 6629893.8 N
36945	basalt basalt, very fine-grained		15.30				379241.99 E 6629547.9 N
36944	basalt basalt, very fine-grained		14.44				379482.12 E 6629550.5 N
37172	basalt basalt, very fine-grained		11.67				329408.20 E 6620544.8 N
37146	basalt basalt, very fine-grained		11.33				335549.60 E 6621532.0 N
36950	basalt basalt, very fine-grained		13.58				378284.97 E 6629492.3 N
36935	basalt basalt, very f.g., amphibolitic		14.30				381641.02 E 6629574.6 N
36943	basalt basalt, v. f.g., qtz amygdaloes		14.44				379721.95 E 6629553.2 N
37382	basalt basalt/dolerite, feldspar-phyrlic?		9.89				289668.57 E 6616619.9 N
37182	basalt basalt?		11.56				327249.24 E 6620528.6 N
37816	basalt basalt?		12.33				327249.24 E 6620528.6 N
37186	basalt feldspar-phyrlic basalt		12.56				326290.09 E 6620491.9 N
37815	basalt feldspar-phyrlic basalt		14.15				383640.44 E 6629596.8 N
37389	basalt feldspar-phyrlic basalt		10.44				287988.87 E 6616593.1 N
37387	basalt feldspar-phyrlic basalt		4.11				288468.84 E 6616601.3 N
36926	basalt feldspar-phyrlic basalt		13.73				383600.50 E 6629596.3 N
37385	basalt felds-phyrlic basalt, amygdaloidal?		11.00				288948.73 E 6616609.0 N
37383	basalt feldspar-phyrlic basalt, f.g.		9.00				289428.72 E 6616616.2 N
37395	basalt felds-phyrlic basalt, leucocratic		7.00				286548.92 E 6616574.4 N
37392	basalt felds-phyrlic basalt, long hornblende		10.78				287268.92 E 6616582.3 N
37021	basalt felds-phyrlic basalt, v. f.g.		13.01				362509.44 E 6629696.0 N
37162	basalt felds-phyrlic basalt, v. f.g.		10.78				331794.45 E 6620754.1 N
37371	basalt felsic bio. schist + amphib'itic basalt		7.11				292308.55 E 6616648.4 N
37037	basalt foliated basalt		13.11				358814.14 E 6628655.1 N
37301	basalt foliated basalt		10.56				298945.93 E 6617542.7 N
37300	basalt foliated basalt		14.33				299183.81 E 6617574.8 N
37295	basalt foliated basalt		9.56				300372.73 E 6617737.5 N
37285	basalt foliated basalt		10.89				302753.02 E 6618043.3 N
37279	basalt foliated basalt		10.67				304182.27 E 6618219.3 N
37278	basalt foliated basalt		10.11				304420.52 E 6618248.6 N
37277	basalt foliated basalt		5.89				304658.75 E 6618278.3 N
37287	basalt foliated basalt		11.44				302276.55 E 6617984.0 N
37275	basalt foliated basalt		13.11				305135.14 E 6618337.6 N
37286	basalt foliated basalt		10.56				302515.28 E 6618013.0 N

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Table D.8: *continued*

37293	basalt leritic	basalt foliated basalt+felds-phyrlic do-		9.11						300848.62 E 6617801.4 N
37299	basalt foliated basalt, coarse felds-phyrlic			11.22						299421.50 E 6617607.1 N
37407	basalt foliated basalt, fine acicular hbl			8.78						283668.86 E 6616547.8 N
37391	basalt foliated feldspar-phyrlic basalt			10.00						287508.80 E 6616585.0 N
37169	basalt fresh basalt			12.67						330128.14 E 6620559.3 N
37168	basalt fresh basalt			10.89						330364.30 E 6620598.2 N
37167	basalt fresh basalt			11.33						330600.31 E 6620640.0 N
76562	basalt harrisite?	8.53		10.22	1.52	35.74		0.13		262464.00 E 6754013.0 N
73097	basalt Low-magnesian basalt			12.40		5.62		11.36		385953.71 E 6436741.3 N
73096	basalt Low-magnesian basalt			12.36		6.30		11.85		385953.71 E 6436741.3 N
73095	basalt Low-magnesian basalt			11.39		5.85		11.36		385953.71 E 6436741.3 N
73094	basalt Low-magnesian basalt			11.87		5.90		10.10		385953.71 E 6436741.3 N
73093	basalt Low-magnesian basalt			12.79		7.75		11.32		374256.15 E 6546361.8 N
73092	basalt Low-magnesian basalt			13.34		7.24		10.24		374256.15 E 6546361.8 N
73091	basalt Low-magnesian basalt			12.62		7.23		11.98		374256.15 E 6546361.8 N
73098	basalt Low-magnesian basalt			12.73		7.46		11.04		385953.71 E 6436741.3 N
36967	basalt massive basalt			14.73						374693.85 E 6629651.1 N
36933	basalt massive basalt, fine grained			15.87						382121.07 E 6629580.0 N
32239	basalt recrystallised basalt	2.00			13.90	5.90		8.40		385151.43 E 6437351.8 N
32370	basalt recrystallised basalt	1.40			8.90	8.80		10.30		374489.07 E 6519901.2 N
32359	basalt recrystallised basalt	1.60			8.20	7.60		10.40		374489.07 E 6519901.2 N
32358	basalt recrystallised basalt	1.40			8.30	7.30		9.80		374304.57 E 6519989.3 N
32355	basalt recrystallised basalt	2.00			7.70	8.80		9.90		374212.16 E 6520079.1 N
32354	basalt recrystallised basalt	1.60			8.40	8.10		10.30		374212.16 E 6520079.1 N
32353	basalt recrystallised basalt	1.40			7.10	7.80		9.80		374212.16 E 6520079.1 N
32351	basalt recrystallised basalt	1.50			8.50	7.90		10.90		374212.16 E 6520079.1 N
32322	basalt recrystallised basalt	1.50			6.70	9.20		10.30		359179.41 E 6749867.2 N
32321	basalt recrystallised basalt	1.20			5.70	8.10		11.60		358269.80 E 6749577.2 N
32320	basalt recrystallised basalt	1.40			8.30	7.90		10.30		358269.80 E 6749577.2 N
32318	basalt recrystallised basalt	3.10			10.80	8.10		11.50		357178.05 E 6749284.3 N
32317	basalt recrystallised basalt	3.70			9.90	7.80		10.90		359994.21 E 6750338.1 N
32311	basalt recrystallised basalt	2.90			11.40	9.70		12.10		371957.14 E 6498368.0 N
32310	basalt recrystallised basalt	1.80			9.80	7.90		9.80		371957.14 E 6498368.0 N
32309	basalt recrystallised basalt	1.30			8.20	6.90		9.10		371957.14 E 6498368.0 N

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Table D.8: *continued*

32307	basalt recrystallised basalt	2.50			8.90	6.70	9.30	371957.14 E 6498368.0 N
32266	basalt recrystallised basalt	1.40			10.90	7.10	11.10	383609.75 E 6436682.8 N
32264	basalt recrystallised basalt	2.00			13.60	3.70	7.80	383609.75 E 6436682.8 N
32252	basalt recrystallised basalt	0.70			9.60	5.50	5.00	383609.75 E 6436682.8 N
32247	basalt recrystallised basalt	1.10			9.10	4.90	10.10	383244.43 E 6436676.1 N
32686	basalt recrystallised basalt	1.80			9.20	8.10	11.30	383244.43 E 6436676.1 N
32678	basalt recrystallised basalt	1.40			10.10	6.60	10.70	382969.79 E 6436670.8 N
32667	basalt recrystallised basalt	1.30			8.70	6.30	6.60	382969.79 E 6436670.8 N
32659	basalt recrystallised basalt	1.30			7.30	8.10	9.40	381485.22 E 6442769.4 N
32655	basalt recrystallised basalt	1.00			8.00	6.20	11.10	381490.59 E 6442494.9 N
32653	basalt recrystallised basalt	1.20			12.20	5.70	11.60	386899.60 E 6436744.3 N
32652	basalt recrystallised basalt	1.00			8.60	8.10	11.00	386899.60 E 6436744.3 N
32651	basalt recrystallised basalt	1.60			11.90	6.80	10.50	386899.60 E 6436744.3 N
32650	basalt recrystallised basalt	1.70			10.30	6.10	9.50	386899.60 E 6436744.3 N
32647	basalt recrystallised basalt	1.10			10.10	7.30	11.40	386899.60 E 6436744.3 N
32615	basalt recrystallised basalt	1.50			8.60	7.70	10.00	387939.46 E 6429997.7 N
32614	basalt recrystallised basalt	1.40			9.10	9.10	11.70	387939.46 E 6429997.7 N
32571	basalt recrystallised basalt	2.30			10.30	6.70	10.90	377523.23 E 6449459.9 N
32570	basalt recrystallised basalt	2.30			10.90	7.40	11.00	377427.93 E 6449551.4 N
33163	basalt recrystallised basalt	2.00			14.50	5.60	8.60	351421.01 E 6526430.6 N
33161	basalt recrystallised basalt	1.40			5.10	10.50	11.70	352013.85 E 6523972.6 N
33160	basalt recrystallised basalt	2.30			8.30	7.40	12.60	360758.12 E 6515810.6 N
33157	basalt recrystallised basalt	1.80			6.60	7.00	11.80	360701.39 E 6518918.7 N
33156	basalt recrystallised basalt	2.20			8.00	9.20	10.50	360701.39 E 6518918.7 N
32771	basalt recrystallised basalt	1.30			7.10	7.30	11.60	325080.00 E 6577349.4 N
33754	basalt recrystallised basalt	14.10				7.20	11.80	333367.82 E 6656511.6 N
33752	basalt recrystallised basalt	11.90				6.90	13.50	333367.82 E 6656511.6 N
32352	basalt recrystallised basalt	1.60			9.20	7.80	11.10	374212.16 E 6520079.1 N
32319	basalt recrystallised basalt	3.50			9.40	9.10	11.40	357173.14 E 6749558.5 N
32257	basalt recrystallised basalt	1.20			9.70	8.30	9.30	383609.75 E 6436682.8 N
32220	basalt recrystallised basalt	1.70			15.20	4.70	8.80	384786.09 E 6437344.7 N
32185	basalt recrystallised basalt	2.00			14.40	4.00	8.60	385517.43 E 6437358.5 N
33904	basalt recrystallised basalt	10.50				6.00	15.40	333367.82 E 6656511.6 N
33162	basalt recrystallised basalt	2.30			8.20	7.90	10.10	352013.85 E 6523972.6 N
33158	basalt recrystallised basalt	2.30			8.30	7.10	11.90	360701.39 E 6518918.7 N

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Table D.8: *continued*

32658	basalt recrystallised basalt	1.10			7.90	7.60	10.30	381485.22 E 6442769.4 N
32360	basalt recrystallised basalt	1.30			9.10	8.70	10.30	374489.07 E 6519901.2 N
32356	basalt recrystallised basalt	1.20			7.50	7.60	9.50	374304.57 E 6519989.3 N
33159	basalt recrystallised basalt	2.20			7.90	7.50	12.80	360758.12 E 6515810.6 N
32357	basalt recrystallised basalt	1.40			8.40	7.30	9.70	374304.57 E 6519989.3 N
32308	basalt recrystallised basalt	3.00			8.70	7.40	10.60	371957.14 E 6498368.0 N
32242	basalt recrystallised basalt	1.50			11.30	6.80	9.60	385151.43 E 6437351.8 N
32657	basalt recrystallised basalt core	1.10			7.60	6.70	9.60	381490.59 E 6442494.9 N
32656	basalt recrystallised basalt skin	4.20			9.00	10.00	12.00	381490.59 E 6442494.9 N
32585	basalt recrystallised carbonated basalt	2.60			6.70	7.60	16.30	388031.48 E 6429999.5 N
32654	basalt recrystallised garnet basalt core	1.40			10.20	2.40	5.90	380935.18 E 6442850.4 N
37409	basalt schistose feldspar-phyrlic basalt		10.33					283188.81 E 6616542.9 N
32823	basalt silicified basalt breccia	0.60			2.50	7.10	9.40	359945.87 E 6545422.5 N
32822	basalt silicified basalt breccia	1.10			4.00	3.10	6.80	359854.32 E 6545420.7 N
32367	basalt silicified recrystallised basalt	3.00			5.80	5.70	9.60	374585.86 E 6519628.8 N
32366	basalt silicified recrystallised basalt	2.20			5.20	3.80	9.60	374585.86 E 6519628.8 N
32293	basalt spilitic basalt	2.40			3.70	4.40	6.80	357924.38 E 6586625.5 N
32292	basalt spilitic basalt	2.30			7.70	8.10	7.00	357924.38 E 6586625.5 N
32291	basalt spilitic basalt	2.50			9.40	9.90	7.60	357924.38 E 6586625.5 N
36835	basalt strongly foliated basalt		10.87					405142.42 E 6632161.9 N
36834	basalt strongly foliated basalt		10.87					405377.28 E 6632210.9 N
37039	basalt strongly foliated basalt		9.11					358355.14 E 6628515.3 N
37038	basalt strongly foliated basalt		13.11					358584.69 E 6628585.2 N
32169	basalt uraltised amygdaloidal basalt	1.40			9.70	8.20	10.30	385517.43 E 6437358.5 N
32226	basalt uraltised basalt	0.70			9.80	9.00	10.30	385060.09 E 6437349.9 N
32224	basalt uraltised basalt	1.50			10.60	5.20	12.80	384877.42 E 6437346.6 N
32223	basalt uraltised basalt	1.40			10.70	7.50	10.60	384877.42 E 6437346.6 N
32222	basalt uraltised basalt	1.70			8.90	4.60	12.60	384877.42 E 6437346.6 N
32221	basalt uraltised basalt	1.80			9.40	5.40	10.80	384786.09 E 6437344.7 N
32219	basalt uraltised basalt	2.40			8.60	5.10	12.00	384786.09 E 6437344.7 N
32218	basalt uraltised basalt	1.70			9.70	6.50	12.20	384786.09 E 6437344.7 N
32186	basalt uraltised basalt	1.50			10.40	6.10	11.20	385517.43 E 6437358.5 N
32183	basalt uraltised basalt	1.90			7.30	4.70	12.60	385517.43 E 6437358.5 N
32182	basalt uraltised basalt	0.90			8.90	8.00	10.00	385517.43 E 6437358.5 N
32181	basalt uraltised basalt	1.20			8.60	6.00	10.60	385517.43 E 6437358.5 N

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Table D.8: *continued*

32179	basalt uralitised basalt	1.60			9.60	6.60	11.20	385517.43 E 6437358.5 N
32178	basalt uralitised basalt	1.40			9.60	7.30	11.00	385517.43 E 6437358.5 N
32176	basalt uralitised basalt	1.10			7.40	4.60	13.20	385517.43 E 6437358.5 N
32174	basalt uralitised basalt	1.30			9.30	6.10	10.10	385517.43 E 6437358.5 N
32173	basalt uralitised basalt	0.90			10.80	8.00	8.80	385517.43 E 6437358.5 N
32171	basalt uralitised basalt	0.80			9.50	6.00	10.80	385517.43 E 6437358.5 N
32168	basalt uralitised basalt	1.20			8.80	4.60	10.80	385517.43 E 6437358.5 N
32166	basalt uralitised basalt	1.20			6.90	4.10	12.40	385426.10 E 6437356.6 N
32339	basalt uralitised basalt	2.70			8.20	7.70	10.30	373637.43 E 6546675.9 N
32316	basalt uralitised basalt	2.50			9.30	6.40	10.60	359387.12 E 6748407.6 N
32315	basalt uralitised basalt	2.20			8.70	6.60	11.90	358107.75 E 6748385.7 N
32313	basalt uralitised basalt	2.80			8.60	6.00	11.40	358380.47 E 6748481.9 N
32312	basalt uralitised basalt	1.40			6.30	3.40	9.20	358922.39 E 6748857.0 N
32271	basalt uralitised basalt	0.80			9.10	4.70	12.30	384786.09 E 6437344.7 N
32268	basalt uralitised basalt	1.20			9.00	5.50	12.30	383609.75 E 6436682.8 N
32267	basalt uralitised basalt	0.70			8.50	4.60	11.70	383609.75 E 6436682.8 N
32263	basalt uralitised basalt	1.50			8.90	5.30	11.70	383609.75 E 6436682.8 N
32262	basalt uralitised basalt	0.90			10.20	7.70	11.10	383609.75 E 6436682.8 N
32259	basalt uralitised basalt	0.90			9.80	8.00	10.40	383609.75 E 6436682.8 N
32254	basalt uralitised basalt	1.50			9.60	6.60	11.20	383609.75 E 6436682.8 N
32251	basalt uralitised basalt	1.70			9.70	5.10	8.70	383609.75 E 6436682.8 N
32246	basalt uralitised basalt	1.30			10.70	7.80	9.00	383244.43 E 6436676.1 N
32245	basalt uralitised basalt	1.50			8.60	5.80	10.20	383244.43 E 6436676.1 N
32684	basalt uralitised basalt	1.20			10.20	7.20	10.10	383244.43 E 6436676.1 N
32683	basalt uralitised basalt	1.10			9.50	7.80	10.40	382969.79 E 6436670.8 N
32679	basalt uralitised basalt	0.90			9.80	8.50	12.00	382969.79 E 6436670.8 N
32676	basalt uralitised basalt	1.10			7.70	6.20	12.00	382969.79 E 6436670.8 N
32674	basalt uralitised basalt	1.00			8.50	7.20	11.40	382969.79 E 6436670.8 N
32673	basalt uralitised basalt	1.30			8.60	4.70	11.10	382969.79 E 6436670.8 N
32670	basalt uralitised basalt	1.10			8.60	6.20	10.80	382969.79 E 6436670.8 N
32669	basalt uralitised basalt	1.00			9.30	6.00	11.90	382969.79 E 6436670.8 N
32668	basalt uralitised basalt	0.70			6.80	4.70	11.20	382969.79 E 6436670.8 N
32661	basalt uralitised basalt	1.70			9.40	7.60	9.50	382969.79 E 6436670.8 N
32660	basalt uralitised basalt	1.60			9.00	7.20	10.80	382969.79 E 6436670.8 N
32648	basalt uralitised basalt	1.30			10.10	8.50	10.70	386899.60 E 6436744.3 N

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Table D.8: *continued*

32646	basalt uraltitised basalt	1.20			9.90	7.90	11.60	386899.60 E 6436744.3 N
32634	basalt uraltitised basalt	1.60			8.70	5.30	9.90	385517.43 E 6437358.5 N
32632	basalt uraltitised basalt	2.70			8.20	7.90	9.90	385517.43 E 6437358.5 N
32572	basalt uraltitised basalt	2.30			9.80	5.30	10.50	377614.53 E 6449372.2 N
33105	basalt uraltitised basalt	2.60			9.90	5.00	13.90	336099.66 E 6746728.4 N
33103	basalt uraltitised basalt	4.00			8.50	6.10	13.90	350467.83 E 6762062.7 N
32862	basalt uraltitised basalt	2.60			8.80	7.00	12.20	318569.29 E 6563056.5 N
32861	basalt uraltitised basalt	2.40			7.90	7.00	11.10	318569.29 E 6563056.5 N
32860	basalt uraltitised basalt	2.60			8.40	6.20	11.50	318569.29 E 6563056.5 N
32858	basalt uraltitised basalt	2.20			8.90	7.80	12.80	318569.29 E 6563056.5 N
32857	basalt uraltitised basalt	2.50			8.70	7.60	11.20	318569.29 E 6563056.5 N
32856	basalt uraltitised basalt	1.60			6.60	7.30	10.00	318569.29 E 6563056.5 N
32855	basalt uraltitised basalt	2.60			9.30	11.70	11.00	318569.29 E 6563056.5 N
32852	basalt uraltitised basalt	2.50			9.20	8.10	12.40	318569.29 E 6563056.5 N
32851	basalt uraltitised basalt	2.90			8.80	8.00	11.80	318569.29 E 6563056.5 N
32805	basalt uraltitised basalt	0.80			11.10	11.90	13.00	359132.65 E 6544859.0 N
32804	basalt uraltitised basalt	1.10			11.00	11.00	13.20	359132.65 E 6544859.0 N
32803	basalt uraltitised basalt	1.00			8.70	7.80	12.10	359043.10 E 6544766.0 N
32802	basalt uraltitised basalt	1.10			5.80	9.20	13.60	359128.31 E 6545133.3 N
32801	basalt uraltitised basalt	1.50			7.20	9.10	13.20	359037.90 E 6545040.2 N
32788	basalt uraltitised basalt	3.80			10.10	5.60	11.20	396162.90 E 6554854.6 N
32787	basalt uraltitised basalt	4.20			10.50	5.40	11.70	396162.90 E 6554854.6 N
32786	basalt uraltitised basalt	1.40			9.10	4.00	8.50	396162.90 E 6554854.6 N
32785	basalt uraltitised basalt	2.30			8.80	3.50	8.30	396162.90 E 6554854.6 N
32770	basalt uraltitised basalt	0.80			9.10	6.80	12.00	327171.63 E 6572905.8 N
32767	basalt uraltitised basalt	1.20			7.10	7.40	10.20	327171.63 E 6572905.8 N
32766	basalt uraltitised basalt	1.60			6.80	5.30	10.00	327171.63 E 6572905.8 N
32764	basalt uraltitised basalt	1.40			8.30	7.80	11.80	327171.63 E 6572905.8 N
32763	basalt uraltitised basalt	3.00			6.20	4.90	10.20	327171.63 E 6572905.8 N
32762	basalt uraltitised basalt	2.90			7.10	7.50	10.10	350538.11 E 6757948.8 N
33753	basalt uraltitised basalt	13.80				7.40	10.90	333367.82 E 6656511.6 N
32340	basalt uraltitised basalt	3.20			8.80	5.70	10.20	373637.43 E 6546675.9 N
32314	basalt uraltitised basalt	3.30			7.30	5.30	12.80	358380.47 E 6748481.9 N
32270	basalt uraltitised basalt	1.60			8.20	4.20	11.40	383609.75 E 6436682.8 N
32265	basalt uraltitised basalt	2.70			9.30	5.70	12.00	383609.75 E 6436682.8 N

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Table D.8: *continued*

32261	basalt uralitised basalt	1.50			8.50	5.10	10.20	383609.75 E 6436682.8 N
32253	basalt uralitised basalt	1.00			8.30	5.40	10.70	383609.75 E 6436682.8 N
32231	basalt uralitised basalt	0.80			9.70	8.50	11.20	385060.09 E 6437349.9 N
32180	basalt uralitised basalt	0.90			8.00	5.70	13.00	385517.43 E 6437358.5 N
32175	basalt uralitised basalt	1.80			11.10	7.00	9.40	385517.43 E 6437358.5 N
32163	basalt uralitised basalt	1.10			7.60	7.00	7.50	385426.10 E 6437356.6 N
32859	basalt uralitised basalt	2.30			7.60	5.80	11.50	318569.29 E 6563056.5 N
32854	basalt uralitised basalt	1.90			9.20	7.50	13.10	318569.29 E 6563056.5 N
32806	basalt uralitised basalt	0.40			8.40	9.30	11.40	359132.65 E 6544859.0 N
32774	basalt uralitised basalt	4.30			10.40	3.40	7.80	342573.92 E 6580864.0 N
32765	basalt uralitised basalt	1.40			7.30	6.70	10.50	327171.63 E 6572905.8 N
32761	basalt uralitised basalt	2.70			10.80	5.50	10.50	349631.21 E 6757476.2 N
32685	basalt uralitised basalt	1.30			8.60	4.50	10.70	383244.43 E 6436676.1 N
32675	basalt uralitised basalt	1.20			8.50	5.90	11.40	382969.79 E 6436670.8 N
32671	basalt uralitised basalt	1.20			7.80	4.80	10.90	382969.79 E 6436670.8 N
32662	basalt uralitised basalt	1.10			9.10	8.70	10.10	382969.79 E 6436670.8 N
32633	basalt uralitised basalt	1.90			9.00	5.40	10.30	385517.43 E 6437358.5 N
32853	basalt uralitised basalt	1.90			9.20	8.10	12.20	318569.29 E 6563056.5 N
32800	basalt uralitised basalt	1.70			12.00	8.20	13.40	359132.65 E 6544859.0 N
32769	basalt uralitised basalt	3.30			10.80	5.20	8.50	332268.10 E 6574277.7 N
32258	basalt uralitised basalt	1.20			9.20	7.10	11.10	383609.75 E 6436682.8 N
32225	basalt uralitised basalt	1.10			9.60	6.50	11.80	384877.42 E 6437346.6 N
32772	basalt uralitised basalt core	3.60			6.80	4.80	10.00	327262.66 E 6572907.5 N
32635	basalt uralitised basalt margin	1.60			10.80	7.10	11.50	385517.43 E 6437358.5 N
32773	basalt uralitised basalt shell	6.50			10.30	8.10	9.50	327262.66 E 6572907.5 N
32172	basalt uralitised basalt skin	1.70			12.50	7.70	9.40	385517.43 E 6437358.5 N
32768	basalt uralitised pillow basalt	2.50			11.50	12.50	10.90	327171.63 E 6572905.8 N
38801	basalt vesicular basalt	4.66			7.81	5.31	12.50	301950.00 E 6676500.0 N
38783	basalt vesicular basalt	2.75			8.02	5.01	7.60	300950.00 E 6652300.0 N
37393	basalt weathered basalt?		8.89					287028.86 E 6616579.6 N
32296	basalt weathered variolitic basalt	4.80			3.30	4.70	11.10	357561.99 E 6586436.1 N
37042	basalt well foliated basalt		13.11					357666.51 E 6628305.6 N
37041	basalt well foliated basalt		8.67					357896.05 E 6628375.6 N
37040	basalt well foliated basalt		13.89					358125.50 E 6628445.4 N
53354	basalt	2.35	14.93		11.32	3.49	8.67	253099.00 E 6777769.0 N

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Table D.8: *continued*

32567	basalt	1.90			8.90	7.10	9.70	386168.96 E 6436730.5 N
32566	basalt	0.80			7.70	4.50	11.50	386168.96 E 6436730.5 N
32565	basalt	0.80			10.40	4.60	9.70	386168.96 E 6436730.5 N
32564	basalt	0.10			10.50	4.20	12.80	386168.96 E 6436730.5 N
32562	basalt	4.20			8.80	5.00	9.10	386168.96 E 6436730.5 N
32561	basalt	1.70			8.60	4.90	10.10	386168.96 E 6436730.5 N
32560	basalt	0.90			10.60	7.90	7.10	386168.96 E 6436730.5 N
33155	basalt	2.50			14.10	5.70	8.40	351421.01 E 6526430.6 N
33154	basalt	2.50			9.10	8.90	12.60	361071.81 E 6518651.1 N
32568	basalt	2.10			9.70	4.20	8.60	386168.96 E 6436730.5 N
32563	basalt	1.60			8.50	3.80	13.80	386168.96 E 6436730.5 N
37102	basalt		10.56					345913.84 E 6623000.5 N
37032	basalt		11.56					359967.77 E 6628984.1 N
37030	basalt		11.78					360429.73 E 6629114.0 N
37380	basalt		10.11					290148.46 E 6616627.1 N
37297	basalt		12.22					299897.27 E 6617671.7 N
37173	basalt		6.56					329168.15 E 6620539.9 N
38856	basalt	2.55			9.66	3.67	9.78	392160.00 E 6563130.0 N
38855	basalt	1.47			6.39	3.16	9.72	392160.00 E 6563130.0 N
38854	basalt	2.35			10.10	3.92	11.20	392160.00 E 6563130.0 N
38853	basalt	2.48			10.10	5.45	10.90	392160.00 E 6563130.0 N
38852	basalt	1.70			6.66	4.29	15.10	392160.00 E 6563130.0 N
38851	basalt	3.80			6.58	3.79	8.95	392160.00 E 6563130.0 N
38850	basalt	-0.58			7.95	4.03	12.20	392160.00 E 6563130.0 N
38849	basalt	1.15			5.43	4.67	6.71	392160.00 E 6563130.0 N
38848	basalt	1.05			6.55	3.81	10.60	392160.00 E 6563130.0 N
38846	basalt	1.53			5.97	3.98	11.30	392573.00 E 6563053.0 N
38845	basalt	0.80			5.63	3.66	11.10	392573.00 E 6563053.0 N
38843	basalt	1.72			7.30	6.06	10.90	392573.00 E 6563053.0 N
38842	basalt	1.47			0.24	3.68	10.60	392573.00 E 6563053.0 N
38841	basalt	1.37			7.56	3.77	10.70	392573.00 E 6563053.0 N
38840	basalt	1.28			6.59	4.39	10.60	392573.00 E 6563053.0 N
38839	basalt	1.54			7.43	5.92	10.80	392573.00 E 6563053.0 N
38837	basalt	0.52			5.11	2.62	9.39	392573.00 E 6563053.0 N
38836	basalt	0.64			4.47	2.90	7.77	392573.00 E 6563053.0 N

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Table D.8: *continued*

38835	basalt	0.95		5.77	3.55	9.20	392573.00 E 6563053.0 N
38834	basalt	3.02		10.60	6.38	11.50	300600.00 E 6603700.0 N
38831	basalt	1.85		9.12	13.00	10.20	294500.00 E 6607000.0 N
38830	basalt	1.98		9.31	9.67	10.80	299600.00 E 6609700.0 N
38828	basalt	1.73		7.45	6.84	11.60	326453.00 E 6574620.0 N
38826	basalt	1.21		9.18	15.00	10.90	326453.00 E 6574620.0 N
38824	basalt	2.09		10.50	6.47	9.15	326453.00 E 6574620.0 N
38823	basalt	1.26		8.42	8.81	12.00	326453.00 E 6574620.0 N
38822	basalt	0.89		8.69	11.20	12.90	326453.00 E 6574620.0 N
38821	basalt	1.31		8.97	12.10	11.60	326453.00 E 6574620.0 N
38820	basalt	0.98		11.50	17.90	8.64	326453.00 E 6574620.0 N
38819	basalt	0.84		9.92	20.70	7.31	326453.00 E 6574620.0 N
38818	basalt	1.27		10.20	15.40	9.01	326453.00 E 6574620.0 N
38817	basalt	1.52		9.17	7.28	11.60	326453.00 E 6574620.0 N
38815	basalt	2.06		8.90	7.25	11.30	371913.00 E 6493859.0 N
38814	basalt	1.81		8.16	7.02	11.60	371913.00 E 6493859.0 N
38813	basalt	1.83		8.69	7.25	11.80	371913.00 E 6493859.0 N
38812	basalt	2.56		9.07	5.79	10.60	371913.00 E 6493859.0 N
38811	basalt	1.71		8.14	7.10	12.10	371913.00 E 6493859.0 N
38810	basalt	1.90		8.63	7.14	11.50	371913.00 E 6493859.0 N
38807	basalt	1.75		8.80	6.92	10.80	359630.00 E 6522560.0 N
38806	basalt	1.78		8.61	7.42	11.60	359630.00 E 6522560.0 N
38805	basalt	1.96		8.55	7.21	10.20	359630.00 E 6522560.0 N
38804	basalt	1.16		9.12	6.70	10.80	359630.00 E 6522560.0 N
38803	basalt	1.96		8.72	7.69	15.20	295090.00 E 6730850.0 N
38802	basalt	2.30		10.10	6.48	12.30	298890.00 E 6726350.0 N
38800	basalt	4.05		11.90	6.06	8.23	301500.00 E 6676000.0 N
38798	basalt	2.64		10.00	7.14	9.92	303000.00 E 6625500.0 N
38797	basalt	3.26		9.62	5.89	9.72	303150.00 E 6624500.0 N
38795	basalt	1.89		8.62	7.52	11.10	295035.00 E 6730100.0 N
38792	basalt	1.50		8.09	8.41	10.60	298350.00 E 6725850.0 N
38791	basalt	1.58		8.77	6.53	12.10	298350.00 E 6725850.0 N
38790	basalt	2.17		8.84	13.20	11.00	298350.00 E 6725850.0 N
38789	basalt	2.60		7.78	8.18	9.23	298950.00 E 6667200.0 N
38787	basalt	2.04		8.34	18.90	8.68	300250.00 E 6665750.0 N

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Table D.8: *continued*

38785	basalt	2.00		8.57	9.57	10.80	298750.00 E 6652850.0 N
38784	basalt	2.47		9.43	6.79	10.40	300750.00 E 6652300.0 N
38782	basalt	1.46		9.01	11.60	10.80	300400.00 E 6652350.0 N
38781	basalt	0.88		4.12	3.57	6.57	392697.00 E 6514499.0 N
38780	basalt	1.46		7.01	5.11	11.52	392697.00 E 6514499.0 N
38779	basalt	2.33		8.78	7.00	11.13	392697.00 E 6514499.0 N
38778	basalt	1.86		8.06	6.22	10.24	392697.00 E 6514499.0 N
38777	basalt	1.45		8.14	5.00	8.17	392697.00 E 6514499.0 N
38774	basalt	1.54		7.96	7.19	1.49	391557.00 E 6514389.0 N
38771	basalt	1.73		7.92	6.58	11.70	391557.00 E 6514389.0 N
38769	basalt	1.62		7.59	6.01	12.14	391557.00 E 6514389.0 N
38768	basalt	1.43		7.20	5.50	12.74	391557.00 E 6514389.0 N
38767	basalt	0.87		5.21	3.44	10.69	380952.00 E 6531098.0 N
38766	basalt	1.21		6.55	3.26	11.35	380952.00 E 6531098.0 N
38765	basalt	2.36		7.57	3.77	9.48	380952.00 E 6531098.0 N
38763	basalt	1.90		6.32	4.15	12.69	381065.00 E 6531189.0 N
38762	basalt	2.36		8.92	7.59	11.22	381065.00 E 6531189.0 N
38761	basalt	2.75		8.61	7.12	12.32	381065.00 E 6531189.0 N
38760	basalt	2.96		7.79	7.35	11.50	373630.00 E 6546179.0 N
38758	basalt	2.30		8.73	7.73	10.65	373630.00 E 6546179.0 N
38757	basalt	3.01		8.26	7.95	10.02	373630.00 E 6546179.0 N
38756	basalt	2.08		8.72	7.21	10.20	373630.00 E 6546179.0 N
38754	basalt	2.71		7.71	8.50	9.79	373630.00 E 6546179.0 N
38753	basalt	2.13		8.56	7.28	10.96	373630.00 E 6546179.0 N
38752	basalt	2.13		8.75	8.04	11.27	373630.00 E 6546179.0 N
38751	basalt	2.23		8.26	8.29	11.39	373630.00 E 6546179.0 N
38750	basalt	3.09		8.56	7.98	12.93	373630.00 E 6546179.0 N
38747	basalt	1.77		8.25	7.53	11.18	373630.00 E 6546179.0 N
38746	basalt	3.70		6.35	6.69	15.54	373630.00 E 6546179.0 N
38745	basalt	2.29		8.02	9.02	10.11	373630.00 E 6546179.0 N
38744	basalt	4.19		7.31	7.75	12.13	373630.00 E 6546179.0 N
38743	basalt	2.18		9.59	9.84	9.51	373630.00 E 6546179.0 N
38742	basalt	2.13		8.64	9.58	9.74	373630.00 E 6546179.0 N
38740	basalt	2.22		8.58	7.65	12.70	373630.00 E 6546179.0 N
38739	basalt	2.14		6.96	5.68	9.05	373748.00 E 6545680.0 N

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Table D.8: continued

38738	basalt	2.04		5.73	4.20	10.24	373748.00 E 6545680.0 N
38736	basalt	1.41		5.14	4.87	8.54	373748.00 E 6545680.0 N
38735	basalt	2.56		10.10	8.65	9.11	373748.00 E 6545680.0 N
38734	basalt	3.38		7.74	5.46	10.63	373748.00 E 6545680.0 N
38733	basalt	2.74		8.91	7.53	10.61	373748.00 E 6545680.0 N
38844	basalt	1.48		5.96	4.07	14.20	392573.00 E 6563053.0 N
38825	basalt	1.57		9.23	8.18	9.31	326453.00 E 6574620.0 N
38808	basalt	2.20		8.29	8.22	10.40	371913.00 E 6493859.0 N
38847	basalt	0.78		4.13	3.07	7.50	392160.00 E 6563130.0 N
38838	basalt	1.20		5.57	3.46	8.82	392573.00 E 6563053.0 N
38827	basalt	1.46		8.25	7.15	11.30	326453.00 E 6574620.0 N
38816	basalt	1.32		8.87	8.03	9.72	326453.00 E 6574620.0 N
38809	basalt	2.44		8.44	8.08	10.50	371913.00 E 6493859.0 N
38799	basalt	2.95		11.40	6.06	9.96	302650.00 E 6625500.0 N
38793	basalt	1.14		7.65	11.30	12.40	296150.00 E 6728600.0 N
38759	basalt	2.38		9.20	7.78	10.35	373630.00 E 6546179.0 N
38749	basalt	2.73		8.90	8.21	12.96	373630.00 E 6546179.0 N
38741	basalt	1.60		9.03	8.64	10.26	373630.00 E 6546179.0 N
34851	basalt	5.86	16.37	9.46	4.86	9.50	264872.40 E 6758118.7 N
Rock Code	Rock Type in solid geology GIS layer	$\frac{Fe_{wt\%} \times Fe}{(Fe+Mg+Ca)}$ l3.l.ch2	$\frac{Fe}{(Fe+Mg+Ca)}$ l3.l.ch1	$\frac{Fe_2O_3}{(Fe_2O_3+FeO)}$ l3.l.ch3	$\frac{Fe_2O_3}{FeO}$ l3.l.ch4	$\frac{Fe^{3+}}{Fe^{2+}}$ l3.l.ch5	
Sct	Chert ⁵	2.14	0.30	0.31	0.69	0.62	No analyses avail. ⁸
X	Mylonite ⁵	2.14	0.30	0.31	0.69	0.62	
?	Unknown/Unclassified unit ⁵	2.14	0.30	0.31	0.69	0.62	
Rock Code	Rock Type in solid geology GIS layer	$\frac{Fe_{wt\%} \times Fe}{(Fe+Mg+Ca)}$ l3.l.ch2	$\frac{Fe}{(Fe+Mg+Ca)}$ l3.l.ch1	$\frac{Fe_2O_3}{(Fe_2O_3+FeO)}$ l3.l.ch3	$\frac{Fe_2O_3}{FeO}$ l3.l.ch4	$\frac{Fe^{3+}}{Fe^{2+}}$ l3.l.ch5	
Upx	Pyroxenite	2.12	0.24	0.14	0.18	0.16	
OZCHEM data							
Rock No.	Total Description ⁴	Fe ₂ O ₃	Fe ₂ O ₃ total	FeO	MgO	CaO	Location
32628	pyroxenite altered pyroxenite	0.90		8.90	13.90	8.20	387939.46 E 6429997.7 N
32621	pyroxenite altered pyroxenite	2.00		10.50	7.90	10.40	387939.46 E 6429997.7 N
32620	pyroxenite altered pyroxenite	1.00		8.70	14.20	9.50	387939.46 E 6429997.7 N

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Table D.8: continued

32619	pyroxenite altered	pyroxenite	4.60			10.60	20.70	7.00	387939.46 E 6429997.7 N
32618	pyroxenite altered	pyroxenite	2.10			10.50	7.90	9.20	387939.46 E 6429997.7 N
32593	pyroxenite altered	pyroxenite	0.70			9.50	15.70	8.50	387756.92 E 6429994.3 N
32592	pyroxenite altered	pyroxenite	4.70			10.50	19.60	7.30	387756.92 E 6429994.3 N
32587	pyroxenite altered	pyroxenite	0.80			10.10	19.70	5.90	388031.48 E 6429999.5 N
32643	pyroxenite altered	pyroxenite	0.40			9.90	17.00	8.30	387210.43 E 6429892.7 N
32627	pyroxenite altered	pyroxenite	0.70			8.10	12.50	8.70	387939.46 E 6429997.7 N
Rock Code	Rock Type in solid geology GIS layer	$\frac{Fe_{wt\%} \times Fe}{(Fe+Mg+Ca)}$ l3_l.ch2	$\frac{Fe}{(Fe+Mg+Ca)}$ l3_l.ch1	$\frac{Fe_2O_3}{(Fe_2O_3+FeO)}$ l3_l.ch3	$\frac{Fe_2O_3}{FeO}$ l3_l.ch4	$\frac{Fe^{3+}}{Fe^{2+}}$ l3_l.ch5			
Mbu	Mafic Ultramafic (Greenstone)	1.74	0.21	0.18	0.24	0.21			
Mmb	Magnesian Basalt	1.74	0.21	0.18	0.24	0.21			
OZCHEM data									
Rock No.	Total Description ⁴	Fe ₂ O ₃	Fe ₂ O ₃ total	FeO	MgO	CaO	Location		
32812	basalt altered high-Mg basalt	1.10		6.50	24.60	7.20	358856.71 E 6544945.6 N		
32810	basalt altered high-Mg basalt	0.80		7.80	20.20	9.00	360673.89 E 6545618.5 N		
32809	basalt altered high-Mg basalt	0.80		7.50	22.40	10.10	360853.13 E 6545804.6 N		
32808	basalt altered high-Mg basalt	1.20		7.20	23.70	8.10	360942.80 E 6545897.6 N		
32807	basalt altered high-Mg basalt	1.20		7.80	20.20	6.80	361032.38 E 6545990.8 N		
32798	basalt altered high-Mg basalt	0.60		8.90	24.10	4.90	360209.69 E 6545975.8 N		
32781	basalt altered high-Mg basalt	4.10		8.70	20.90	9.00	341970.78 E 6578841.2 N		
32780	basalt altered high-Mg basalt	3.60		8.10	18.70	9.50	340589.65 E 6579365.2 N		
33764	basalt altered high-Mg basalt	2.70		8.40	21.70	7.80	374481.63 E 6545502.8 N		
33763	basalt altered high-Mg basalt	3.00		8.50	20.60	7.30	374481.63 E 6545502.8 N		
33762	basalt altered high-Mg basalt	3.00		8.20	21.20	7.10	374481.63 E 6545502.8 N		
33286	basalt altered high-Mg basalt	1.70		8.80	26.40	6.00	357455.69 E 6521419.9 N		
33285	basalt altered high-Mg basalt	1.50		10.30	21.60	8.90	357455.69 E 6521419.9 N		
33283	basalt altered high-Mg basalt	1.20		7.80	23.40	9.40	358465.94 E 6526193.1 N		
33282	basalt altered high-Mg basalt	1.70		11.20	22.50	7.00	358465.94 E 6526193.1 N		
33281	basalt altered high-Mg basalt	1.30		8.90	24.40	6.60	358465.94 E 6526193.1 N		
33280	basalt altered high-Mg basalt	2.30		15.20	22.40	5.00	358465.94 E 6526193.1 N		
33277	basalt altered high-Mg basalt	1.80		11.90	22.00	7.20	358465.94 E 6526193.1 N		
33275	basalt altered high-Mg basalt	1.60		11.00	25.90	5.40	358465.94 E 6526193.1 N		
33274	basalt altered high-Mg basalt	1.60		10.50	24.10	7.20	358465.94 E 6526193.1 N		

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Table D.8: *continued*

33272	basalt altered high-Mg basalt	1.50			9.90	24.00	7.60	358964.48 E 6518886.9 N
33271	basalt altered high-Mg basalt	1.30			8.60	21.10	10.70	360675.04 E 6515352.0 N
33270	basalt altered high-Mg basalt	1.30			8.80	23.70	9.30	360675.04 E 6515352.0 N
33269	basalt altered high-Mg basalt	1.20			8.20	25.40	8.80	360675.04 E 6515352.0 N
33267	basalt altered high-Mg basalt	1.90			12.80	20.50	9.00	360675.04 E 6515352.0 N
33266	basalt altered high-Mg basalt	1.40			9.30	24.60	7.90	360675.04 E 6515352.0 N
33265	basalt altered high-Mg basalt	1.40			9.20	26.50	8.00	360675.04 E 6515352.0 N
33264	basalt altered high-Mg basalt	1.40			9.10	24.20	8.60	360675.04 E 6515352.0 N
33263	basalt altered high-Mg basalt	1.40			9.20	22.90	9.00	360675.04 E 6515352.0 N
33907	basalt altered high-Mg basalt	2.30			8.50	21.70	6.90	373925.31 E 6545949.6 N
33906	basalt altered high-Mg basalt	2.30			8.20	24.30	6.10	373918.74 E 6546315.4 N
33869	basalt altered high-Mg basalt	2.80			7.30	24.20	6.40	373918.74 E 6546315.4 N
33868	basalt altered high-Mg basalt	3.30			7.60	26.60	3.10	373918.74 E 6546315.4 N
33865	basalt altered high-Mg basalt	1.90			9.10	22.00	6.80	373918.74 E 6546315.4 N
33864	basalt altered high-Mg basalt	2.70			8.60	23.10	6.90	373918.74 E 6546315.4 N
33863	basalt altered high-Mg basalt	1.60			8.20	26.20	3.20	373918.74 E 6546315.4 N
33861	basalt altered high-Mg basalt	1.90			9.30	24.20	5.30	373918.74 E 6546315.4 N
33860	basalt altered high-Mg basalt	0.90			9.80	24.20	5.30	373918.74 E 6546315.4 N
33853	basalt altered high-Mg basalt	5.10			4.70	27.50	5.00	374375.14 E 6546323.5 N
33852	basalt altered high-Mg basalt	3.20			8.60	23.40	7.20	374375.14 E 6546323.5 N
33845	basalt altered high-Mg basalt	1.00			10.60	23.50	5.80	374375.14 E 6546323.5 N
33844	basalt altered high-Mg basalt	0.30			8.70	26.90	0.70	374375.14 E 6546323.5 N
33839	basalt altered high-Mg basalt	1.60			9.10	23.40	6.60	374375.14 E 6546323.5 N
33833	basalt altered high-Mg basalt	0.40			9.10	23.30	8.10	374558.32 E 6546327.0 N
33820	basalt altered high-Mg basalt	1.10			8.40	21.60	9.20	373735.56 E 6546312.1 N
33818	basalt altered high-Mg basalt	3.20			17.90	23.90	2.90	373918.74 E 6546315.4 N
33812	basalt altered high-Mg basalt	3.20			6.20	25.80	5.10	374375.14 E 6546323.5 N
33811	basalt altered high-Mg basalt	3.40			5.30	24.80	5.80	374375.14 E 6546323.5 N
33810	basalt altered high-Mg basalt	4.40			7.40	23.40	5.40	374375.14 E 6546323.5 N
33809	basalt altered high-Mg basalt	3.60			7.60	19.60	4.90	374375.14 E 6546323.5 N
33801	basalt altered high-Mg basalt	1.30			11.20	19.90	2.70	374558.32 E 6546327.0 N
33797	basalt altered high-Mg basalt	2.80			8.40	22.90	7.50	374107.73 E 6545952.8 N
33796	basalt altered high-Mg basalt	2.40			8.20	20.90	7.30	374107.73 E 6545952.8 N
33786	basalt altered high-Mg basalt	1.60			6.50	21.80	9.80	373827.10 E 6546313.6 N
33785	basalt altered high-Mg basalt	1.90			8.40	21.70	8.10	373827.10 E 6546313.6 N

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Table D.8: *continued*

33784	basalt altered high-Mg basalt	3.40			7.30	22.50	6.70	373827.10 E 6546313.6 N
33778	basalt altered high-Mg basalt	4.60			7.50	22.60	6.40	373827.10 E 6546313.6 N
33862	basalt altered high-Mg basalt	1.80			7.30	26.70	4.90	373918.74 E 6546315.4 N
33851	basalt altered high-Mg basalt	1.00			9.20	22.70	8.60	374375.14 E 6546323.5 N
33819	basalt altered high-Mg basalt	1.10			9.60	22.00	7.50	373735.56 E 6546312.1 N
33808	basalt altered high-Mg basalt	3.80			7.70	21.20	5.00	374375.14 E 6546323.5 N
33771	basalt altered high-Mg basalt	4.10			6.20	25.70	5.20	373735.56 E 6546312.1 N
33760	basalt altered high-Mg basalt	1.40			7.80	23.10	6.30	373925.31 E 6545949.6 N
33755	basalt altered high-Mg basalt	12.40				12.90	7.00	411940.70 E 6567023.5 N
33284	basalt altered high-Mg basalt	1.80			12.00	21.90	7.00	358465.94 E 6526193.1 N
33278	basalt altered high-Mg basalt	1.50			9.80	24.50	7.00	358465.94 E 6526193.1 N
33273	basalt altered high-Mg basalt	1.60			10.30	21.60	8.00	358964.48 E 6518886.9 N
33268	basalt altered high-Mg basalt	1.70			10.40	24.20	7.90	360675.04 E 6515352.0 N
33262	basalt altered high-Mg basalt	1.10			7.50	23.30	9.60	360675.04 E 6515352.0 N
32815	basalt altered high-Mg basalt	1.00			7.90	21.50	7.40	358861.91 E 6544671.3 N
32811	basalt altered high-Mg basalt	1.30			8.70	23.00	7.40	360582.25 E 6545616.9 N
32799	basalt altered high-Mg basalt	1.40			7.60	26.80	4.80	360550.58 E 6547353.6 N
33838	basalt altered high-Mg basalt	1.30			8.30	23.90	5.70	374375.14 E 6546323.5 N
33276	basalt altered high-Mg basalt	2.00			13.80	25.40	3.50	358465.94 E 6526193.1 N
33279	basalt altered spinifex high-Mg basalt	1.60			10.80	22.60	6.90	358465.94 E 6526193.1 N
33261	basalt altered spinifex high-Mg basalt	1.40			9.50	25.30	6.10	360675.04 E 6515352.0 N
73107	basalt High-magnesian basalt			11.81		6.89	11.95	385953.71 E 6436741.3 N
73106	basalt High-magnesian basalt			11.36		12.10	11.96	359980.43 E 6545073.0 N
73105	basalt High-magnesian basalt			11.10		7.03	11.97	359980.43 E 6545073.0 N
73104	basalt High-magnesian basalt			12.43		12.90	12.56	371090.65 E 6494217.2 N
73103	basalt High-magnesian basalt			11.20		7.72	11.89	371090.65 E 6494217.2 N
73102	basalt High-magnesian basalt			11.26		7.77	11.93	371090.65 E 6494217.2 N
73101	basalt High-magnesian basalt			11.81		8.33	11.32	374256.15 E 6546361.8 N
73100	basalt High-magnesian basalt			11.71		8.65	12.16	374256.15 E 6546361.8 N
73099	basalt High-magnesian basalt			11.80		8.03	11.50	374256.15 E 6546361.8 N
73108	basalt High-magnesian basalt			12.81		7.89	11.72	385953.71 E 6436741.3 N
30863	basalt komatiitic basalt	1.08		11.02	8.94	16.52	9.28	263357.01 E 6752971.9 N
76565	basalt komatiitic basalt	1.45		10.63	8.26	15.02	10.93	263000.00 E 6751060.0 N
76567	basalt komatiitic basalt, f.g. grey-green	1.56		10.29	7.86	9.78	8.45	263000.00 E 6751060.0 N
33301	basalt recrystallised high-Mg basalt	1.80			10.20	20.00	8.30	358465.94 E 6526193.1 N

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Table D.8: *continued*

33299	basalt recrystallised high-Mg basalt	2.30		9.30	15.90	11.20	357491.90 E 6519408.7 N
33298	basalt recrystallised high-Mg basalt	2.50		9.80	15.20	11.60	358465.94 E 6526193.1 N
33297	basalt recrystallised high-Mg basalt	2.40		9.60	13.80	11.40	358465.94 E 6526193.1 N
33296	basalt recrystallised high-Mg basalt	2.50		10.00	13.40	11.40	358964.48 E 6518886.9 N
33295	basalt recrystallised high-Mg basalt	1.70		9.10	13.60	9.60	358465.94 E 6526193.1 N
33293	basalt recrystallised high-Mg basalt	2.40		9.50	11.40	10.40	360675.04 E 6515352.0 N
33291	basalt recrystallised high-Mg basalt	2.40		9.60	9.80	9.30	360675.04 E 6515352.0 N
33290	basalt recrystallised high-Mg basalt	2.40		9.40	9.80	9.90	357491.90 E 6519408.7 N
33288	basalt recrystallised high-Mg basalt	2.60		10.40	7.90	8.90	357491.90 E 6519408.7 N
33287	basalt recrystallised high-Mg basalt	1.90		9.80	14.30	10.80	357455.69 E 6521419.9 N
33300	basalt recrystallised high-Mg basalt	1.10		10.70	16.40	9.20	358465.94 E 6526193.1 N
33294	basalt recrystallised high-Mg basalt	2.40		9.40	13.20	9.10	358465.94 E 6526193.1 N
33289	basalt recrystallised high-Mg basalt	2.20		9.00	8.80	7.80	357491.90 E 6519408.7 N
33292	basalt recrystallised high-Mg basalt	2.20		9.00	10.70	10.30	358964.48 E 6518886.9 N
73113	basalt Siliceous high-magnesian basalt		11.40		8.82	8.31	377003.41 E 6475441.8 N
73112	basalt Siliceous high-magnesian basalt		11.42		10.29	9.63	374256.15 E 6546361.8 N
73111	basalt Siliceous high-magnesian basalt		11.24		9.77	10.39	374256.15 E 6546361.8 N
73116	basalt Siliceous high-magnesian basalt		11.10		6.78	10.48	353518.10 E 6599308.9 N
73115	basalt Siliceous high-magnesian basalt		10.90		7.71	8.68	353518.10 E 6599308.9 N
73114	basalt Siliceous high-magnesian basalt		10.61		8.26	9.82	357495.65 E 6588276.5 N
73110	basalt Siliceous high-magnesian basalt		11.32		12.29	8.26	357495.65 E 6588276.5 N
73109	basalt Siliceous high-magnesian basalt		11.56		12.78	8.57	357495.65 E 6588276.5 N
38832	basalt spinifex-textured basalt	2.59		9.87	11.30	10.00	294600.00 E 6606900.0 N
38788	basalt spinifex-textured basalt	2.06		8.68	8.54	10.50	300000.00 E 6665700.0 N
32295	basalt tremolitic high-Mg basalt	2.80		7.30	11.10	8.90	357194.51 E 6586521.1 N
32294	basalt tremolitic high-Mg basalt	1.40		8.40	11.90	8.40	356827.03 E 6586606.0 N
32290	basalt tremolitic high-Mg basalt	1.90		7.10	8.20	10.20	357269.13 E 6587436.8 N
32289	basalt tremolitic high-Mg basalt	2.10		7.70	10.20	8.40	356990.41 E 6587706.2 N
32288	basalt tremolitic high-Mg basalt	3.10		6.50	7.60	9.60	356990.41 E 6587706.2 N
32814	basalt tremolitic high-Mg basalt	1.20		9.20	12.80	12.70	358948.35 E 6544947.2 N
32813	basalt tremolitic high-Mg basalt	1.00		10.10	11.80	13.00	358856.71 E 6544945.6 N
32287	basalt tremolitic high-Mg basalt	1.40		7.80	22.80	7.90	395708.90 E 6504379.8 N
32784	basalt tremolitic high-Mg basalt	1.00		10.30	11.50	9.70	296083.06 E 6728481.0 N
73125	basalt variolitic siliceous high-Mg basalt		9.27		7.40	7.78	374256.15 E 6546361.8 N
73120	basalt variolitic siliceous high-Mg basalt		15.10		9.97	8.20	374256.15 E 6546361.8 N

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Table D.8: *continued*

73119	basalt variolitic siliceous high-Mg basalt		15.50		11.78	10.02	357495.65 E 6588276.5 N
73123	basaltic andesite variolitic silic. high-Mg		5.04		2.65	12.92	374256.15 E 6546361.8 N
Rock Code	Rock Type in solid geology GIS layer	$\frac{Fe\ wt\% \times Fe_2O_3}{(Fe+Mg+Ca)}$ l3.1.ch2	$\frac{Fe}{(Fe+Mg+Ca)}$ l3.1.ch1	$\frac{Fe_2O_3}{(Fe_2O_3+FeO)}$ l3.1.ch3	$\frac{Fe_2O_3}{FeO}$ l3.1.ch4	$\frac{Fe^{3+}}{Fe^{2+}}$ l3.1.ch5	
Hou	Mg-rich Ortho Amphibolite	1.56	0.21	0.14	0.16	0.15	
Hou	Mg-rich Ortho Hornfels	1.56	0.21	0.14	0.16	0.15	
OZCHEM data							
Rock No.	Total Description ⁴	Fe ₂ O ₃	Fe ₂ O ₃ total	FeO	MgO	CaO	Location
30863	basalt komatiitic basalt	1.08	11.02	8.94	16.52	9.28	263357.01 E 6752971.9 N
76565	basalt komatiitic basalt	1.45	10.63	8.26	15.02	10.93	263000.00 E 6751060.0 N
76567	basalt komatiitic basalt, f.g. grey-green v	1.56	10.29	7.86	9.78	8.45	263000.00 E 6751060.0 N
Rock Code	Rock Type in solid geology GIS layer	$\frac{Fe\ wt\% \times Fe_2O_3}{(Fe+Mg+Ca)}$ l3.1.ch2	$\frac{Fe}{(Fe+Mg+Ca)}$ l3.1.ch1	$\frac{Fe_2O_3}{(Fe_2O_3+FeO)}$ l3.1.ch3	$\frac{Fe_2O_3}{FeO}$ l3.1.ch4	$\frac{Fe^{3+}}{Fe^{2+}}$ l3.1.ch5	
Sfw	Feldspathic Wacke	1.53	0.39	0.40	0.96	0.86	
Ivs	Int. Volcanogenic Sed. Rock	1.53	0.39	0.40	0.96	0.86	
Sw	Undivided Wacke	1.53	0.39	0.40	0.96	0.86	
Svfw	Volcanic Feldspathic Wacke	1.53	0.39	0.40	0.96	0.86	
Svsw	Volcanic Wacke	1.53	0.39	0.40	0.96	0.86	
Svg	Volcanogenic Sed. Rock	1.53	0.39	0.40	0.96	0.86	
OZCHEM data							
Rock No.	Total Description ⁴	Fe ₂ O ₃	Fe ₂ O ₃ total	FeO	MgO	CaO	Location
96418	sediment f.g. felsic tuffaceous sediments	1.38	2.01	0.57	0.83	1.89	296040.10 E 6965330.0 N
96412	sediment	1.61	2.83	1.10	1.28	0.77	296140.10 E 6965380.0 N
96269	sediment	0.72	5.41	4.22	1.04	7.77	294800.10 E 6967700.0 N
96268	sediment	1.52	5.91	3.95	1.36	2.97	294800.10 E 6967700.0 N
96260	sediment	2.65	11.23	7.72	3.93	5.25	295200.10 E 6966100.0 N
96418	sediment f.g. felsic tuffaceous sediments	1.38	2.01	0.57	0.83	1.89	296040.10 E 6965330.0 N
Rock Code	Rock Type in solid geology GIS layer	$\frac{Fe\ wt\% \times Fe_2O_3}{(Fe+Mg+Ca)}$ l3.1.ch2	$\frac{Fe}{(Fe+Mg+Ca)}$ l3.1.ch1	$\frac{Fe_2O_3}{(Fe_2O_3+FeO)}$ l3.1.ch3	$\frac{Fe_2O_3}{FeO}$ l3.1.ch4	$\frac{Fe^{3+}}{Fe^{2+}}$ l3.1.ch5	
Zac	Actinolite Schist	1.49	0.20	0.17	0.20	0.18	
OZCHEM data							

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Table D.8: *continued*

Rock No.	Total Description ⁴	Fe ₂ O ₃	Fe ₂ O ₃ total	FeO	MgO	CaO	Location
31509	amphibolite actinolite schist	1.75	11.07	8.39	7.94	11.11	256019.00 E 6762931.0 N
31508	schist actinolite schist (meta-high Mg basalt)	1.54	9.81	7.44	15.51	10.16	255910.00 E 6763039.0 N
53941	schist actinolite-chlorite schist	1.58	10.55	8.07	19.96	9.43	256278.00 E 6761183.0 N
Rock Code	Rock Type in solid geology GIS layer	$\frac{Fe\ wt\% \times Fe}{(Fe+Mg+Ca)}$ l3.1.ch2	$\frac{Fe}{(Fe+Mg+Ca)}$ l3.1.ch1	$\frac{Fe_2O_3}{(Fe_2O_3+FeO)}$ l3.1.ch3	$\frac{Fe_2O_3}{FeO}$ l3.1.ch4	$\frac{Fe^{3+}}{Fe^{2+}}$ l3.1.ch5	
Gsdi	Syenodiorite	1.39	0.31	0.30	0.51	0.46	
OZCHEM data							
Rock No.	Total Description ⁴	Fe ₂ O ₃	Fe ₂ O ₃ total	FeO	MgO	CaO	Location
31915	diorite barite-filled vugs in megacrystic xenolith		6.30		5.73	5.77	372600.02 E 6551900.0 N
38964	diorite Bt-Hbl diorite xenolith	2.16		4.26	6.84	6.85	342700.00 E 6652500.0 N
39010	diorite Hbl diorite	2.57		2.57	2.61	3.78	348000.00 E 6555400.0 N
39021	diorite Hbl-Bt diorite	3.83		3.89	4.07	6.21	328300.00 E 6624200.0 N
31883	diorite malchite		5.67		4.98	5.70	380800.04 E 6533600.0 N
31907	diorite malchite		5.25		5.22	6.21	382900.04 E 6533400.0 N
31906	diorite malchite		3.87		1.47	4.00	382900.04 E 6533400.0 N
31885	diorite megacrystic malchite		4.91		3.30	4.75	375100.05 E 6544500.0 N
31884	diorite megacrystic malchite		5.01		3.45	3.87	375100.05 E 6544500.0 N
31914	diorite megacrystic malchite		4.93		3.33	4.33	372200.00 E 6552199.9 N
32330	diorite	0.90		3.20	1.30	3.70	358632.55 E 6749766.4 N
32329	diorite	0.40		8.10	1.30	3.20	358632.55 E 6749766.4 N
32586	diorite	1.90		7.60	4.40	8.10	388031.48 E 6429999.5 N
Rock Code	Rock Type in solid geology GIS layer	$\frac{Fe\ wt\% \times Fe}{(Fe+Mg+Ca)}$ l3.1.ch2	$\frac{Fe}{(Fe+Mg+Ca)}$ l3.1.ch1	$\frac{Fe_2O_3}{(Fe_2O_3+FeO)}$ l3.1.ch3	$\frac{Fe_2O_3}{FeO}$ l3.1.ch4	$\frac{Fe^{3+}}{Fe^{2+}}$ l3.1.ch5	
Mdq	Quartz Dolerite	1.27	0.30	0.41	0.72	0.65	
OZCHEM data							
Rock No.	Total Description ⁴	Fe ₂ O ₃	Fe ₂ O ₃ total	FeO	MgO	CaO	Location
39024	quartz diorite Bt quartz diorite	3.49		3.31	3.64	6.01	328300.00 E 6624200.0 N
39017	quartz diorite Bt-Hbl quartz diorite	2.80		3.00	3.26	4.53	328000.00 E 6626000.0 N
38967	qtz diorite Bt-Hbl qtz diorite gneiss xenolith	2.31		4.54	5.52	6.46	350600.00 E 6645800.0 N
39013	qtz diorite Hbl-Bt qtz diorite xenolith	1.89		2.69	3.07	4.50	331000.00 E 6623500.0 N
32040	quartz diorite	1.96		3.36	2.42	4.93	324724.18 E 6583720.1 N

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Table D.8: *continued*

32039	quartz diorite	1.57		2.92	2.31	4.48	324724.18 E 6583720.1 N
Rock	Rock Type in solid	$\frac{Fe\ wt\% \times Fe}{(Fe+Mg+Ca)}$	$\frac{Fe_2O_3}{(Fe_2O_3+FeO)}$	$\frac{Fe_2O_3}{(Fe_2O_3+FeO)}$	$\frac{Fe_2O_3}{FeO}$	$\frac{Fe^{3+}}{Fe^{2+}}$	
Code	geology GIS layer	l3.1.ch2	l3.1.ch1	l3.1.ch3	l3.1.ch4	l3.1.ch5	
Utc	Talc-Chl. Ultramafic Rock	1.26	0.17	0.21	0.26	0.24	1 analysis ⁹
OZCHEM data							
Rock No.	Total Description ⁴	Fe ₂ O ₃	Fe ₂ O ₃ total	FeO	MgO	CaO	Location
15	Talc-chlorite schist	2.05		7.80	21.70	7.07	
Rock	Rock Type in solid	$\frac{Fe\ wt\% \times Fe}{(Fe+Mg+Ca)}$	$\frac{Fe}{(Fe+Mg+Ca)}$	$\frac{Fe_2O_3}{(Fe_2O_3+FeO)}$	$\frac{Fe_2O_3}{FeO}$	$\frac{Fe^{3+}}{Fe^{2+}}$	
Code	geology GIS layer	l3.1.ch2	l3.1.ch1	l3.1.ch3	l3.1.ch4	l3.1.ch5	
Uac	Amph.-Chl U/mafic Rock	1.23	0.17	0.16	0.20	0.18	
OZCHEM data							
Rock No.	Total Description ⁴	Fe ₂ O ₃	Fe ₂ O ₃ total	FeO	MgO	CaO	Location
53941	schist actinolite-chlorite schist	1.58	10.55	8.07	19.96	9.43	256278.00 6761183.0
Rock	Rock Type in solid	$\frac{Fe\ wt\% \times Fe}{(Fe+Mg+Ca)}$	$\frac{Fe}{(Fe+Mg+Ca)}$	$\frac{Fe_2O_3}{(Fe_2O_3+FeO)}$	$\frac{Fe_2O_3}{FeO}$	$\frac{Fe^{3+}}{Fe^{2+}}$	
Code	geology GIS layer	l3.1.ch2	l3.1.ch1	l3.1.ch3	l3.1.ch4	l3.1.ch5	
Shl	Shale	1.16	0.44	0.37	0.78	0.70	
Sha	Shale (altered)	1.16	0.44	0.37	0.78	0.70	
OZCHEM data							
Rock No.	Total Description ⁴	Fe ₂ O ₃	Fe ₂ O ₃ total	FeO	MgO	CaO	Location
53974	shale shale - siliceous	0.91	3.13	2.00	1.50	2.65	378530.00 E 6787354.0 N
53972	shale shale - siliceous	0.61	1.97	1.22	1.08	2.12	378466.00 E 6787280.0 N
53956	shale shale - siliceous	0.86	3.59	2.46	0.70	0.78	379392.00 E 6798039.0 N
68772	shale qtz clay sediment, bedding with variable	0.27	0.83	0.99	0.12	0.04	261151.10 E 6957581.0 N
93394	shale graphitic slate or phyllite	6.53	9.51	2.68	4.24	2.14	277550.30 E 7029826.8 N
92247	shale Meta shale with chalcopryrite	1.49	4.00	2.26	5.50	3.41	270805.30 E 7045064.8 N
Rock	Rock Type in solid	$\frac{Fe\ wt\% \times Fe}{(Fe+Mg+Ca)}$	$\frac{Fe}{(Fe+Mg+Ca)}$	$\frac{Fe_2O_3}{(Fe_2O_3+FeO)}$	$\frac{Fe_2O_3}{FeO}$	$\frac{Fe^{3+}}{Fe^{2+}}$	
Code	geology GIS layer	l3.1.ch2	l3.1.ch1	l3.1.ch3	l3.1.ch4	l3.1.ch5	
Homc	Fe-Ortho Amphibolite (c.g.)	1.15	0.20	0.40	0.67	0.61	
Hom	Fe-Ortho Amphibolite (f.g.)	1.15	0.20	0.40	0.67	0.61	
Homh	Fe-rich Ortho Hornfels	1.15	0.20	0.40	0.67	0.61	

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Table D.8: *continued*

Hpt	Para Amphibolite (mafic)	1.15	0.20	0.40	0.67	0.61	Location
OZCHEM data							
Rock No.	Total Description ⁴	Fe ₂ O ₃	Fe ₂ O ₃ total	FeO	MgO	CaO	Location
38936	hornfels Pyrx hornfels	3.05		4.53	7.35	11.90	402000.00 E 6688000.0 N
Rock Code	Rock Type in solid geology GIS layer	$\frac{Fe_{wt\%} \times Fe}{(Fe+Mg+Ca)}$ l3.l_ch2	$\frac{Fe}{(Fe+Mg+Ca)}$ l3.l_ch1	$\frac{Fe_2O_3}{(Fe_2O_3+FeO)}$ l3.l_ch3	$\frac{Fe_2O_3}{FeO}$ l3.l_ch4	$\frac{Fe^{3+}}{Fe^{2+}}$ l3.l_ch5	
U	Undivided Ultramafic Rock	0.93	0.13	0.29	0.49	0.44	
OZCHEM data							
Rock No.	Total Description ⁴	Fe ₂ O ₃	Fe ₂ O ₃ total	FeO	MgO	CaO	Location
33769	peridotite altered peridotite	3.50		3.10	33.70	0.10	374481.63 E 6545502.8 N
33768	peridotite altered peridotite	3.60		2.70	34.60	0.10	374481.63 E 6545502.8 N
33767	peridotite altered peridotite	2.60		3.10	32.70	1.80	374481.63 E 6545502.8 N
33765	peridotite altered peridotite	3.40		6.70	25.10	4.40	374481.63 E 6545502.8 N
33761	peridotite altered peridotite	2.10		5.60	25.70	7.00	374481.63 E 6545502.8 N
33256	peridotite altered peridotite	1.00		8.60	27.10	5.40	358465.94 E 6526193.1 N
33253	peridotite altered peridotite	1.40		9.40	28.40	4.50	358465.94 E 6526193.1 N
33877	peridotite altered peridotite	3.10		4.90	34.70	1.30	373918.74 E 6546315.4 N
33876	peridotite altered peridotite	2.20		5.00	32.70	1.30	373918.74 E 6546315.4 N
33875	peridotite altered peridotite	1.90		5.80	33.10	1.00	373918.74 E 6546315.4 N
33874	peridotite altered peridotite	3.40		5.70	29.10	0.90	373918.74 E 6546315.4 N
33873	peridotite altered peridotite	3.80		5.20	31.70	2.40	373918.74 E 6546315.4 N
33871	peridotite altered peridotite	3.30		5.00	31.80	2.60	373918.74 E 6546315.4 N
33866	peridotite altered peridotite	2.80		6.40	27.10	4.40	373918.74 E 6546315.4 N
33859	peridotite altered peridotite	4.40		4.40	36.00	1.10	374375.14 E 6546323.5 N
33858	peridotite altered peridotite	2.30		5.00	36.30	0.60	374375.14 E 6546323.5 N
33857	peridotite altered peridotite	3.40		4.40	36.80	0.70	374375.14 E 6546323.5 N
33855	peridotite altered peridotite	6.50		5.00	27.00	7.50	374375.14 E 6546323.5 N
33850	peridotite altered peridotite	3.80		5.80	29.10	1.50	374375.14 E 6546323.5 N
33849	peridotite altered peridotite	3.60		4.00	31.60	2.80	374375.14 E 6546323.5 N
33848	peridotite altered peridotite	4.20		3.90	31.40	2.20	374375.14 E 6546323.5 N
33847	peridotite altered peridotite	3.60		3.80	31.70	2.20	374375.14 E 6546323.5 N
33843	peridotite altered peridotite	0.80		6.60	31.80	2.60	374375.14 E 6546323.5 N
33842	peridotite altered peridotite	2.40		4.90	27.80	5.20	374375.14 E 6546323.5 N

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Table D.8: *continued*

33841	peridotite altered peridotite	2.60		4.70	29.00	1.00	374375.14 E 6546323.5 N
33837	peridotite altered peridotite	2.60		5.70	33.10	1.50	374558.32 E 6546327.0 N
33836	peridotite altered peridotite	2.90		5.50	33.30	1.30	374558.32 E 6546327.0 N
33834	peridotite altered peridotite	2.60		6.20	33.80	1.10	374558.32 E 6546327.0 N
33832	peridotite altered peridotite	0.80		6.60	30.50	1.50	374558.32 E 6546327.0 N
33831	peridotite altered peridotite	2.90		4.20	32.10	1.30	374558.32 E 6546327.0 N
33829	peridotite altered peridotite	2.90		4.80	27.80	5.30	374558.32 E 6546327.0 N
33828	peridotite altered peridotite	0.70		6.20	27.80	5.60	374558.32 E 6546327.0 N
33827	peridotite altered peridotite	2.00		4.90	30.60	3.00	374558.32 E 6546327.0 N
33826	peridotite altered peridotite	2.30		4.40	30.40	5.80	374558.32 E 6546327.0 N
33825	peridotite altered peridotite	2.60		6.80	26.70	6.00	374558.32 E 6546327.0 N
33823	peridotite altered peridotite	3.80		6.40	27.00	4.20	374558.32 E 6546327.0 N
33821	peridotite altered peridotite	1.90		7.20	26.00	6.90	374558.32 E 6546327.0 N
33817	peridotite altered peridotite	2.60		7.20	30.80	2.30	373918.74 E 6546315.4 N
33816	peridotite altered peridotite	3.60		5.70	32.20	2.50	373918.74 E 6546315.4 N
33815	peridotite altered peridotite	2.50		8.80	31.50	2.20	373918.74 E 6546315.4 N
33813	peridotite altered peridotite	2.30		8.90	32.20	1.70	373918.74 E 6546315.4 N
33807	peridotite altered peridotite	2.20		5.00	26.30	5.80	374558.32 E 6546327.0 N
33805	peridotite altered peridotite	1.80		4.00	26.40	6.10	374558.32 E 6546327.0 N
33804	peridotite altered peridotite	1.90		6.40	26.50	4.00	374558.32 E 6546327.0 N
33802	peridotite altered peridotite	1.10		8.40	25.50	5.30	374558.32 E 6546327.0 N
33800	peridotite altered peridotite	1.40		4.40	35.60	0.10	374107.73 E 6545952.8 N
33799	peridotite altered peridotite	2.30		3.70	33.90	0.10	374107.73 E 6545952.8 N
33795	peridotite altered peridotite	3.30		4.60	29.10	2.10	374107.73 E 6545952.8 N
33794	peridotite altered peridotite	5.00		3.50	28.50	1.60	374107.73 E 6545952.8 N
33793	peridotite altered peridotite	5.70		5.90	29.30	0.10	374107.73 E 6545952.8 N
33791	peridotite altered peridotite	0.60		7.10	26.00	1.40	374107.73 E 6545952.8 N
33789	peridotite altered peridotite	3.90		1.90	30.00	0.10	373828.96 E 6546222.3 N
33788	peridotite altered peridotite	4.10		3.20	35.80	0.80	373828.96 E 6546222.3 N
33783	peridotite altered peridotite	4.20		5.30	27.90	3.20	373827.10 E 6546313.6 N
33781	peridotite altered peridotite	3.10		4.70	29.20	2.50	373827.10 E 6546313.6 N
33780	peridotite altered peridotite	4.70		3.60	28.60	3.40	373827.10 E 6546313.6 N
33779	peridotite altered peridotite	4.10		4.40	28.70	2.10	373827.10 E 6546313.6 N
33777	peridotite altered peridotite	7.60		4.50	22.70	0.30	373735.56 E 6546312.1 N
33775	peridotite altered peridotite	3.50		3.50	33.90	0.30	373735.56 E 6546312.1 N

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Table D.8: *continued*

33773	peridotite altered peridotite	2.90		4.20	33.70	0.40	373735.56 E 6546312.1 N
33772	peridotite altered peridotite	4.10		4.80	26.30	7.60	373735.56 E 6546312.1 N
33770	peridotite altered peridotite	2.30		5.80	30.50	1.90	374481.63 E 6545502.8 N
33872	peridotite altered peridotite	2.50		4.90	32.90	1.80	373918.74 E 6546315.4 N
33867	peridotite altered peridotite	2.50		5.70	28.30	2.90	373918.74 E 6546315.4 N
33856	peridotite altered peridotite	4.30		4.40	36.40	0.50	374375.14 E 6546323.5 N
33846	peridotite altered peridotite	3.00		5.00	28.30	4.50	374375.14 E 6546323.5 N
33840	peridotite altered peridotite	3.10		4.50	27.90	4.90	374375.14 E 6546323.5 N
33835	peridotite altered peridotite	2.50		6.30	34.10	1.00	374558.32 E 6546327.0 N
33830	peridotite altered peridotite	3.40		5.00	31.90	1.70	374558.32 E 6546327.0 N
33824	peridotite altered peridotite	2.70		6.30	26.70	5.70	374558.32 E 6546327.0 N
33814	peridotite altered peridotite	2.00		9.00	32.50	1.70	373918.74 E 6546315.4 N
33803	peridotite altered peridotite	1.90		5.80	25.60	7.40	374558.32 E 6546327.0 N
33798	peridotite altered peridotite	3.70		3.70	33.20	0.20	374107.73 E 6545952.8 N
33792	peridotite altered peridotite	1.30		7.00	25.20	4.90	374107.73 E 6545952.8 N
33787	peridotite altered peridotite	3.50		2.60	29.50	0.10	373828.96 E 6546222.3 N
33782	peridotite altered peridotite	2.40		4.70	30.60	2.40	373827.10 E 6546313.6 N
33776	peridotite altered peridotite	2.50		4.00	33.30	0.20	373735.56 E 6546312.1 N
33766	peridotite altered peridotite	2.60		4.50	33.20	0.60	374481.63 E 6545502.8 N
33252	peridotite altered peridotite	1.20		7.90	25.60	7.60	358465.94 E 6526193.1 N
33870	peridotite altered peridotite	3.50		4.50	28.20	5.40	373918.74 E 6546315.4 N
33854	peridotite altered peridotite	4.30		3.70	33.00	1.90	374375.14 E 6546323.5 N
33822	peridotite altered peridotite	2.70		8.30	26.40	3.60	374558.32 E 6546327.0 N
33806	peridotite altered peridotite	2.60		5.00	26.20	6.70	374558.32 E 6546327.0 N
33790	peridotite altered peridotite	3.70		2.60	33.00	1.60	373828.96 E 6546222.3 N
33774	peridotite altered peridotite	3.00		3.40	34.50	0.10	373735.56 E 6546312.1 N
33180	peridotite altered peridotite	0.90		9.20	44.60	0.40	360675.04 E 6515352.0 N
33749	peridotite altered peridotite tuff	11.10			31.20	4.90	333367.82 E 6656511.6 N
33748	peridotite altered spinifex peridotite	10.70			31.90	5.70	333367.82 E 6656511.6 N
33750	peridotite altered spinifex peridotite	11.00			30.00	5.60	333367.82 E 6656511.6 N
76564	peridotite grey-green olivine peridotite	3.72	10.30	5.92	34.38	0.83	263000.00 E 6751060.0 N
33759	peridotite spinifex peridotite	12.80			28.60	5.90	317048.65 E 6586625.5 N
33756	peridotite spinifex peridotite	11.90			29.10	6.10	317048.65 E 6586625.5 N
33259	peridotite spinifex peridotite	1.40		9.10	28.40	6.80	355896.46 E 6516636.4 N
33258	peridotite spinifex peridotite	1.50		10.10	24.60	7.30	355896.46 E 6516636.4 N

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Table D.8: *continued*

33255	peridotite spinifex peridotite	1.70			11.40	24.60	6.70	358465.94 E 6526193.1 N
33251	peridotite spinifex peridotite	1.60			10.80	30.50	4.70	358465.94 E 6526193.1 N
33249	peridotite spinifex peridotite	1.40			9.00	32.00	4.20	360675.04 E 6515352.0 N
33248	peridotite spinifex peridotite	0.90			9.20	33.80	3.60	360675.04 E 6515352.0 N
33247	peridotite spinifex peridotite	1.30			8.60	34.10	4.20	360675.04 E 6515352.0 N
33245	peridotite spinifex peridotite	1.00			9.80	32.60	4.20	360675.04 E 6515352.0 N
33257	peridotite spinifex peridotite	1.20			8.10	27.60	7.40	355896.46 E 6516636.4 N
33246	peridotite spinifex peridotite	1.30			8.40	32.40	5.30	360675.04 E 6515352.0 N
33758	peridotite spinifex peridotite	11.60				30.70	5.90	317048.65 E 6586625.5 N
33260	peridotite spinifex peridotite	1.60			10.50	25.40	7.50	355896.46 E 6516636.4 N
33208	peridotite	0.70			6.70	42.10	1.40	358566.92 E 6525646.4 N
33206	peridotite	0.80			7.60	43.20	0.40	358566.92 E 6525646.4 N
33205	peridotite	0.70			6.80	42.10	2.10	358566.92 E 6525646.4 N
33189	peridotite	0.90			9.20	38.80	3.10	360500.03 E 6514891.6 N
33170	peridotite	0.90			8.60	40.60	2.40	360675.04 E 6515352.0 N
33169	peridotite	0.80			8.30	39.00	2.40	360675.04 E 6515352.0 N
33167	peridotite	0.80			8.20	41.80	0.80	360675.04 E 6515352.0 N
33250	peridotite	1.20			7.60	30.10	6.80	358465.94 E 6526193.1 N
33233	peridotite	0.90			8.60	37.20	3.60	358964.48 E 6518886.9 N
33232	peridotite	1.10			10.70	33.90	4.30	358964.48 E 6518886.9 N
33226	peridotite	1.10			7.20	33.60	4.80	358760.02 E 6525101.1 N
33236	peridotite	1.00			10.00	35.30	4.10	358964.48 E 6518886.9 N
33230	peridotite	0.70			7.40	43.20	2.60	358964.48 E 6518886.9 N
33209	peridotite	0.80			8.30	44.00	1.30	358566.92 E 6525646.4 N
33204	peridotite	0.80			7.50	40.50	1.10	358566.92 E 6525646.4 N
33188	peridotite	0.90			9.40	35.20	3.20	360500.03 E 6514891.6 N
32628	pyroxenite altered pyroxenite	0.90			8.90	13.90	8.20	387939.46 E 6429997.7 N
32621	pyroxenite altered pyroxenite	2.00			10.50	7.90	10.40	387939.46 E 6429997.7 N
32620	pyroxenite altered pyroxenite	1.00			8.70	14.20	9.50	387939.46 E 6429997.7 N
32619	pyroxenite altered pyroxenite	4.60			10.60	20.70	7.00	387939.46 E 6429997.7 N
32618	pyroxenite altered pyroxenite	2.10			10.50	7.90	9.20	387939.46 E 6429997.7 N
32593	pyroxenite altered pyroxenite	0.70			9.50	15.70	8.50	387756.92 E 6429994.3 N
32592	pyroxenite altered pyroxenite	4.70			10.50	19.60	7.30	387756.92 E 6429994.3 N
32587	pyroxenite altered pyroxenite	0.80			10.10	19.70	5.90	388031.48 E 6429999.5 N
32643	pyroxenite altered pyroxenite	0.40			9.90	17.00	8.30	387210.43 E 6429892.7 N

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Table D.8: *continued*

32627	pyroxenite altered pyroxenite	0.70			8.10	12.50	8.70	387939.46 E 6429997.7 N
Rock Code	Rock Type in solid geology GIS layer	$\frac{Fe\ wt\% \times Fe}{(Fe+Mg+Ca)}$ l3.1.ch2	$\frac{Fe}{(Fe+Mg+Ca)}$ l3.1.ch1	$\frac{Fe_2O_3}{(Fe_2O_3+FeO)}$ l3.1.ch3	$\frac{Fe_2O_3}{FeO}$ l3.1.ch4	$\frac{Fe^{3+}}{Fe^{2+}}$ l3.1.ch5		
Hpq	Quartzite	0.91	0.29	0.38	0.62	0.56		
OZCHEM data								
Rock No.	Total Description ⁴	Fe ₂ O ₃	Fe ₂ O ₃ total	FeO	MgO	CaO	Location	
53975	sandstone - pale grey	1.58	4.42	2.56	2.32	4.26	378530.00 E 6787354.0 N	
Rock Code	Rock Type in solid geology GIS layer	$\frac{Fe\ wt\% \times Fe}{(Fe+Mg+Ca)}$ l3.1.ch2	$\frac{Fe}{(Fe+Mg+Ca)}$ l3.1.ch1	$\frac{Fe_2O_3}{(Fe_2O_3+FeO)}$ l3.1.ch3	$\frac{Fe_2O_3}{FeO}$ l3.1.ch4	$\frac{Fe^{3+}}{Fe^{2+}}$ l3.1.ch5		
Usk	Serpentinised Komatiite	0.90	0.12	0.11	0.15	0.13		
Uspd	Serpentinised Peridotite	0.90	0.12	0.11	0.15	0.13		
Us	Serpentine	0.90	0.12	0.11	0.15	0.13		
OZCHEM data								
Rock No.	Total Description ⁴	Fe ₂ O ₃	Fe ₂ O ₃ total	FeO	MgO	CaO	Location	
32817	peridotite serpentinised carbonated peridotite	1.90		6.30	28.50	2.10	360493.89 E 6545432.3 N	
32816	peridotite serpentinised carbonated peridotite	2.10		6.90	29.40	2.00	360492.67 E 6545523.9 N	
32300	peridotite serpentinised peridotite	4.80		5.20	28.50	3.10	358168.78 E 6588275.9 N	
32299	peridotite serpentinised peridotite	2.80		5.90	32.90	2.40	357738.05 E 6586805.0 N	
32221	peridotite serpentinised peridotite	0.80		8.30	42.30	0.10	360701.39 E 6518918.7 N	
33219	peridotite serpentinised peridotite	0.80		7.70	38.20	1.70	360701.39 E 6518918.7 N	
33218	peridotite serpentinised peridotite	1.50		14.90	33.00	2.30	360701.39 E 6518918.7 N	
33217	peridotite serpentinised peridotite	0.90		8.80	41.50	0.40	360701.39 E 6518918.7 N	
33216	peridotite serpentinised peridotite	0.80		8.30	39.20	2.10	360701.39 E 6518918.7 N	
33215	peridotite serpentinised peridotite	0.80		8.20	43.40	0.50	361071.81 E 6518651.1 N	
33213	peridotite serpentinised peridotite	0.80		8.00	45.40	0.10	361071.81 E 6518651.1 N	
33211	peridotite serpentinised peridotite	1.10		10.70	39.10	1.40	358465.94 E 6526193.1 N	
33210	peridotite serpentinised peridotite	0.90		8.80	37.80	2.80	358465.94 E 6526193.1 N	
33207	peridotite serpentinised peridotite	0.80		7.70	43.90	0.90	358566.92 E 6525646.4 N	
33203	peridotite serpentinised peridotite	0.90		9.20	39.30	1.60	360758.12 E 6515810.6 N	
33202	peridotite serpentinised peridotite	0.80		8.50	42.20	1.00	360758.12 E 6515810.6 N	
33201	peridotite serpentinised peridotite	1.00		9.60	44.90		360758.12 E 6515810.6 N	
33200	peridotite serpentinised peridotite	1.20		11.60	43.50	0.10	360758.12 E 6515810.6 N	

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Table D.8: *continued*

33199	peridotite serpentinised peridotite	0.90			9.10	46.90	0.10	360758.12 E 6515810.6 N
33197	peridotite serpentinised peridotite	0.80			8.00	44.00		360758.12 E 6515810.6 N
33195	peridotite serpentinised peridotite	0.50			5.40	44.90	0.80	360500.03 E 6514891.6 N
33194	peridotite serpentinised peridotite	0.60			6.40	45.90	0.20	360500.03 E 6514891.6 N
33192	peridotite serpentinised peridotite	0.70			7.40	42.20	0.80	360500.03 E 6514891.6 N
33191	peridotite serpentinised peridotite	0.70			6.90	40.80	2.90	360500.03 E 6514891.6 N
33190	peridotite serpentinised peridotite	0.80			8.20	42.40	1.80	360500.03 E 6514891.6 N
33187	peridotite serpentinised peridotite	0.80			8.20	38.30	2.80	360500.03 E 6514891.6 N
33186	peridotite serpentinised peridotite	0.90			8.70	40.90	0.50	360675.04 E 6515352.0 N
33185	peridotite serpentinised peridotite	1.00			9.90	39.00	1.30	360675.04 E 6515352.0 N
33184	peridotite serpentinised peridotite	0.90			9.20	34.00	3.60	360675.04 E 6515352.0 N
33183	peridotite serpentinised peridotite	0.80			8.00	37.20	2.90	360675.04 E 6515352.0 N
33181	peridotite serpentinised peridotite	0.90			9.30	39.70	0.70	360675.04 E 6515352.0 N
33179	peridotite serpentinised peridotite	0.80			8.10	41.80	1.20	360675.04 E 6515352.0 N
33178	peridotite serpentinised peridotite	0.80			7.50	43.60	0.30	360675.04 E 6515352.0 N
33176	peridotite serpentinised peridotite	1.10			11.30	40.50	0.20	360675.04 E 6515352.0 N
33175	peridotite serpentinised peridotite	0.80			8.30	41.80	1.40	360675.04 E 6515352.0 N
33174	peridotite serpentinised peridotite	0.70			6.80	42.10	0.60	360675.04 E 6515352.0 N
33173	peridotite serpentinised peridotite	0.70			7.20	42.20	0.30	360675.04 E 6515352.0 N
33171	peridotite serpentinised peridotite	0.90			8.80	38.90	2.30	360675.04 E 6515352.0 N
33168	peridotite serpentinised peridotite	0.90			8.80	38.80	2.60	360675.04 E 6515352.0 N
33166	peridotite serpentinised peridotite	0.70			7.10	40.40	3.40	360675.04 E 6515352.0 N
33165	peridotite serpentinised peridotite	0.80			8.00	40.60	3.20	360675.04 E 6515352.0 N
33164	peridotite serpentinised peridotite	1.00			9.80	38.00	2.20	360675.04 E 6515352.0 N
33309	peridotite serpentinised peridotite	1.60			10.50	27.00	5.60	351421.01 E 6526430.6 N
33307	peridotite serpentinised peridotite	1.00			10.00	39.00	1.70	351421.01 E 6526430.6 N
33306	peridotite serpentinised peridotite	1.00			10.50	38.20	2.60	351421.01 E 6526430.6 N
33304	peridotite serpentinised peridotite	1.10			10.60	41.00	0.80	351421.01 E 6526430.6 N
33303	peridotite serpentinised peridotite	1.00			9.80	39.00	1.90	351421.01 E 6526430.6 N
33302	peridotite serpentinised peridotite	1.00			10.40	38.30	2.60	351421.01 E 6526430.6 N
33243	peridotite serpentinised peridotite	1.30			8.80	27.40	7.20	360675.04 E 6515352.0 N
33242	peridotite serpentinised peridotite	0.80			8.30	37.30	2.70	357455.69 E 6521419.9 N
33240	peridotite serpentinised peridotite	0.80			8.10	42.40		358912.93 E 6516691.4 N
33239	peridotite serpentinised peridotite	1.00			9.80	42.70		358912.93 E 6516691.4 N
33238	peridotite serpentinised peridotite	0.80			8.30	43.00		358912.93 E 6516691.4 N

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Table D.8: *continued*

33237	peridotite serpentinised peridotite	0.90		9.10	43.00		358912.93 E 6516691.4 N
33235	peridotite serpentinised peridotite	1.10		11.30	41.60	0.40	358964.48 E 6518886.9 N
33234	peridotite serpentinised peridotite	0.90		8.20	38.80	3.40	358964.48 E 6518886.9 N
33231	peridotite serpentinised peridotite	0.90		8.70	41.60	1.80	358964.48 E 6518886.9 N
33229	peridotite serpentinised peridotite	0.90		9.10	40.70	1.40	358964.48 E 6518886.9 N
33227	peridotite serpentinised peridotite	0.70		6.80	39.20	3.60	358760.02 E 6525101.1 N
33224	peridotite serpentinised peridotite	0.70		7.40	42.80	1.10	358760.02 E 6525101.1 N
33223	peridotite serpentinised peridotite	0.80		8.20	40.60	1.00	360701.39 E 6518918.7 N
33222	peridotite serpentinised peridotite	0.80		7.90	43.30		360701.39 E 6518918.7 N
33297	peridotite serpentinised peridotite	3.00		5.20	30.20	4.60	357835.59 E 6586440.9 N
33305	peridotite serpentinised peridotite	0.90		9.30	37.70	2.80	351421.01 E 6526430.6 N
33241	peridotite serpentinised peridotite	0.80		8.10	43.20	0.50	357455.69 E 6521419.9 N
33225	peridotite serpentinised peridotite	0.80		7.80	45.50	0.20	358760.02 E 6525101.1 N
33220	peridotite serpentinised peridotite	0.90		9.40	35.30	2.60	360701.39 E 6518918.7 N
33214	peridotite serpentinised peridotite	0.80		7.50	44.60		361071.81 E 6518651.1 N
33198	peridotite serpentinised peridotite	0.70		7.20	46.20		360758.12 E 6515810.6 N
33193	peridotite serpentinised peridotite	0.90		9.20	43.10	0.20	360500.03 E 6514891.6 N
33182	peridotite serpentinised peridotite	0.90		8.60	42.20	0.80	360675.04 E 6515352.0 N
33177	peridotite serpentinised peridotite	0.90		8.80	40.30	0.80	360675.04 E 6515352.0 N
33172	peridotite serpentinised peridotite	0.70		6.70	42.00	0.20	360675.04 E 6515352.0 N
33269	peridotite serpentinised peridotite	7.10		4.50	23.70	3.90	374870.18 E 6519085.4 N
33308	peridotite serpentinised peridotite	1.10		10.60	33.40	3.10	351421.01 E 6526430.6 N
33244	peridotite serpentinised peridotite	1.40		9.50	28.00	6.20	360675.04 E 6515352.0 N
33228	peridotite serpentinised peridotite	0.90		8.80	36.40	4.30	358760.02 E 6525101.1 N
33212	peridotite serpentinised peridotite	0.90		9.20	42.00	0.20	361071.81 E 6518651.1 N
33196	peridotite serpentinised peridotite	0.90		8.80	43.30	0.10	360758.12 E 6515810.6 N
Rock Code	Rock Type in solid geology GFS layer	$\frac{Fe^{wt\%} \times Fe}{(Fe+Mg+Ca)}$ l3.1.ch2	$\frac{Fe}{(Fe+Mg+Ca)}$ l3.1.ch1	$\frac{Fe_2O_3}{(Fe_2O_3+FeO)}$ l3.1.ch3	$\frac{Fe_2O_3}{FeO}$ l3.1.ch4	$\frac{Fe^{3+}}{Fe^{2+}}$ l3.1.ch5	
Zu	Ultramafic Schist	0.89	0.14	0.22	0.18	0.16	Ave. of 10 ¹⁰
OZCHEM data							
Rock No.	Total Description ^a	Fe ₂ O ₃	Fe ₂ O ₃ total	FeO	MgO	CaO	Location
	ultramafic schist	0.60		7.75	22.00	7.43	
	ultramafic schist	0.65		3.60	7.84	12.30	

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Table D.8: *continued*

	ultramafic schist	0.64			8.20	20.40	6.66	
	ultramafic schist	0.64			6.18	29.80	2.22	
	ultramafic schist	1.00			8.41	23.20	4.56	
	ultramafic schist	0.88			7.71	21.50	7.78	
	ultramafic schist	0.95			7.33	25.10	5.61	
	ultramafic schist	1.95			4.27	18.20	4.60	
	ultramafic schist	2.17			7.01	24.20	5.95	
	ultramafic schist	1.26			8.27	21.80	8.72	
Rock Code	Rock Type in solid geology GIS layer	$\frac{Fe\ wt\% \times Fe}{(Fe+Mg+Ca)}$ l3_lch2	$\frac{Fe}{(Fe+Mg+Ca)}$ l3_lch1	$\frac{Fe_2O_3}{(Fe_2O_3+FeO)}$ l3_lch3	$\frac{Fe_2O_3}{FeO}$ l3_lch4	$\frac{Fe^{3+}}{Fe^{2+}}$ l3_lch5		
Uk	Komatiite	0.88	0.13	0.39	0.73	0.66		
Uxa	Ultramafic Autobreccia	0.88	0.13	0.39	0.73	0.66		
OZCHEM data								
Rock No.	Total Description ⁴	Fe ₂ O ₃	Fe ₂ O ₃ total	FeO	MgO	CaO	Location	
30864	komatiite high Mg basalt	5.43	10.56	4.62	26.39	5.26	263486.99 E 6753570.9 N	
30862	komatiite spinifex komatiite	3.86	9.25	4.85	24.93	7.04	263129.97 E 6752856.9 N	
31482	komatiite	1.48	8.73	6.52	34.81	1.27	256904.00 E 6759974.0 N	
Rock Code	Rock Type in solid geology GIS layer	$\frac{Fe\ wt\% \times Fe}{(Fe+Mg+Ca)}$ l3_lch2	$\frac{Fe}{(Fe+Mg+Ca)}$ l3_lch1	$\frac{Fe_2O_3}{(Fe_2O_3+FeO)}$ l3_lch3	$\frac{Fe_2O_3}{FeO}$ l3_lch4	$\frac{Fe^{3+}}{Fe^{2+}}$ l3_lch5		
Gto	Tonalite	0.84	0.34	0.42	0.75	0.67		
OZCHEM data								
Rock No.	Total Description ⁴	Fe ₂ O ₃	Fe ₂ O ₃ total	FeO	MgO	CaO	Location	
98390	tonalite biotite tonalite	1.38	3.64	2.03	0.59	2.05	471149.90 6635700.1	
38987	tonalite BT tonalite	1.64		2.26	2.09	2.53	301000.00 E 6663000.0 N	
38889	tonalite BT tonalite	2.27		2.42	1.59	4.12	330300.00 E 6689900.0 N	
38993	tonalite BT tonalite	0.57		1.15	0.79	2.18	323000.00 E 6584300.0 N	
10223	tonalite BT tonalite xenolith	1.35		1.26	0.86	3.39	266385.18 E 6550677.7 N	
38908	tonalite HBL-BT tonalite	1.38		2.31	0.81	3.58	364000.00 E 6732000.0 N	
38999	tonalite HBL-BT tonalite	0.97		1.35	1.16	3.07	293700.00 E 6619500.0 N	
Rock Code	Rock Type in solid geology GIS layer	$\frac{Fe\ wt\% \times Fe}{(Fe+Mg+Ca)}$ l3_lch2	$\frac{Fe}{(Fe+Mg+Ca)}$ l3_lch1	$\frac{Fe_2O_3}{(Fe_2O_3+FeO)}$ l3_lch3	$\frac{Fe_2O_3}{FeO}$ l3_lch4	$\frac{Fe^{3+}}{Fe^{2+}}$ l3_lch5		

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Table D.8: *continued*

Upd	Peridotite (olivine cumulate)	0.83	0.12	0.30	0.52	0.47	
OZCHEM data							
Rock No.	Total Description ⁴	Fe ₂ O ₃	Fe ₂ O ₃ total	FeO	MgO	CaO	Location
33769	peridotite altered peridotite	3.50		3.10	33.70	0.10	374481.63 E 6545502.8 N
33768	peridotite altered peridotite	3.60		2.70	34.60	0.10	374481.63 E 6545502.8 N
33767	peridotite altered peridotite	2.60		3.10	32.70	1.80	374481.63 E 6545502.8 N
33765	peridotite altered peridotite	3.40		6.70	25.10	4.40	374481.63 E 6545502.8 N
33761	peridotite altered peridotite	2.10		5.60	25.70	7.00	374481.63 E 6545502.8 N
33256	peridotite altered peridotite	1.00		8.60	27.10	5.40	358465.94 E 6526193.1 N
33253	peridotite altered peridotite	1.40		9.40	28.40	4.50	358465.94 E 6526193.1 N
33877	peridotite altered peridotite	3.10		4.90	34.70	1.30	373918.74 E 6546315.4 N
33876	peridotite altered peridotite	2.20		5.00	32.70	1.30	373918.74 E 6546315.4 N
33875	peridotite altered peridotite	1.90		5.80	33.10	1.00	373918.74 E 6546315.4 N
33874	peridotite altered peridotite	3.40		5.70	29.10	0.90	373918.74 E 6546315.4 N
33873	peridotite altered peridotite	3.80		5.20	31.70	2.40	373918.74 E 6546315.4 N
33871	peridotite altered peridotite	3.30		5.00	31.80	2.60	373918.74 E 6546315.4 N
33866	peridotite altered peridotite	2.80		6.40	27.10	4.40	373918.74 E 6546315.4 N
33859	peridotite altered peridotite	4.40		4.40	36.00	1.10	374375.14 E 6546323.5 N
33858	peridotite altered peridotite	2.30		5.00	36.30	0.60	374375.14 E 6546323.5 N
33857	peridotite altered peridotite	3.40		4.40	36.80	0.70	374375.14 E 6546323.5 N
33855	peridotite altered peridotite	6.50		5.00	27.00	7.50	374375.14 E 6546323.5 N
33850	peridotite altered peridotite	3.80		5.80	29.10	1.50	374375.14 E 6546323.5 N
33849	peridotite altered peridotite	3.60		4.00	31.60	2.80	374375.14 E 6546323.5 N
33848	peridotite altered peridotite	4.20		3.90	31.40	2.20	374375.14 E 6546323.5 N
33847	peridotite altered peridotite	3.60		3.80	31.70	2.20	374375.14 E 6546323.5 N
33843	peridotite altered peridotite	0.80		6.60	31.80	2.60	374375.14 E 6546323.5 N
33842	peridotite altered peridotite	2.40		4.90	27.80	5.20	374375.14 E 6546323.5 N
33841	peridotite altered peridotite	2.60		4.70	29.00	1.00	374375.14 E 6546323.5 N
33837	peridotite altered peridotite	2.60		5.70	33.10	1.50	374558.32 E 6546327.0 N
33836	peridotite altered peridotite	2.90		5.50	33.30	1.30	374558.32 E 6546327.0 N
33834	peridotite altered peridotite	2.60		6.20	33.80	1.10	374558.32 E 6546327.0 N
33832	peridotite altered peridotite	0.80		6.60	30.50	1.50	374558.32 E 6546327.0 N
33831	peridotite altered peridotite	2.90		4.20	32.10	1.30	374558.32 E 6546327.0 N
33829	peridotite altered peridotite	2.90		4.80	27.80	5.30	374558.32 E 6546327.0 N

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Table D.8: *continued*

33828	peridotite altered peridotite	0.70			6.20	27.80	5.60	374558.32 E 6546327.0 N
33827	peridotite altered peridotite	2.00			4.90	30.60	3.00	374558.32 E 6546327.0 N
33826	peridotite altered peridotite	2.30			4.40	30.40	5.80	374558.32 E 6546327.0 N
33825	peridotite altered peridotite	2.60			6.80	26.70	6.00	374558.32 E 6546327.0 N
33823	peridotite altered peridotite	3.80			6.40	27.00	4.20	374558.32 E 6546327.0 N
33821	peridotite altered peridotite	1.90			7.20	26.00	6.90	374558.32 E 6546327.0 N
33817	peridotite altered peridotite	2.60			7.20	30.80	2.30	373918.74 E 6546315.4 N
33816	peridotite altered peridotite	3.60			5.70	32.20	2.50	373918.74 E 6546315.4 N
33815	peridotite altered peridotite	2.50			8.80	31.50	2.20	373918.74 E 6546315.4 N
33813	peridotite altered peridotite	2.30			8.90	32.20	1.70	373918.74 E 6546315.4 N
33807	peridotite altered peridotite	2.20			5.00	26.30	5.80	374558.32 E 6546327.0 N
33805	peridotite altered peridotite	1.80			4.00	26.40	6.10	374558.32 E 6546327.0 N
33804	peridotite altered peridotite	1.90			6.40	26.50	4.00	374558.32 E 6546327.0 N
33802	peridotite altered peridotite	1.10			8.40	25.50	5.30	374558.32 E 6546327.0 N
33800	peridotite altered peridotite	1.40			4.40	35.60	0.10	374107.73 E 6545952.8 N
33799	peridotite altered peridotite	2.30			3.70	33.90	0.10	374107.73 E 6545952.8 N
33795	peridotite altered peridotite	3.30			4.60	29.10	2.10	374107.73 E 6545952.8 N
33794	peridotite altered peridotite	5.00			3.50	28.50	1.60	374107.73 E 6545952.8 N
33793	peridotite altered peridotite	5.70			5.90	29.30	0.10	374107.73 E 6545952.8 N
33791	peridotite altered peridotite	0.60			7.10	26.00	1.40	374107.73 E 6545952.8 N
33789	peridotite altered peridotite	3.90			1.90	30.00	0.10	373828.96 E 6546222.3 N
33788	peridotite altered peridotite	4.10			3.20	35.80	0.80	373828.96 E 6546222.3 N
33783	peridotite altered peridotite	4.20			5.30	27.90	3.20	373827.10 E 6546313.6 N
33781	peridotite altered peridotite	3.10			4.70	29.20	2.50	373827.10 E 6546313.6 N
33780	peridotite altered peridotite	4.70			3.60	28.60	3.40	373827.10 E 6546313.6 N
33779	peridotite altered peridotite	4.10			4.40	28.70	2.10	373827.10 E 6546313.6 N
33777	peridotite altered peridotite	7.60			4.50	22.70	0.30	373735.56 E 6546312.1 N
33775	peridotite altered peridotite	3.50			3.50	33.90	0.30	373735.56 E 6546312.1 N
33773	peridotite altered peridotite	2.90			4.20	33.70	0.40	373735.56 E 6546312.1 N
33772	peridotite altered peridotite	4.10			4.80	26.30	7.60	373735.56 E 6546312.1 N
33770	peridotite altered peridotite	2.30			5.80	30.50	1.90	374481.63 E 6545502.8 N
33872	peridotite altered peridotite	2.50			4.90	32.90	1.80	373918.74 E 6546315.4 N
33867	peridotite altered peridotite	2.50			5.70	28.30	2.90	373918.74 E 6546315.4 N
33856	peridotite altered peridotite	4.30			4.40	36.40	0.50	374375.14 E 6546323.5 N
33846	peridotite altered peridotite	3.00			5.00	28.30	4.50	374375.14 E 6546323.5 N

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Table D.8: *continued*

33840	peridotite altered peridotite	3.10		4.50	27.90	4.90	374375.14 E 6546323.5 N
33835	peridotite altered peridotite	2.50		6.30	34.10	1.00	374558.32 E 6546327.0 N
33830	peridotite altered peridotite	3.40		5.00	31.90	1.70	374558.32 E 6546327.0 N
33824	peridotite altered peridotite	2.70		6.30	26.70	5.70	374558.32 E 6546327.0 N
33814	peridotite altered peridotite	2.00		9.00	32.50	1.70	373918.74 E 6546315.4 N
33803	peridotite altered peridotite	1.90		5.80	25.60	7.40	374558.32 E 6546327.0 N
33798	peridotite altered peridotite	3.70		3.70	33.20	0.20	374107.73 E 6545952.8 N
33792	peridotite altered peridotite	1.30		7.00	25.20	4.90	374107.73 E 6545952.8 N
33787	peridotite altered peridotite	3.50		2.60	29.50	0.10	373828.96 E 6546222.3 N
33782	peridotite altered peridotite	2.40		4.70	30.60	2.40	373827.10 E 6546313.6 N
33776	peridotite altered peridotite	2.50		4.00	33.30	0.20	373735.56 E 6546312.1 N
33766	peridotite altered peridotite	2.60		4.50	33.20	0.60	374481.63 E 6545502.8 N
33252	peridotite altered peridotite	1.20		7.90	25.60	7.60	358465.94 E 6526193.1 N
33870	peridotite altered peridotite	3.50		4.50	28.20	5.40	373918.74 E 6546315.4 N
33854	peridotite altered peridotite	4.30		3.70	33.00	1.90	374375.14 E 6546323.5 N
33822	peridotite altered peridotite	2.70		8.30	26.40	3.60	374558.32 E 6546327.0 N
33806	peridotite altered peridotite	2.60		5.00	26.20	6.70	374558.32 E 6546327.0 N
33790	peridotite altered peridotite	3.70		2.60	33.00	1.60	373828.96 E 6546222.3 N
33774	peridotite altered peridotite	3.00		3.40	34.50	0.10	373735.56 E 6546312.1 N
33180	peridotite altered peridotite	0.90		9.20	44.60	0.40	360675.04 E 6515352.0 N
33749	peridotite altered peridotite tuff	11.10			31.20	4.90	333367.82 E 6656511.6 N
33748	peridotite altered spinifex peridotite	10.70			31.90	5.70	333367.82 E 6656511.6 N
33750	peridotite altered spinifex peridotite	11.00			30.00	5.60	333367.82 E 6656511.6 N
76564	peridotite grey-green olivine peridotite	3.72	10.30	5.92	34.38	0.83	263000.00 E 6751060.0 N
33759	peridotite spinifex peridotite	12.80			28.60	5.90	317048.65 E 6586625.5 N
33756	peridotite spinifex peridotite	11.90			29.10	6.10	317048.65 E 6586625.5 N
33259	peridotite spinifex peridotite	1.40		9.10	28.40	6.80	355896.46 E 6516636.4 N
33258	peridotite spinifex peridotite	1.50		10.10	24.60	7.30	355896.46 E 6516636.4 N
33255	peridotite spinifex peridotite	1.70		11.40	24.60	6.70	358465.94 E 6526193.1 N
33251	peridotite spinifex peridotite	1.60		10.80	30.50	4.70	358465.94 E 6526193.1 N
33249	peridotite spinifex peridotite	1.40		9.00	32.00	4.20	360675.04 E 6515352.0 N
33248	peridotite spinifex peridotite	0.90		9.20	33.80	3.60	360675.04 E 6515352.0 N
33247	peridotite spinifex peridotite	1.30		8.60	34.10	4.20	360675.04 E 6515352.0 N
33245	peridotite spinifex peridotite	1.00		9.80	32.60	4.20	360675.04 E 6515352.0 N
33257	peridotite spinifex peridotite	1.20		8.10	27.60	7.40	355896.46 E 6516636.4 N

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Table D.8: *continued*

33246	peridotite spinifex peridotite	1.30			8.40		32.40	5.30	360675.04 E 6515352.0 N
33758	peridotite spinifex peridotite	11.60					30.70	5.90	317048.65 E 6580625.5 N
33260	peridotite spinifex peridotite	1.60			10.50		25.40	7.50	355896.46 E 6516636.4 N
33208	peridotite	0.70			6.70		42.10	1.40	358566.92 E 6525646.4 N
33206	peridotite	0.80			7.60		43.20	0.40	358566.92 E 6525646.4 N
33205	peridotite	0.70			6.80		42.10	2.10	358566.92 E 6525646.4 N
33189	peridotite	0.90			9.20		38.80	3.10	360500.03 E 6514891.6 N
33170	peridotite	0.90			8.60		40.60	2.40	360675.04 E 6515352.0 N
33169	peridotite	0.80			8.30		39.00	2.40	360675.04 E 6515352.0 N
33167	peridotite	0.80			8.20		41.80	0.80	360675.04 E 6515352.0 N
33250	peridotite	1.20			7.60		30.10	6.80	358465.94 E 6526193.1 N
33233	peridotite	0.90			8.60		37.20	3.60	358964.48 E 6518886.9 N
33232	peridotite	1.10			10.70		33.90	4.30	358964.48 E 6518886.9 N
33226	peridotite	1.10			7.20		33.60	4.80	358760.02 E 6525101.1 N
33236	peridotite	1.00			10.00		35.30	4.10	358964.48 E 6518886.9 N
33230	peridotite	0.70			7.40		43.20	2.60	358964.48 E 6518886.9 N
33209	peridotite	0.80			8.30		44.00	1.30	358566.92 E 6525646.4 N
33204	peridotite	0.80			7.50		40.50	1.10	358566.92 E 6525646.4 N
33188	peridotite	0.90			9.40		35.20	3.20	360500.03 E 6514891.6 N
Rock Code	Rock Type in solid geology GIS layer	$\frac{Fe_{wt\%} \times Fe}{(Fe+Mg+Ca)}$ l3_l_ch2	$\frac{Fe}{(Fe+Mg+Ca)}$ l3_l_ch1	$\frac{Fe_2O_3}{(Fe_2O_3+FeO)}$ l3_l_ch3	$\frac{Fe_2O_3}{FeO}$ l3_l_ch4	$\frac{Fe^{3+}}{Fe^{2+}}$ l3_l_ch5			
Fd	Dacite (even grained)	0.82	0.29	0.38	0.76	0.68			
OZCHEM data									
Rock No.	Total Description ⁴	Fe ₂ O ₃	Fe ₂ O ₃ total	FeO	MgO	CaO	Location		
32752	dacite altered intrusive porphyritic quartz-oligoc	1.10		1.40	1.80	0.70	366348.30 E 6575712.6 N		
33100	dacite amygdaloidal dacite	0.90		1.70	0.50	2.90	337845.04 E 6751605.2 N		
31935	dacite BT-Pl-phyrac dacite		5.03		1.72	3.93	387399.97 E 6445500.0 N		
45589	dacite Feld-phyrac dacite dyke	1.42	2.86	1.30	1.05	1.30	341591.00 E 6746184.0 N		
31924	dacite glassy Qz-Kfs-phyrac dacite		1.11		0.12	1.00	386300.05 E 6435500.0 N		
32750	dacite intrusive porphyritic amphibole-oligoclase	1.40		1.80	3.40	5.50	366333.58 E 6576535.1 N		
32747	dacite intrusive porphyritic oligoclase-amphibole	0.40		2.90	1.60	3.30	366973.58 E 6576546.6 N		
32746	dacite intrusive porphyritic oligoclase-amphibole	0.40		0.80	5.10	6.30	366626.10 E 6575534.6 N		
32749	dacite intrusive porphyritic quartz-amphibole-olig	0.10		2.20	2.70	2.70	366533.15 E 6575624.3 N		

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Table D.8: *continued*

31899	dacite Pl-phyrhic dacite		2.85		2.39	3.55	383299.97 E 6533300.0 N
31898	dacite Pl-phyrhic dacite		2.19		1.66	2.35	383299.97 E 6533300.0 N
30630	dacite porphyritic Amph-OGC dacite	2.33		0.87	2.28	4.26	346903.10 E 6594475.5 N
30616	dacite porphyritic Amph-Ogc dacite	1.47		3.58	4.41	4.28	365969.59 E 6576437.3 N
30615	dacite porphyritic Amph-Ogc dacite	2.60		2.29	4.42	4.03	354298.84 E 6589944.1 N
30614	dacite porphyritic Amph-OGC dacite	1.74		1.86	3.19	4.38	366337.40 E 6576352.4 N
80329	dacite porphyritic dacite	0.61	1.49	0.79	0.27	1.13	455600.00 E 6615400.0 N
30657	dacite porphyritic Qz-Amph-OGC dacite	0.56		1.93	3.02	3.10	366333.96 E 6576626.6 N
31925	dacite spherulitic Qz-Kfs-phyrhic dacite		1.13			0.79	386300.05 E 6435500.0 N
33104	dacite uraltised porphyritic dacite	3.50		6.30	1.60	4.50	351389.31 E 6761621.2 N
31889	dacite		7.66		4.26	5.10	376100.01 E 6541300.0 N
31888	dacite		3.04		2.34	3.38	376100.01 E 6541300.0 N
Rock Code	Rock Type in solid geology GIS layer	$\frac{Fe\ wt\% \times Fe}{(Fe+Mg+Ca)}$ l3.l.ch2	$\frac{Fe}{(Fe+Mg+Ca)}$ l3.l.ch1	$\frac{Fe_2O_3}{(Fe_2O_3+FeO)}$ l3.l.ch3	$\frac{Fe_2O_3}{FeO}$ l3.l.ch4	$\frac{Fe^{3+}}{Fe^{2+}}$ l3.l.ch5	
la	Andesite (even grained)	0.80	0.25	0.43	2.25	2.02	
lfp	Porphyritic Andesite	0.80	0.25	0.43	2.25	2.02	
OZCHEM data							
Rock No.	Total Description ⁴	Fe ₂ O ₃	Fe ₂ O ₃ total	FeO	MgO	CaO	Location
38786	andesite basaltic andesite	1.83		5.27	4.09	8.31	298800.00 E 6652150.0 N
31893	andesite Hbl-Pl-phyrhic andesite		3.98		4.59	4.84	382900.04 E 6533400.0 N
31892	andesite Hbl-Pl-phyrhic andesite		4.63		4.15	3.64	382900.04 E 6533400.0 N
31876	andesite Hbl-Pl-phyrhic andesite		4.75		4.69	4.86	373000.02 E 6544500.0 N
32019	andesite Hbl-Pl-phyrhic andesite		3.72		2.49	2.56	371999.96 E 6553200.0 N
31870	andesite Hbl-Pl-phyrhic andesite		4.12		4.11	4.65	373000.02 E 6544500.0 N
32748	andesite intrusive porphyritic oligoclase-amphibol	0.80		4.10	4.00	4.40	364542.98 E 6579520.5 N
31923	andesite Pl-phyrhic quartz andesite		3.65		2.43	2.54	371999.96 E 6553200.0 N
31922	andesite Pl-phyrhic quartz andesite		3.78		2.58	3.55	371999.96 E 6553200.0 N
31913	andesite Pl-phyrhic quartz andesite		4.91		4.28	4.22	371499.98 E 6552799.9 N
31910	andesite Pl-phyrhic quartz andesite		5.01		4.29	4.14	371499.98 E 6552799.9 N
33933	andesite Pl-phyrhic quartz andesite		3.80		2.88	3.86	371999.96 E 6553200.0 N
33932	andesite Pl-phyrhic quartz andesite		3.68		2.83	3.84	371999.96 E 6553200.0 N
32272	andesite	3.10		0.50	3.60	5.30	356910.14 E 6748913.8 N
Rock	Rock Type in solid	$\frac{Fe\ wt\% \times Fe}{(Fe+Mg+Ca)}$	$\frac{Fe}{(Fe+Mg+Ca)}$	$\frac{Fe_2O_3}{(Fe_2O_3+FeO)}$	$\frac{Fe_2O_3}{FeO}$	$\frac{Fe^{3+}}{Fe^{2+}}$	

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Table D.8: *continued*

Code	geology GIS layer	l3_lch2	l3_lch1	l3_lch3	l3_lch4	l3_lch5	
Svcm	Volc.-derived Congl. (m - u/m)	0.70	0.23	0.25	0.52	0.47	11
OZCHEM data							
Rock No.	Total Description ⁴	Fe ₂ O ₃	Fe ₂ O ₃ total	FeO	MgO	CaO	Location
8	meta-arkose (matrix)	0.99		0.94	0.70	2.04	
9	meta-arkose (matrix)	0.64		1.02	0.95	3.12	
10	meta-arkose (matrix)	0.45		0.16	0.24	1.17	
11	meta-arkose (matrix)	0.65		2.19	1.42	3.21	
12	meta-arkose (matrix)	0.05		1.51	0.68	3.50	
13	meta-arkose (matrix)	0.25		1.18	0.38	2.00	
7	mafic clasts	1.15		6.53	13.92	11.62	
8	mafic clasts	1.38		7.85	6.26	11.68	
9	mafic clasts	1.58		6.81	13.32	12.74	
10	mafic clasts	1.51		8.35	24.16	5.68	
11	mafic clasts	1.00		7.81	23.72	7.69	
12	mafic clasts	1.27		3.48	2.53	6.45	
13	mafic clasts	0.26		2.28	0.84	6.36	
Rock Code	Rock Type in solid geology GIS layer	$\frac{Fe_{int\%} \times Fe}{(Fe+Mg+Ca)}$ l3_lch2	$\frac{Fe}{(Fe+Mg+Ca)}$ l3_lch1	$\frac{Fe_2O_3}{(Fe_2O_3+FeO)}$ l3_lch3	$\frac{Fe_2O_3}{FeO}$ l3_lch4	$\frac{Fe^{3+}}{Fe^{2+}}$ l3_lch5	
Hgf	Felsic Gneiss	0.69	0.36	0.46	1.02	0.92	
OZCHEM data							
Rock No.	Total Description ⁴	Fe ₂ O ₃	Fe ₂ O ₃ total	FeO	MgO	CaO	Location
45605	gneiss Bt gneiss enclave	4.05	9.40	4.81	1.27	4.58	348890.00 E 6747369.0 N
10195	gneiss Bt granodiorite gneiss	0.50		0.77	0.22	1.72	338892.91 E 6536444.4 N
38916	gneiss Bt tonalite gneiss	1.19		1.59	1.05	3.70	312300.00 E 6766100.0 N
10192	gneiss Bt tonalite gneiss xenolith in leuco-adamel	2.33		2.25	1.61	2.44	333545.51 E 6478732.9 N
33680	gneiss felsic gneiss	1.20		4.30	3.60	7.00	342764.85 E 6747299.9 N
33679	gneiss felsic gneiss	1.00		0.30	0.10	1.20	343944.15 E 6747868.8 N
30817	gneiss granite gneiss	0.87	2.58	1.54	0.37	1.51	266172.00 E 6754000.9 N
10194	gneiss granodiorite gneiss with concordant leucove	0.77		0.33	0.28	1.60	280545.16 E 6732972.7 N
10207	gneiss HBL leucogranodiorite gneiss	0.43		0.39	0.11	0.79	336925.35 E 6535615.7 N
10188	gneiss laminated bt adamellite gneiss	0.52		1.20	0.66	2.28	331772.94 E 6475953.9 N

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Table D.8: *continued*

10198	gneiss leucocratic aplogranite gneiss from concord	0.40		0.45	0.17	1.41	269736.93 E 6723641.3 N
10203	gneiss lineated granodiorite gneiss	0.40		0.70	0.33	1.72	269736.93 E 6723641.3 N
10182	gneiss lineated granodiorite gneiss	0.64		0.53	0.47	1.74	370229.89 E 6473008.0 N
10201	gneiss migmatitic bt adamellite gneiss	0.71		0.55	0.48	1.55	316887.69 E 6539709.7 N
10185	gneiss migmatitic granite gneiss	0.98		1.87	0.73	1.11	370229.89 E 6473008.0 N
90804	gneiss	0.42	1.13	0.64	0.31	1.44	338705.30 E 6535974.9 N
34850	gneiss	0.91	2.09	1.06	0.22	1.21	262450.41 E 6763768.5 N
Rock Code	Rock Type in solid geology GIS layer	$\frac{Fe\ wt\% \times Fe}{(Fe+Mg+Ca)}$ l3_l.ch2	$\frac{Fe}{(Fe+Mg+Ca)}$ l3_l.ch1	$\frac{Fe_2O_3}{(Fe_2O_3+FeO)}$ l3_l.ch3	$\frac{Fe_2O_3}{FeO}$ l3_l.ch4	$\frac{Fe^{3+}}{Fe^{2+}}$ l3_l.ch5	
Gdi	Granodiorite	0.69	0.32	0.44	0.89	0.80	
Gdi-wee	Weebo Granodiorite	0.69	0.32	0.44	0.89	0.80	
OZCHEM data							
Rock No.	Total Description ⁴	Fe ₂ O ₃	Fe ₂ O ₃ total	FeO	MgO	CaO	Location
39004	granodiorite BT granodiorite	0.94		0.71	0.64	1.81	311500.00 E 6676500.0 N
38969	granodiorite BT granodiorite	0.75		0.90	0.54	1.93	331000.00 E 6630000.0 N
38968	granodiorite BT granodiorite	0.72		1.03	0.51	2.07	311000.00 E 6681000.0 N
38873	granodiorite BT granodiorite	0.40		1.41	0.48	2.49	315300.00 E 6743400.0 N
38870	granodiorite BT granodiorite	0.46		1.44	0.53	2.70	315300.00 E 6743400.0 N
10231	granodiorite BT granodiorite xenolith	1.97		1.65	0.95	2.41	257803.88 E 6620970.0 N
38966	granodiorite BT-HBL granodiorite	0.99		1.48	1.25	2.90	350600.00 E 6645800.0 N
39023	granodiorite BT-HBL granodiorite	1.71		1.75	1.73	3.27	328300.00 E 6624200.0 N
39022	granodiorite BT-HBL granodiorite	1.62		1.54	1.49	3.01	328300.00 E 6624200.0 N
39020	granodiorite BT-HBL granodiorite	1.93		1.47	1.63	3.42	328000.00 E 6625000.0 N
39018	granodiorite BT-HBL granodiorite	1.73		1.67	1.62	3.30	328000.00 E 6625000.0 N
39016	granodiorite BT-HBL granodiorite	1.62		1.23	1.25	2.81	328000.00 E 6626000.0 N
39014	granodiorite BT-HBL granodiorite	1.59		1.88	1.59	3.04	331000.00 E 6623500.0 N
38998	granodiorite BT-HBL granodiorite	1.17		1.07	0.98	2.88	302500.00 E 6608500.0 N
38997	granodiorite BT-HBL granodiorite	1.33		1.28	1.35	3.21	302500.00 E 6608500.0 N
38996	granodiorite BT-HBL granodiorite	1.04		1.22	1.02	3.06	302500.00 E 6608500.0 N
39012	granodiorite BT-HBL granodiorite	1.54		1.83	1.59	2.97	327900.00 E 6624000.0 N
10244	granodiorite Fl-BT granodiorite xenolith	0.53		1.04	0.79	3.00	356776.88 E 6508420.4 N
45587	granodiorite foliated BT granodiorite	0.87	6.87	5.40	1.01	3.49	355109.00 E 6754111.0 N
31953	granodiorite granodiorite with micro granodiorite ^x		5.16		0.61	3.44	384399.97 E 6434499.9 N

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Table D.8: *continued*

31950	granodiorite	granodiorite with micro granodiorite		3.93			0.51	2.95	384399.97 E 6434499.9 N
39009	granodiorite	HBL granodiorite	1.09			0.71			348000.00 E 6555400.0 N
38963	granodiorite	HBL-BT granodiorite	1.24			1.60	1.93	1.77	342700.00 E 6652500.0 N
38887	granodiorite	HBL-BT granodiorite	0.62			0.94	0.24	1.91	332000.00 E 6705300.0 N
38874	granodiorite	HBL-BT granodiorite	0.86			1.89	1.22	2.72	315300.00 E 6743400.0 N
10189	granodiorite	HBL-DI leuco granodiorite, gneissic	1.00			0.70	0.54	1.52	347686.56 E 6555812.0 N
10245	granodiorite	lineated BT-HBL granodiorite	1.91			2.06	1.75	3.86	289259.85 E 6550183.3 N
31954	granodiorite	micro granodiorite		5.93			0.91	4.12	384399.97 E 6434499.9 N
10115	granodiorite	porphyritic BT granodiorite	0.50			1.10	0.56	2.11	328111.28 E 6526193.7 N
10141	granodiorite	porphyritic BT granodiorite	1.28			1.20	0.73	2.26	340167.53 E 6466972.8 N
10128	granodiorite	porphyritic BT granodiorite	0.88			1.37	0.65	2.48	303243.01 E 6535803.3 N
10125	granodiorite	porphyritic BT granodiorite	0.68			0.68	0.42	1.81	344183.90 E 6497217.6 N
10127	granodiorite	porphyritic BT granodiorite dyke	0.94			0.80	0.60	2.33	323435.00 E 6531593.8 N
10134	granodiorite	porphyroblastic BT granodiorite	1.15			0.54	0.52	1.98	308545.95 E 6700521.9 N
10135	granodiorite	porphyroblastic mafic granodiorite	0.90			1.12	1.03	2.26	356776.88 E 6508420.4 N
10136	granodiorite	strongly lineated BT granodiorite	0.71			0.66	0.46	1.84	366916.20 E 6504031.8 N
10132	granodiorite	weakly foliated BT granodiorite	0.62			0.21	0.19	1.25	304380.36 E 6574228.9 N
90800	granodiorite		0.76	2.20		1.30	0.47	2.09	253750.30 E 6752850.4 N
30643	granodiorite			1.40			0.40	2.00	374099.97 E 6550399.9 N
33672	granodiorite		0.90			4.90	1.20	3.80	353719.26 E 6753705.5 N
32048	granodiorite		0.62			2.66	1.62	3.29	333687.06 E 6622668.5 N
32041	granodiorite		0.42			1.20	0.73	2.36	324724.18 E 6583720.1 N
32038	granodiorite		0.30			1.31	0.73	2.24	324724.18 E 6583720.1 N
32015	granodiorite		1.73			1.56	1.52	2.95	333687.06 E 6622668.5 N
32013	granodiorite		2.00			1.89	1.84	3.66	333687.06 E 6622668.5 N
32042	granodiorite		0.28			1.38	0.76	2.18	324724.18 E 6583720.1 N
32014	granodiorite		1.86			1.92	1.79	3.49	333687.06 E 6622668.5 N
32049	granodiorite		1.57			1.73	1.58	3.17	333687.06 E 6622668.5 N
32012	granodiorite		1.69			1.85	1.66	3.25	333687.06 E 6622668.5 N
Rock Code	Rock Type in solid geology GIS layer		$\frac{Fe\ wt\% \times Fe}{(Fe+Mg+Ca)}$ l3.1.ch2	$\frac{Fe}{(Fe+Mg+Ca)}$ l3.1.ch1	$\frac{Fe_2O_3}{(Fe_2O_3+FeO)}$ l3.1.ch3	$\frac{Fe_2O_3}{FeO}$ l3.1.ch4	$\frac{Fe^{3+}}{Fe^{2+}}$ l3.1.ch5		
Hpqh	Si-rich Hornfels		0.67	0.61	0.86	6.33	5.70		
OZCHEM data									

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Table D.8: *continued*

Rock No.	Total Description ⁴	Fe ₂ O ₃	Fe ₂ O ₃ total	FeO	MgO	CaO	Location
72651	siltstone hard grey silicified rock	1.33	1.56	0.21	0.48	0.02	309918.10 6959474.0
Rock Code	Rock Type in solid geology GIS layer	$\frac{Fe\ wt\% \times Fe_2O_3}{(Fe+Mg+Ca)}$ l3.1.ch2	$\frac{Fe}{(Fe+Mg+Ca)}$ l3.1.ch1	$\frac{Fe_2O_3}{(Fe_2O_3+FeO)}$ l3.1.ch3	$\frac{Fe_2O_3}{FeO}$ l3.1.ch4	$\frac{Fe^{3+}}{Fe^{2+}}$ l3.1.ch5	
Pfbh	Feldspar Hbl. Bio. Porphyry	0.67	0.40	0.40	0.78	0.70	
Pf	Feldspar Porphyry	0.67	0.40	0.40	0.78	0.70	
Pfqb	Feldspar Qtz Bio. Porphyry	0.67	0.40	0.40	0.78	0.70	
Pfqh	Feldspar Qtz Hbl. Porphyry	0.67	0.40	0.40	0.78	0.70	
Pfq	Feldspar Qtz Porphyry	0.67	0.40	0.40	0.78	0.70	
Pfh	Plag. ± Hbl. Porphyry	0.67	0.40	0.40	0.78	0.70	
OZCHEM data							
Rock No.	Total Description ⁴	Fe ₂ O ₃	Fe ₂ O ₃ total	FeO	MgO	CaO	Location
80400	porphyry metadacite porphyry	1.07	2.14	0.96	0.23	0.80	475750.00 E 6637300.0 N
34853	porphyry quartz porphyry dyke	1.34	2.86	1.37	0.83	2.01	255190.30 E 6762572.4 N
32016	porphyry	0.43		1.83	1.04	4.48	333687.06 E 6622668.5 N
Rock Code	Rock Type in solid geology GIS layer	$\frac{Fe\ wt\% \times Fe_2O_3}{(Fe+Mg+Ca)}$ l3.1.ch2	$\frac{Fe}{(Fe+Mg+Ca)}$ l3.1.ch1	$\frac{Fe_2O_3}{(Fe_2O_3+FeO)}$ l3.1.ch3	$\frac{Fe_2O_3}{FeO}$ l3.1.ch4	$\frac{Fe^{3+}}{Fe^{2+}}$ l3.1.ch5	
Gmo	Monzonite	0.67	0.30	0.59	1.45	1.31	
OZCHEM data							
Rock No.	Total Description ⁴	Fe ₂ O ₃	Fe ₂ O ₃ total	FeO	MgO	CaO	Location
38955	monzonite Pyrx quartz monzonite	1.80		1.24	1.38	3.26	328000.00 6730000.0
Rock Code	Rock Type in solid geology GIS layer	$\frac{Fe\ wt\% \times Fe_2O_3}{(Fe+Mg+Ca)}$ l3.1.ch2	$\frac{Fe}{(Fe+Mg+Ca)}$ l3.1.ch1	$\frac{Fe_2O_3}{(Fe_2O_3+FeO)}$ l3.1.ch3	$\frac{Fe_2O_3}{FeO}$ l3.1.ch4	$\frac{Fe^{3+}}{Fe^{2+}}$ l3.1.ch5	
Gsy	Syenite	0.65	0.38	0.54	1.95	1.76	
OZCHEM data							
Rock No.	Total Description ⁴	Fe ₂ O ₃	Fe ₂ O ₃ total	FeO	MgO	CaO	Location
38950	quartz syenite Pyrx quartz syenite	0.90		0.22	0.16	0.84	360000.00 E 6687000.0 N
38947	quartz syenite Pyrx quartz syenite	1.40		1.22	1.61	3.33	360000.00 E 6687000.0 N
38954	quartz syenite Pyrx quartz syenite	1.80		0.35	0.70	1.21	347000.00 E 6737000.0 N
38953	quartz syenite Pyrx quartz syenite	1.40		0.29	0.55	0.70	347000.00 E 6737000.0 N
13453	syenite alkali syenite	0.72		1.14	0.23	1.18	325349.39 E 6360125.7 N

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Table D.8: *continued*

13452	syenite alkali syenite	1.79			2.71	1.35	2.72	326240.27 E 6357368.5 N
13454	syenite alkali syenite	0.83			2.19	1.09	2.48	330059.83 E 6358322.4 N
32045	syenite fluorite-rich porphyry	0.35			1.62	0.53	1.64	362100.90 E 6517560.4 N
38949	syenite Pyrx syenite	1.20			0.57	0.85	2.63	360000.00 E 6687000.0 N
38948	syenite Pyrx syenite	1.30			0.79	1.06	2.41	360000.00 E 6687000.0 N
32017	syenite quartz-feldspar porphyry		0.67				0.74	333687.06 E 6622668.5 N
13455	syenite	1.15			1.85	0.58	2.61	328499.59 E 6361955.6 N
Rock Code	Rock Type in solid geology GIS layer	$\frac{Fe_{wt\%} \times Fe}{(Fe+Mg+Ca)}$ l3_l.ch2	$\frac{Fe}{(Fe+Mg+Ca)}$ l3_l.ch1	$\frac{Fe_2O_3}{(Fe_2O_3+FeO)}$ l3_l.ch3	$\frac{Fe_2O_3}{FeO}$ l3_l.ch4	$\frac{Fe^{3+}}{Fe^{2+}}$ l3_l.ch5		
Svcf	Coarse-grained Fragmental	0.63	0.37	0.40	1.62	1.46		
Fpbx	Felsic Pyroclastic Breccia	0.63	0.37	0.40	1.62	1.46		
Ftc	Felsic Tuff (crystal lithic)	0.63	0.37	0.40	1.62	1.46		
Svff	Fine-grained Fragmental	0.63	0.37	0.40	1.62	1.46		
Svmf	Medium-grained Fragmental	0.63	0.37	0.40	1.62	1.46		
Ft	M/morphosed Felsic Tuff & Lava	0.63	0.37	0.40	1.62	1.46		
Fvx	Undiv. Felsic Autoclastic Rock	0.63	0.37	0.40	1.62	1.46		
Fvy	Undiv. Felsic Pyroclastic Rock	0.63	0.37	0.40	1.62	1.46		
Fv	Undivided Felsic Volc. Rock	0.63	0.37	0.40	1.62	1.46		
OZCHEM data								
Rock No.	Total Description ¹	Fe ₂ O ₃	Fe ₂ O ₃ total	FeO	MgO	CaO	Location	
32754	agglomerate volcanic agglomerate			5.70	4.60	2.10	358327.24 E 6584529.7 N	
32753	agglomerate volcanic agglomerate	1.10		4.00	2.70	11.30	358327.24 E 6584529.7 N	
80386	felsic volcanic felsic volcanic	0.58	1.37	0.71	0.47	2.41	300000.00 E 6724300.0 N	
32720	rhyolite alt'd intrusive porphyritic qtz-albi	0.10		0.50	0.70	2.00	354512.96 E 6567818.8 N	
32755	rhyolite alt'd intrusive porphyritic qtz-albi	0.90		1.30	1.40	0.40	361724.11 E 6578646.9 N	
31943	rhyolite glassy Qz-Kfs-phyrnc rhyolite		1.38		0.59	0.99	387899.96 E 6446200.0 N	
31947	rhyolite glassy Qz-Kfs-phyrnc rhyolite (spherulitic)		1.23		0.03	0.92	387400.04 E 6444600.0 N	
31932	rhyolite glassy Qz-Kfs-phyrnc		1.26		0.15	0.68	387500.02 E 6444500.0 N	
32704	rhyolite intrusive porphyritic act.-qtz-a	2.10		0.30	4.80	3.30	333017.09 E 6573285.1 N	
32703	rhyolite intrusive porphyritic act.-qtz-a	0.70		1.40	2.40	0.70	340589.65 E 6579365.2 N	
32701	rhyolite intrusive porphyritic act.-qtz-a	1.90		1.60	3.50	2.20	366520.73 E 6566114.9 N	
32700	rhyolite intrusive porphyritic act.-qtz-a	0.10		0.90	1.00	0.80	366886.95 E 6566121.3 N	

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Table D.8: *continued*

32702	rhyolite intrusive porphyritic act-qtz-a	0.50			1.50	1.90	0.70	360504.99 E 6580362.6 N
32699	rhyolite intrusive porphyritic ep-qtz-alb	0.50			0.80	0.60	1.20	374282.50 E 6546413.3 N
32698	rhyolite intrusive porphyritic ep-qtz-alb				1.00	0.30	0.60	370504.42 E 6553111.3 N
32751	rhyolite intrusive porphyritic ep-qtz-olig	1.30			0.50	1.00	1.70	371775.18 E 6548562.3 N
32730	rhyolite intrusive porphyritic ep-qtz-olig	0.50			1.00	1.00	1.80	374603.41 E 6548887.9 N
32729	rhyolite intrusive porphyritic ep-qtz-olig	1.10			0.60	0.80	1.80	373069.68 E 6547763.1 N
32728	rhyolite intrusive porphyritic ep-qtz-olig	0.30			1.20	0.80	1.90	374156.31 E 6548331.1 N
32726	rhyolite intrusive porphyritic ep-qtz-olig	0.10			1.10	0.80	1.50	366328.09 E 6566659.9 N
32727	rhyolite intrusive porphyritic ep-qtz-olig	0.10			1.10	0.90	1.70	374874.61 E 6549075.5 N
32303	rhyolite intrusive porphyritic mcln-qtz-a	0.10			1.20	0.50	1.90	342180.65 E 6613137.7 N
32302	rhyolite intrusive porphyritic mcln-qtz-a	0.40			0.80	0.70	1.70	337057.01 E 6613321.0 N
32689	rhyolite intrusive porphyritic mcln-qtz-a	0.70			0.50	0.40	0.50	350467.55 E 6604780.6 N
32687	rhyolite intrusive porphyritic mcln-qtz-a	1.20			0.20	0.70	0.50	336456.82 E 6621357.9 N
32301	rhyolite intrusive porphyritic mcln-qtz-a	0.70			0.80	0.60	0.40	336206.85 E 6614860.5 N
32688	rhyolite intrusive porphyritic mcln-qtz-a	1.00			0.50	0.90	0.50	336383.47 E 6620350.6 N
32304	rhyolite intrusive porphyritic mcln-qtz-a	0.20			1.00	0.80	1.70	342275.46 E 6612956.6 N
32719	rhyolite intrusive porphyritic qtz-albite rhyol	0.10			0.60	0.40	2.00	354702.21 E 6567456.6 N
32716	rhyolite intrusive porphyritic qtz-alb rhyol	0.10			0.40	0.20	1.80	354778.39 E 6568280.9 N
32714	rhyolite intrusive porphyritic qtz-alb rhyol	0.20			0.60	0.30	2.10	352292.48 E 6569241.4 N
32717	rhyolite intrusive porphyritic qtz-alb rhyol	0.10			1.60	0.60	1.50	353716.64 E 6566341.4 N
32721	rhyolite intrusive porphyritic qtz-alb sodic	0.40			1.00	0.80	2.30	354220.21 E 6568819.4 N
32718	rhyolite intrusive porphyritic qtz-alb sodic	0.20			1.40	1.00	3.40	354341.13 E 6567175.8 N
32715	rhyolite intrusive porphyritic qtz-alb sodic	1.20				0.50	0.70	355451.52 E 6566464.1 N
32712	rhyolite intrusive porphyritic qtz-alb sodic	0.10			0.90	0.10	0.10	347565.26 E 6588086.2 N
32711	rhyolite intrusive porphyritic qtz-alb sodic	2.10			0.30	1.00	1.10	333777.54 E 6576773.9 N
32710	rhyolite intrusive porphyritic qtz-alb sodic	1.00			1.40	0.10	0.10	346718.52 E 6594563.6 N
32695	rhyolite intrusive porphyritic qtz-alb sodic	0.20			1.40	0.90	0.40	373624.28 E 6547407.1 N
32694	rhyolite intrusive porphyritic qtz-alb sodic	1.50			0.70	1.30	0.80	347193.59 E 6593566.1 N
32693	rhyolite intrusive porphyritic qtz-alb sodic	0.10			0.80	0.70	0.50	372979.89 E 6547669.8 N
32691	rhyolite intrusive porphyritic qtz-alb sodic	1.20			0.90	0.70	1.70	348667.18 E 6592952.3 N
32758	rhyolite intrusive porphyritic qtz-alb sodic	0.20			0.60	0.60	0.30	374015.00 E 6546042.8 N
32757	rhyolite intrusive porphyritic qtz-alb sodic	3.90			1.10	1.30	0.10	363271.54 E 6579040.5 N
32756	rhyolite intrusive porphyritic qtz-alb sodic	1.00			0.90	0.60	0.30	363362.61 E 6579042.1 N
32713	rhyolite intrusive porphyritic qtz-alb sodic	0.10			3.40	0.90	1.40	353386.11 E 6569444.7 N

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Table D.8: *continued*

32690	rhyolite intrusive porphyritic qtz-alb sodic	0.30			1.10	0.10	1.70	373357.55 E 6552065.4 N
32709	rhyolite intrusive porphyritic qtz-alb sodic	1.90			0.20	2.00	1.20	347565.26 E 6588086.2 N
32692	rhyolite intrusive porphyritic qtz-alb sodic	0.20			1.90	1.40	2.00	356151.17 E 6593726.1 N
32725	rhyolite intrusive porphyritic qtz-olig s	1.70			0.10	0.50	1.10	374177.84 E 6547142.8 N
32723	rhyolite intrusive porphyritic qtz-olig s	0.70			1.30	1.10	1.30	374089.80 E 6546958.5 N
32722	rhyolite intrusive porphyritic qtz-olig s	0.40			1.20	0.50	1.10	374180.69 E 6546960.2 N
32724	rhyolite intrusive porphyritic qtz-olig s	0.80			0.90	0.90	1.00	374297.37 E 6545590.8 N
30638	rhyolite porphyritic alb rhyolite	1.44			0.37	1.14	2.01	348313.10 E 6587185.0 N
32708	rhyolite porphyritic alb rhyolite	2.10			0.60	2.10	0.10	346634.89 E 6588983.8 N
32707	rhyolite porphyritic alb rhyolite	0.80			2.10	0.80	1.30	348410.86 E 6586821.0 N
32705	rhyolite porphyritic alb rhyolite	0.50				0.40	1.30	348882.98 E 6586006.6 N
32740	rhyolite porphyritic alb-orth potassic rh	0.50			0.50	0.10	0.10	350617.87 E 6570857.8 N
32744	rhyolite porphyritic alb-orth rhyolite	0.90			0.70	0.10	0.30	356568.63 E 6570416.2 N
32742	rhyolite porphyritic alb-orth rhyolite	0.10			0.80	0.10	0.60	350612.49 E 6571132.2 N
32741	rhyolite porphyritic alb-orth rhyolite	0.10			0.70	0.80	0.30	350795.36 E 6571135.3 N
30617	rhyolite porphyritic HBL-P1 sodic rhyolite	1.14			0.99	0.93	0.81	384181.25 E 6597466.6 N
30612	rhyolite porphyritic Mc-Ab-Qz rhyolite	0.10			0.97	0.34	0.44	333687.06 E 6622668.5 N
30627	rhyolite porphyritic Mc-Qz-Ab rhyolite	1.58				0.57	0.29	336299.62 E 6614770.7 N
30660	rhyolite porphyritic Mica-Ab-Qz rhyolite		1.41			1.40	2.38	373000.02 E 6544500.0 N
32737	rhyolite porphyritic potassic rhyolite volc. ag	0.20			1.00	0.30	0.10	370490.61 E 6609983.4 N
32731	rhyolite porphyritic potassic rhyolite volc. ag	0.10			0.50	0.20	0.10	370779.06 E 6609165.7 N
32734	rhyolite porphyritic qtz-albite-orth pota				0.30	0.10	0.10	371035.34 E 6610176.1 N
32736	rhyolite porphyritic qtz-albite-orth rhyo	0.10			0.60	0.10	0.10	370394.44 E 6610256.1 N
32738	rhyolite porphyritic qtz-orth potassic rh				0.90	0.20	0.10	349939.29 E 6608794.9 N
32739	rhyolite porphyritic qtz-orth potassic rh	0.40			0.70	1.90	1.50	347875.65 E 6611684.5 N
30642	rhyolite porphyritic Qz-Ab sodic rhyolite	1.92			1.06	0.84	2.04	347877.71 E 6611592.9 N
30641	rhyolite porphyritic Qz-Ab sodic rhyolite	0.03			0.98	0.64	1.81	369855.82 E 6553556.7 N
30640	rhyolite porphyritic Qz-Ab sodic rhyolite	1.69			2.18	3.67	3.12	356300.00 E 6594600.0 N
30639	rhyolite porphyritic Qz-Ab sodic rhyolite	0.20			1.15	1.25	1.57	370195.88 E 6560054.8 N
30637	rhyolite porphyritic Qz-Ab sodic rhyolite	0.53			0.24	0.11	0.16	346465.38 E 6593370.2 N
30636	rhyolite porphyritic Qz-Ab sodic rhyolite	0.51			0.42	0.08	1.39	355071.08 E 6567280.3 N
30635	rhyolite porphyritic Qz-Ab sodic rhyolite	0.81			2.24	1.06	0.64	345673.20 E 6622435.7 N
30634	rhyolite porphyritic Qz-Ab sodic rhyolite	0.11			0.92	0.87	0.50	354489.68 E 6589490.3 N

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Table D.8: *continued*

30633	rhyolite porphyritic Qz-Ab sodic rhyolite	0.02			0.87	0.47	0.96	370197.67 E 6559963.3 N
30632	rhyolite porphyritic Qz-Ab sodic rhyolite	2.07			1.46	3.03	1.38	358327.24 E 6584529.7 N
30629	rhyolite porphyritic Qz-Ab sodic rhyolite	0.39			1.13	0.71	1.77	373888.31 E 6558109.7 N
30628	rhyolite porphyritic Qz-Ab sodic rhyolite	4.75			0.42	0.43	1.53	349594.74 E 6602479.1 N
30631	rhyolite porphyritic Qz-Ab sodic rhyolite	0.32			1.73	2.43	0.18	361912.09 E 6578376.0 N
30613	rhyolite porphyritic Qz-OGC sodic rhyolite	0.88			1.10	0.29	0.74	332594.50 E 6622569.7 N
33099	rhyolite porphyritic rhyolite tuff	1.30			2.10	0.80	2.10	337699.47 E 6749407.7 N
32733	rhyolite porphyritic rhyolite volc. agglomerate				0.40	0.20	0.10	370591.49 E 6609436.7 N
30655	rhyolite Qz-Pl-Mica-phyric rhyolite		1.19			0.45	0.72	386499.97 E 6434600.0 N
32276	rhyolite rhyolite porphyry dyke	1.40			0.30	0.90	0.30	359378.08 E 6748956.1 N
32275	rhyolite rhyolite porphyry dyke	1.50			0.50	0.80	0.50	358205.59 E 6748021.6 N
32574	rhyolite rhyolite porphyry dyke				0.90	0.80	0.10	386168.96 E 6436730.5 N
33127	rhyolite rhyolite porphyry dyke	0.10			1.20	0.50	0.30	349716.55 E 6779332.4 N
33126	rhyolite rhyolite porphyry dyke	0.10			0.90	0.30	0.20	349261.15 E 6779233.3 N
33098	rhyolite rhyolite porphyry dyke				1.40	0.30	1.50	337907.73 E 6747948.3 N
32759	rhyolite rhyolite porphyry dyke	0.90			1.10	0.20	1.00	350397.51 E 6766176.2 N
32760	rhyolite rhyolite porphyry dyke	1.30			0.40	1.50	1.60	341542.49 E 6749290.6 N
33128	rhyolite rhyolite tuff	1.10			4.80	1.10	1.80	351978.14 E 6780742.5 N
33101	rhyolite rhyolite tuff	0.30			1.70	0.50	0.90	334177.34 E 6752182.4 N
33897	rhyolite rhyolite tuff	2.30				0.30	0.60	353148.49 E 6776464.6 N
32697	rhyolite sheared intrusive porphyritic quartz-albi	1.30			0.50	0.10	0.10	346266.03 E 6594281.1 N
31930	rhyolite spherulitic Qz-Kfs-phyric rhyolite (weak)		1.19			0.05	0.67	386599.98 E 6435499.9 N
32273	rhyolite	3.30			2.20	1.00	3.20	357009.27 E 6748458.4 N
33106	rhyolite	1.30			0.30	0.10	0.20	350678.41 E 6760420.3 N
32883	rhyolite	1.90			0.30	0.50	0.60	467322.34 E 6634006.1 N
32882	rhyolite	1.10			0.90	0.80	1.50	470501.30 E 6640276.9 N
32881	rhyolite	3.70			0.80	1.20	1.60	470581.88 E 6635708.7 N
33693	rhyolite	1.30			0.70	0.50	0.60	386560.54 E 6647297.7 N
33692	rhyolite	1.20			0.90	0.30	0.80	377585.72 E 6663780.2 N
32274	rhyolite	1.20			0.20	0.30	2.40	356921.23 E 6748273.9 N
33694	rhyolite	0.50			1.20	0.20	0.80	440665.37 E 6606570.4 N
31896	trachyte megacrystic quartz keratophyre		1.43			1.70	1.57	383299.97 E 6533300.0 N

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Table D.8: *continued*

31895	trachyte megacrystic quartz keratophyre	1.91		1.09	2.50	382999.99 E 6533500.0 N
31894	trachyte megacrystic quartz keratophyre	1.52		0.66	1.90	382999.99 E 6533500.0 N
31882	trachyte megacrystic quartz keratophyre	3.86		3.24	4.58	380800.04 E 6533600.0 N
30648	trachyte megacrystic quartz keratophyre	2.88		1.38	2.32	383000.03 E 6533300.0 N
30647	trachyte megacrystic quartz keratophyre	2.32		0.92	2.05	383000.03 E 6533300.0 N
30646	trachyte megacrystic quartz keratophyre	2.57		1.22	2.46	383000.03 E 6533300.0 N
30645	trachyte megacrystic quartz keratophyre	2.67		1.39	2.63	383000.03 E 6533300.0 N
30644	trachyte megacrystic quartz keratophyre	4.61		4.31	4.51	382900.04 E 6533400.0 N
31908	trachyte megacrystic quartz keratophyre	1.98		1.00	1.75	382900.04 E 6533400.0 N
31905	trachyte megacrystic quartz keratophyre	3.03		3.37	2.97	382900.04 E 6533400.0 N
31903	trachyte megacrystic quartz keratophyre	2.78		2.07	4.14	382900.04 E 6533400.0 N
31902	trachyte megacrystic quartz keratophyre	2.89		2.34	3.09	382900.04 E 6533400.0 N
31897	trachyte megacrystic quartz keratophyre	1.39		1.65	2.17	383299.97 E 6533300.0 N
30649	trachyte megacrystic quartz keratophyre	2.50		1.21	2.24	383000.03 E 6533300.0 N
31904	trachyte megacrystic quartz keratophyre	3.68		2.65	4.56	382900.04 E 6533400.0 N
31867	trachyte quartz keratophyre	1.38		1.77	2.18	373000.02 E 6544500.0 N
31866	trachyte quartz keratophyre	1.46		1.35	2.24	373000.02 E 6544500.0 N
31865	trachyte quartz keratophyre	1.51		1.74	2.55	373000.02 E 6544500.0 N
30656	trachyte quartz keratophyre	1.37		0.45	1.72	387399.97 E 6445500.0 N
31945	trachyte quartz keratophyre	1.13		0.14	0.78	388600.03 E 6447300.0 N
31940	trachyte quartz keratophyre	1.46		0.33	1.89	387899.96 E 6446200.0 N
31939	trachyte quartz keratophyre	1.42		0.40	1.91	387899.96 E 6446200.0 N
31938	trachyte quartz keratophyre	1.44		0.41	2.02	387899.96 E 6446200.0 N
31933	trachyte quartz keratophyre	1.51		0.34	2.00	387399.97 E 6445500.0 N
31887	trachyte quartz keratophyre	2.35		1.80	2.24	374700.03 E 6544500.0 N
31875	trachyte quartz keratophyre	2.29		1.27	2.75	373000.02 E 6544500.0 N
31886	trachyte quartz keratophyre	2.40		1.91	2.69	374700.03 E 6544500.0 N
31901	trachyte quartz keratophyre	1.28		0.10	1.86	374099.97 E 6550399.9 N
31937	trachyte quartz keratophyre (weakly foliated)	1.46		0.38	1.80	387899.96 E 6446200.0 N
31936	trachyte quartz keratophyre (weakly foliated)	1.49		0.34	1.90	387399.97 E 6445500.0 N
32286	trachyte unalutised trachyte	1.10	8.00	5.60	3.20	395708.90 E 6504379.8 N
32285	trachyte unalutised trachyte	2.40	7.80	4.80	6.10	395708.90 E 6504379.8 N
32284	trachyte unalutised trachyte	2.60	8.10	4.50	3.80	395708.90 E 6504379.8 N

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Table D.8: continued

32283	trachyte unalutised trachyte	2.60		8.20	5.50	6.50	395708.90 E 6504379.8 N
32282	trachyte unalutised trachyte	2.40		7.60	4.90	5.90	395708.90 E 6504379.8 N
Rock Code	Rock Type in solid geology GIS layer	$\frac{Fe \text{ wt\%} \times Fe}{(Fe+Mg+Ca)}$ l3.l.ch2	$\frac{Fe}{(Fe+Mg+Ca)}$ l3.l.ch1	$\frac{Fe_2O_3}{(Fe_2O_3+FeO)}$ l3.l.ch3	$\frac{Fe_2O_3}{FeO}$ l3.l.ch4	$\frac{Fe^{3+}}{Fe^{2+}}$ l3.l.ch5	
Ipbx	Int. Pyroclastic Breccia	0.56	0.42	0.38	0.63	0.57	
Ivx	Undiv. Int. Autoclastic Rock	0.56	0.42	0.38	0.63	0.57	
Iv	Undivided Int. Volc. Rock	0.56	0.42	0.38	0.63	0.57	
OZCHEM data							
Rock No.	Total Description ⁴	Fe ₂ O ₃	Fe ₂ O ₃ total	FeO	MgO	CaO	Location
40467	ignimbrite ?ignimbrite	0.63	2.30	1.50	0.35	1.25	268082.30 E 6719806.4 N
98391	ignimbrite porphyritic dacite/rhyolite	0.60	1.39	0.71	0.13	1.54	337300.30 E 6748750.4 N
Rock Code	Rock Type in solid geology GIS layer	$\frac{Fe \text{ wt\%} \times Fe}{(Fe+Mg+Ca)}$ l3.l.ch2	$\frac{Fe}{(Fe+Mg+Ca)}$ l3.l.ch1	$\frac{Fe_2O_3}{(Fe_2O_3+FeO)}$ l3.l.ch3	$\frac{Fe_2O_3}{FeO}$ l3.l.ch4	$\frac{Fe^{3+}}{Fe^{2+}}$ l3.l.ch5	
Gt	Granitoid	0.50	0.37	0.46	1.03	0.93	Ave. data ¹²
Rock Code	Rock Type in solid geology GIS layer	$\frac{Fe \text{ wt\%} \times Fe}{(Fe+Mg+Ca)}$ l3.l.ch2	$\frac{Fe}{(Fe+Mg+Ca)}$ l3.l.ch1	$\frac{Fe_2O_3}{(Fe_2O_3+FeO)}$ l3.l.ch3	$\frac{Fe_2O_3}{FeO}$ l3.l.ch4	$\frac{Fe^{3+}}{Fe^{2+}}$ l3.l.ch5	
Gr	Granite	0.48	0.40	0.43	0.82	0.74	
OZCHEM data							
Rock No.	Total Description ⁴	Fe ₂ O ₃	Fe ₂ O ₃ total	FeO	MgO	CaO	Location
33678	granite aplitic granite dyke			0.10	0.10	0.20	341354.91 E 6749561.8 N
33671	granite biotite granite	0.20		1.60	0.60	1.60	353719.26 E 6753705.5 N
10120	granite BT adamellite	0.57		0.82	0.33	1.65	304223.69 E 6481854.3 N
10093	granite BT adamellite	1.10		1.10	0.58	2.16	267161.66 E 6507697.2 N
16486	granite BT adamellite						341099.49 E 6722128.7 N
45606	granite bt granite	0.58	1.88	1.17	0.35	1.81	353472.00 E 6747965.0 N
45602	granite bt granite	0.76	2.45	1.52	0.28	1.35	355148.00 E 6754583.0 N
45586	granite bt granite	0.43	2.34	1.72	0.36	1.11	352043.00 E 6757352.0 N
45604	granite bt granite dyke	1.12	2.56	1.30	0.19	2.78	348890.00 E 6747369.0 N
10109	granite BT leuco-adamellite	0.59		1.13	0.42	1.30	299401.91 E 6495481.6 N
45588	granite bt micro granite dyke	0.41	0.80	0.35	0.04	1.32	341609.00 E 6746158.0 N
45610	granite bt micro granite dyke, porphyritic	1.16	2.33	1.05	0.14	3.60	334845.00 E 6750310.0 N

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Table D.8: *continued*

45599	granite bt micro granite dyke, porphyritic	0.50	0.99	0.44	0.09	0.44	0.44	342600.00 E 6748000.0 N
45597	granite bt micro granite dyke, porphyritic	0.04	0.33	0.26	0.02	0.10	0.10	341713.00 E 6749321.0 N
45593	granite bt micro granite dyke, porphyritic	1.39	1.86	0.42	0.53	0.37	0.37	342679.00 E 6749342.0 N
45591	granite bt micro granite dyke, porphyritic	0.87	2.54	1.50	1.10	2.55	2.55	341187.00 E 6746087.0 N
45609	granite bt micro granite dyke, porphyritic	0.37	0.81	0.40	0.05	0.75	0.75	353922.00 E 6748090.0 N
45598	granite bt micro granite dyke, porphyritic	1.21	1.93	0.65	0.51	0.40	0.40	342518.00 E 6749087.0 N
45592	granite bt-gnt micro granite dyke, porphyritic	0.34	0.83	0.44	0.07	0.65	0.65	340620.00 E 6746232.0 N
36783	granite epidote-rich granitoid		3.86					417433.21 E 6634296.2 N
90788	granite FELD POR BT GRT	0.51	1.41	0.81	0.27	0.94	0.94	241409.30 E 6694452.4 N
108688	granite fine to v.fine bt micro granite	1.00	2.08	0.97	0.16	0.54	0.54	352043.00 E 6757352.0 N
10256	granite Fl-bearing BT adamellite							243861.72 E 6738742.6 N
10152	granite foliated aplo granite	0.31		0.15	0.05	0.78	0.78	304380.36 E 6574228.9 N
45608	granite foliated BT granite	0.46	2.28	1.64	0.49	2.21	2.21	353860.00 E 6748056.0 N
45603	granite foliated BT granite, porphyritic	0.52	2.69	1.95	0.70	2.62	2.62	348890.00 E 6747369.0 N
10237	granite foliated chloritised adamellite, lined	0.39		0.50	0.08	0.70	0.70	232837.25 E 6584844.4 N
10155	granite foliated Kfs-Qz-phyrlic adamellite	0.54		0.53	0.27	1.53	1.53	312655.02 E 6571638.8 N
38995	granite GNT-Ms micro granite	0.37		-0.10	0.13	0.35	0.35	314400.00 E 6603400.0 N
30654	granite graphic micro granite		1.02			0.67	0.67	386599.98 E 6435499.9 N
31928	granite graphic micro granite		1.18			1.00	1.00	386599.98 E 6435499.9 N
30652	granite graphic micro granite		1.08			0.88	0.88	386599.98 E 6435499.9 N
75709	granite kfs-plag-bt-qtz lineated granite	0.66	0.95	0.26	0.09	0.80	0.80	257050.00 E 6777757.0 N
10118	granite leuco-adamellite	0.75		0.42	0.19	1.01	1.01	261168.83 E 6586269.7 N
10117	granite leuco-adamellite	0.40		0.75	0.23	1.00	1.00	257616.18 E 6631947.3 N
10110	granite leuco-adamellite	0.65		1.22	0.38	1.28	1.28	318328.65 E 6461074.5 N
16485	granite leuco-adamellite							348147.12 E 6684749.0 N
10042	granite leuco-adamellite	0.22		0.77	0.19	0.64	0.64	332583.57 E 6582061.1 N
10039	granite leuco-adamellite	0.78		0.59	0.25	0.90	0.90	263035.33 E 6687845.5 N
10106	granite leuco-adamellite interbanded with 82102	0.87		0.62	0.46	2.02	2.02	266385.18 E 6550677.7 N
30653	granite micro granite		1.73		0.01	1.04	1.04	386599.98 E 6435499.9 N
30651	granite micro granite		0.96			0.73	0.73	386599.98 E 6435499.9 N
31929	granite micro granite		0.95		0.13	0.90	0.90	386599.98 E 6435499.9 N
31926	granite micro granite		0.94			0.75	0.75	386599.98 E 6435499.9 N

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Table D.8: *continued*

10041	granite partly sheared leuco-adamellite	0.67			0.74	0.19	0.88	281514.45 E 6573828.2 N
10142	granite porphyritic BT adamellite	0.78			1.38	0.60	2.13	323825.76 E 6460261.4 N
10126	granite porphyritic BT adamellite	0.81			1.30	0.58	2.50	329361.65 E 6457627.2 N
10123	granite porphyritic BT adamellite	0.68			1.34	0.46	1.62	301393.67 E 6436978.4 N
10122	granite porphyritic BT adamellite	0.56			0.86	0.31	1.41	255388.94 E 6706923.0 N
10121	granite porphyritic BT adamellite	0.73			1.00	0.54	1.89	233236.61 E 6665369.0 N
10098	granite porphyritic BT adamellite	1.57			1.38	0.58	1.77	264720.17 E 6643960.5 N
10066	granite porphyritic BT adamellite	0.64			0.89	0.28	1.28	231545.63 E 6605860.0 N
10103	granite porphyritic BT adamellite	0.52			0.94	0.52	1.26	273192.25 E 6630387.1 N
10129	granite porphyritic BT adamellite	0.91			0.63	0.51	1.77	335042.46 E 6497053.7 N
10124	granite porphyritic BT adamellite	0.94			1.09	0.55	1.91	304775.42 E 6552289.5 N
45613	granite porphyritic BT granite	0.47	1.76		1.16	0.19	0.65	334597.00 E 6744240.0 N
45612	granite porphyritic BT granite	0.66	1.24		0.52	0.15	0.15	334424.00 E 6744278.0 N
45600	granite porphyritic BT granite	0.76	2.67		1.72	0.27	1.37	355096.00 E 6754208.0 N
31927	granite porphyritic graphic micro granite		1.13				0.88	386599.98 E 6435499.9 N
31864	granite porphyritic micro granite		2.27			1.53	2.79	388200.05 E 6520399.9 N
31900	granite porphyritic micro granite		1.40			0.42	1.93	374099.97 E 6550399.9 N
32044	granite porphyritic quartz-albite granite	0.89			1.06	1.08	1.26	310073.04 E 6624242.5 N
30626	granite sodic granite	1.07			1.35	1.11	0.49	345716.61 E 6622480.8 N
30620	granite sodic granite	0.35			2.41	2.35	2.64	366700.00 E 6614100.0 N
30619	granite sodic granite	0.02			1.04	0.54	0.84	368000.00 E 6554400.0 N
30624	granite sodic granite	1.85			0.89	1.12	2.74	374000.00 E 6550500.0 N
30659	granite sodic granite porphyry	1.46			1.40	2.91	0.75	364000.00 E 6579200.0 N
30658	granite sodic granite porphyry	1.25			0.62	0.68	1.26	375300.00 E 6547700.0 N
30622	granite sodic granite porphyry	0.63			0.57	0.43	0.44	371000.00 E 6553100.0 N
30621	granite sodic granite porphyry	0.07			1.01	0.71	0.36	370400.00 E 6552000.0 N
30618	granite sodic granite porphyry	0.01			1.28	1.11	0.92	369500.00 E 6554500.0 N
30625	granite sodic granite with zoned plag	0.26			1.04	1.54	0.48	374100.00 E 6546500.0 N
10104	granite weakly lineated BT adamellite	0.70			1.26	0.31	1.32	297173.83 E 6567706.0 N
90805	granite	0.63	1.41		0.70	0.32	1.87	256860.30 E 6546539.9 N
90803	granite	1.01	2.07		0.95	0.51	1.50	235745.30 E 6768750.4 N
90802	granite	0.40	0.93		0.48	0.16	0.77	237880.30 E 6754625.4 N
90801	granite	0.41	1.33		0.83	0.30	1.68	253630.30 E 6752845.4 N
90799	granite	0.76	2.08		1.19	0.37	1.32	244145.30 E 6738150.4 N
90798	granite	0.58	1.24		0.59	0.18	0.93	233595.30 E 6720330.4 N

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Table D.8: *continued*

90796	granite	0.93	1.95	0.92	0.37	1.18	233875.30 E 6710960.4 N
90795	granite	0.67	1.48	0.73	0.30	1.16	234130.30 E 6704235.4 N
90794	granite	0.72	1.78	0.95	0.34	1.21	233185.30 E 6700015.4 N
90793	granite	1.59	3.55	1.76	0.74	2.03	233125.30 E 6698295.4 N
90791	granite	0.86	1.62	0.68	0.27	1.11	231328.30 E 6679830.4 N
30623	granite	0.19		1.00	0.77	1.31	371400.00 E 6554400.0 N
30835	granite	1.06	1.97	0.82	0.35	1.54	259012.00 E 6747249.0 N
38872	syenogranite BT syenogranite	0.35		0.71	0.25	1.32	315300.00 E 6743400.0 N
38914	syenogranite Ms-BT syenogranite	0.74		0.43	0.13	0.83	332800.00 E 6750300.0 N
38884	syenogranite Ms-BT syenogranite	0.57		0.64	0.29	1.13	344900.00 E 6694200.0 N
32060	syenogranite	0.62		0.66	0.29	0.74	384310.15 E 6415656.7 N
Rock Code	Rock Type in solid geology GIS layer	$\frac{Fe\ wt\% \times Fe}{(Fe+Mg+Ca)}$ l3.l.ch2	$\frac{Fe}{(Fe+Mg+Ca)}$ l3.l.ch1	$\frac{Fe_2O_3}{(Fe_2O_3+FeO)}$ l3.l.ch3	$\frac{Fe_2O_3}{FeO}$ l3.l.ch4	$\frac{Fe^{3+}}{Fe^{2+}}$ l3.l.ch5	
Scpf	Jones Creek Conglomerate	0.36	0.34	0.44	0.78	0.70	
Sxcp	Polymict Congl. (Kurrawang)	0.36	0.34	0.44	0.78	0.70	13
OZCHEM data							
Rock No.	Total Description ⁴	Fe ₂ O ₃	Fe ₂ O ₃ total	FeO	MgO	CaO	Location
68721	conglomerate oligomictic conglomerate ⁶						259143.10 E 6956310.0 N
Rock Code	Rock Type in solid geology GIS layer	$\frac{Fe\ wt\% \times Fe}{(Fe+Mg+Ca)}$ l3.l.ch2	$\frac{Fe}{(Fe+Mg+Ca)}$ l3.l.ch1	$\frac{Fe_2O_3}{(Fe_2O_3+FeO)}$ l3.l.ch3	$\frac{Fe_2O_3}{FeO}$ l3.l.ch4	$\frac{Fe^{3+}}{Fe^{2+}}$ l3.l.ch5	
Gmoq	Quartz Monzonite	0.35	0.36	0.51	1.40	1.26	
OZCHEM data							
Rock No.	Total Description ⁴	Fe ₂ O ₃	Fe ₂ O ₃ total	FeO	MgO	CaO	Location
38890	monzogranite BI monzogranite	0.27		0.40	0.18	0.82	330500.00 E 6690000.0 N
36502	monzogranite biotite monzogranite	1.01	2.58	1.41	0.58	1.63	313100.00 E 6571900.0 N
36501	monzogranite biotite monzogranite	0.50	1.90	1.26	0.82	2.32	323700.00 E 6584300.0 N
36500	monzogranite biotite monzogranite	0.60	1.91	1.18	0.74	2.41	332800.00 E 6584200.0 N
39015	monzogranite BT micro monzogranite	1.27		0.84	0.66	2.10	328000.00 E 6626000.0 N
39002	monzogranite BT monzogranite	0.14		0.25	0.12	0.59	301000.00 E 6674000.0 N
38985	monzogranite BT monzogranite	1.68		0.44	0.89	2.16	305000.00 E 6663000.0 N
38917	monzogranite BT monzogranite	0.91		0.78	0.44	1.24	313700.00 E 6765600.0 N
38871	monzogranite BT monzogranite	0.73		1.32	0.56	2.44	315300.00 E 6743400.0 N

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Table D.8: *continued*

38915	monzogranite BT monzogranite	0.79			0.82	0.49	2.02	312200.00 E 6766100.0 N
39003	monzogranite BT monzogranite	0.75			0.28	0.30	1.46	311500.00 E 6676500.0 N
38991	monzogranite BT monzogranite	0.23			0.46	0.28	0.85	298500.00 E 6652000.0 N
38990	monzogranite BT monzogranite	0.37			0.14	0.10	0.40	299500.00 E 6654000.0 N
38988	monzogranite BT monzogranite	0.46			0.29	0.22	0.72	300000.00 E 6665000.0 N
38986	monzogranite BT monzogranite	0.50			0.31	0.26	0.91	301000.00 E 6663000.0 N
38934	monzogranite BT monzogranite	0.49			0.64	0.41	1.93	396200.00 E 6691200.0 N
38984	monzogranite BT monzogranite	0.63			0.68	0.46	1.73	305000.00 E 6663000.0 N
38983	monzogranite BT monzogranite	0.47			-0.10	0.12	0.51	316500.00 E 6645500.0 N
38982	monzogranite BT monzogranite	0.07			-0.10	0.09	0.35	317000.00 E 6645000.0 N
38981	monzogranite BT monzogranite	0.58			-0.10	0.14	0.43	318000.00 E 6643800.0 N
38980	monzogranite BT monzogranite	0.51			-0.10	0.13	0.39	318000.00 E 6643800.0 N
38965	monzogranite BT monzogranite	0.76			1.00	0.56	1.99	342700.00 E 6652500.0 N
38919	monzogranite BT monzogranite	0.64			0.99	0.54	1.84	318400.00 E 6771800.0 N
38918	monzogranite BT monzogranite	0.39			0.71	0.32	1.43	316900.00 E 6770900.0 N
38891	monzogranite BT monzogranite	0.64			0.87	0.44	1.64	331500.00 E 6691800.0 N
38888	monzogranite BT monzogranite	0.49			0.48	0.33	1.44	330300.00 E 6689900.0 N
38886	monzogranite BT monzogranite	0.31			0.42	0.09	0.50	332000.00 E 6705300.0 N
38885	monzogranite BT monzogranite	0.71			1.21	0.89	2.46	331200.00 E 6709900.0 N
38883	monzogranite BT monzogranite	0.41			0.48	0.18	0.82	342200.00 E 6721400.0 N
38876	monzogranite BT monzogranite	0.65			0.90	0.34	1.61	315300.00 E 6743400.0 N
38875	monzogranite BT monzogranite	0.71			1.38	0.62	2.59	315300.00 E 6743400.0 N
39011	monzogranite BT monzogranite	0.43			0.53	0.26	0.57	332700.00 E 6581600.0 N
39001	monzogranite BT monzogranite	0.51			0.25	0.24	1.21	290000.00 E 6655000.0 N
39000	monzogranite BT monzogranite	0.92			0.46	0.45	1.52	288000.00 E 6647000.0 N
38992	monzogranite BT monzogranite	0.90			0.32	0.39	1.54	294000.00 E 6640500.0 N
38945	monzogranite BT monzogranite	0.99			1.35	0.47	1.55	297500.00 E 6567000.0 N
38941	monzogranite BT monzogranite	0.83			0.90	0.51	2.29	361500.00 E 6554000.0 N
38962	monzogranite BT monzogranite	0.84			0.91	0.63	1.45	332300.00 E 6625300.0 N
38913	monzogranite BT monzogranite	0.86			0.67	0.13	0.88	358100.00 E 6755500.0 N
38946	monzogranite BT monzogranite	0.74			1.16	0.51	1.91	305000.00 E 6552000.0 N
38938	monzogranite BT monzogranite	0.84			0.75	0.37	1.10	309500.00 E 6495500.0 N
38944	monzogranite BT monzogranite	0.64			0.38	0.23	0.42	326000.00 E 6470500.0 N
38943	monzogranite BT monzogranite	0.56			1.06	0.31	1.05	324500.00 E 6459500.0 N
38942	monzogranite BT monzogranite	0.50			0.50	0.21	0.87	340000.00 E 6463000.0 N

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Table D.8: *continued*

38940	monzogranite BT monzogranite	1.10		1.49	0.70	2.15	321500.00 E 6465500.0 N
38939	monzogranite BT monzogranite	0.90		1.25	0.63	2.06	324500.00 E 6461500.0 N
38937	monzogranite BT monzogranite	0.54		0.80	0.30	1.49	310000.00 E 6481500.0 N
39007	monzogranite BT-Ms monzogranite	0.78		0.28	0.29	0.65	314000.00 E 6571600.0 N
39006	monzogranite BT-Ms monzogranite	0.95		0.14	0.30	0.64	314000.00 E 6571600.0 N
39005	monzogranite BT-Ms monzogranite	0.58		0.43	0.33	1.53	313100.00 E 6571700.0 N
38994	monzogranite BT-Ms monzogranite	0.47		0.43	0.30	1.31	315300.00 E 6602800.0 N
98392	monzogranite fluorite-bio. monzogranite	0.47	1.15	0.61	0.25	0.71	264000.30 E 6715400.4 N
36503	monzogranite fractionated leuco monzo-granite	0.23	1.05	0.74	0.24	0.76	332800.00 E 6581800.0 N
39008	monzogranite HBL monzogranite	1.30		0.53	0.67	1.69	348000.00 E 6555400.0 N
38906	monzogranite HBL-BT monzogranite	0.69		1.03	0.38	1.49	367500.00 E 6719800.0 N
38907	monzogranite HBL-BT monzogranite	1.49		0.88	0.42	1.96	364000.00 E 6732000.0 N
38910	monzogranite HBL-BT monzogranite	0.73		0.59	0.09	0.93	368200.00 E 6739200.0 N
38877	monzogranite Ms monzogranite	0.47		0.70	0.18	0.92	333700.00 E 6742100.0 N
38880	monzogranite Ms-BT monzogranite	0.46		0.59	0.22	0.92	333300.00 E 6725100.0 N
38989	monzogranite Ms-BT monzogranite	0.48		0.29	0.24	0.90	302000.00 E 6655000.0 N
38882	monzogranite Ms-BT monzogranite	0.39		0.71	0.24	1.00	332900.00 E 6726300.0 N
38881	monzogranite Ms-BT monzogranite	0.60		0.87	0.29	0.93	333800.00 E 6725800.0 N
38879	monzogranite Ms-BT monzogranite	0.40		0.63	0.17	0.87	333700.00 E 6742100.0 N
38878	monzogranite Ms-BT monzogranite	0.43		0.71	0.18	0.87	333700.00 E 6742100.0 N
38869	monzogranite Ms-BT monzogranite	0.37		0.14	0.10	0.51	318100.00 E 6724500.0 N
38868	monzogranite Ms-BT monzogranite	0.29		0.24	0.09	0.77	295800.00 E 6733000.0 N
Rock Code	Rock Type in solid geology GIS layer	$\frac{Fe\ wt\% \times Fe}{(Fe+Mg+Ca)}$ l3.l.ch2	$\frac{Fe}{(Fe+Mg+Ca)}$ l3.l.ch1	$\frac{Fe_2O_3}{(Fe_2O_3+FeO)}$ l3.l.ch3	$\frac{Fe_2O_3}{FeO}$ l3.l.ch4	$\frac{Fe^{3+}}{Fe^{2+}}$ l3.l.ch5	
Gp	Pegmatite	0.07	0.31	0.67	2.00	1.80	
OZCHEM data							
Rock No.	Total Description ⁴	Fe ₂ O ₃	Fe ₂ O ₃ total	FeO	MgO	CaO	Location
33676	pegmatite graphitic pegmatite	0.20		0.10	0.10	0.20	343847.79 E 6748141.5 N
33677	pegmatite	0.20		0.10	0.10	0.60	343855.54 E 6747684.3 N
Rock Code	Rock Type in solid geology GIS layer	$\frac{Fe\ wt\% \times Fe}{(Fe+Mg+Ca)}$ l3.l.ch2	$\frac{Fe}{(Fe+Mg+Ca)}$ l3.l.ch1	$\frac{Fe_2O_3}{(Fe_2O_3+FeO)}$ l3.l.ch3	$\frac{Fe_2O_3}{FeO}$ l3.l.ch4	$\frac{Fe^{3+}}{Fe^{2+}}$ l3.l.ch5	

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Table D.8: *continued*

Perm	Permian Sedimentary Rock	-999	-999	-999	-999	-999
Pmd	Proterozoic Dolerite	-999	-999	-999	-999	-999
Pd	Proterozoic Mafic-U/M Dykes	-999	-999	-999	-999	-999
Qv	Stacked Plutonic-style Lodes	-999	-999	-999	-999	-999

¹ $\text{Fe}\%*\text{Fe}/(\text{Fe}+\text{Mg}+\text{Ca}) = \text{Fe}_2\text{O}_3\text{ total wt}\% \times \text{Fe}_{\text{total}}/(\text{Fe}_{\text{total}}+\text{Mg}+\text{Ca})$.

³Rock names in the “Rock type in solid GIS layer” column are those in the ArcView solid geology coverage, containing 108 rock types. This layer was used to calculate the differences between the chemical ratio values at boundaries between lithological units.

⁴Total Description field is identical to the OZCHEM database field which is a combination of LITHNAME & DESCRIPTIO fields.

⁵Chert, mylonite & Unknown/Unclassified lithological units were assigned the average chemical ratio values for the entire data set.

⁶Data refers to an analysis of Jones Creek Conglomerate.

⁷Values for shale used for ratios in layers l3.Lch3–5.

⁸No data available. Used weighted average of all data.

⁹Single analysis from Witt (1993), sample 15, p.92.

¹⁰Average of 10 analyses from Witt (1993).

¹¹Assumed 50% matrix & 50% clasts. Matrix & clasts represented by 6 meta-arkoses & 7 mafic conglomerates, respectively Marston (1978).

¹²Average of all granite, granodiorite, tonalite. Quatzr monzonite & monzogranite samples.

¹³Used Jones Creek Conglomerate sample data for Polymict Conglomerate (Kurrawang).

¹⁴Abbreviations: alb = albite, bt = biotite, ep = epidote, mcn = microcline, olig = oligoclase, orth = orthoclase, qtz = quartz.

D.7 Geophysical Data

D.7.1 Data dictionary for Gravity Layer

The layer shows the station locations for gravity measurements in the Kalgoorlie area. The data set was used to produce the gridded Bouguer gravity anomaly layer described below. Table D.9 shows the data dictionary for the *grav_pts* layer.

Lineage

The layer was produced from point-located survey data in ASCII format which was supplied by AGSO. Different sets of data, which were acquired at different times have been combined by Goldfields Exploration Pty Ltd. The earliest data were acquired in 1971 and is based on an 11 km station spacing (AGSOs 1:1,000,000 scale gravity data set entitled, *Kalgoorlie gravity digital data 1:1M, Catalog #21302*. A later data set (probably (AGSO's 1:250000 scale gravity data set entitled, *Kalgoorlie gravity database digital, Catalog #21535* has been added to the original data.

Table D.9: Data dictionary for gravity station Layer

Coverage name: <i>grav_pts</i>		
Coverage type: Point		
Item names	Type	Item description
amg_north	F	Australian Map Grid (AMG84) grid coordinate; northing
amg_east	F	Australian Map Grid (AMG84) grid coordinate; easting
rl	F	Relative level or elevation above datum (m)
mgal_bouge	F	Bouguer gravity anomaly value in gravity units (g.u. = 0.1 mgal)

D.7.2 Metadata for Bouguer Gravity Anomaly Layer

The layer shows the gridded Bouguer gravity anomaly data over the Kalgoorlie area. The data set was derived from the point-located data in the *grav_pts* layer described in Section D.7.1 above. Table D.10 shows the metadata for the *gravity* layer below.

Lineage

Point-located data were re-gridded with a 100 metre cell size by Dr Mike House using the ERMAPPER data analysis package (refer to the lineage information for Section D.7.1 above).

Table D.10: Metadata for Bouguer gravity anomaly layer

Grid name: <i>gravity</i>	
Grid parameters: cell size = 100 m, rows = 441, columns = 441, grid type = float	
Cell value	Description
1	Bouguer gravity anomaly data
-999	no data

D.7.3 Metadata for Aeromagnetic Survey Layer

The layer is an ARCVIEW grid showing the first vertical derivative of total magnetic intensity (RTP) from an airborne survey. Table D.11 shows the data dictionary for the *magnetic* layer.

Lineage

Goldfields Exploration obtained the aeromagnetic data as point-located and gridded data sets from World Geosciences (now Fugro Airborne Surveys Ltd). World Geoscience refers to the data set as *Group B: Yilgarn 1989*. It is a multiclient data set and was flown in multiple stages from 1986 to 1989. Reduction-to-pole corrections and the calculation of the first vertical derivative were performed by World Geoscience. The ASCII data were gridded with a 100 m cell size and clipped to the boundaries shown in Table D.1 by Dr Mike House (geophysicist, Goldfields Exploration Pty Ltd) using the ERMAPPER data processing and analysis software package.

The details for the aeromagnetic survey are as follows;

Traverse line spacing	200 m
Tie line spacing	2000 m
Traverse line direction	east/west
Tie line direction	north/south
Sensor height	60 m

Navigation	radio positioning
Cesium vapour magnetometer	
Magnetometer sample interval	17 m
Geometrics 256 channel spectrometer	
Spectrometer sample interval	68 m
Crystal volume	16 litres

Table D.11: Metadata for the Kalgoorlie airborne magnetic survey layer

Grid name: <i>magnetic</i>	
Grid parameters: cell size = 100 m, grid type = float	
Cell value	Description
1	airborne total magnetic intensity
-999	no data

D.8 Deposit Data

D.8.1 Data Dictionary for Deposit Layer

The layer, *deps-23-11-01*, shows point locations for 1437 gold deposits in the the Kalgoorlie study area (boundaries are shown at the top of Table D.1. The data dictionary for the layer is given in Table D.12 below.

Lineage

The layer is based on a subset the 2000 edition of the Mines and Mineral Deposits Database (MINEDEX) which was available as an Microsoft ACCESS 97 database from the Geological Survey of Western Australia (Townsend *et al.*, 2000). MINEDEX is a textual database containing information on production and remaining resources from over 11,000 historic mines and 1,000 recent mines and deposits in the Yilgarn craton. Additional information includes the tectonic unit, commodity, current ownership, and development status.

Estimates of pre-mining resources were calculated by Paul Hodkiewicz at the Centre for Global Metallogeny, Department of Geology and Geophysics, University of Western Australia in the following way; tonnes of gold, corresponding to the largest resource category

from the Australian Institute of Mining and Metallurgy's (AusIMM) JORC code (inferred, indicated, and measured) for which data were available was added to any historic and recent production. The database was also updated by Paul Hodkiewicz to include new deposit locations (using data from Australian Gold Annual) and some errors in deposit names and locations were corrected by An ArcView point coverage including just the gold deposits for the Kalgoorlie study area was created by Stephen Gardoll, from the GIS Laboratory (in the same department), Only those attributes shown in Table D.12 were retained. The gold endowment expressed as kilograms of total-contained-gold for each deposit was determined by taking the value of the largest resource estimate available (where values for more than one of the parameters; inferred, indicated, measure, probable and proven were given).

Table D.12: Data dictionary for layer showing gold deposits in the Kalgoorlie area, *deps-23-11-01*.

Coverage name: <i>deps-23-11-01</i>		
Coverage type: polygon		
Item names	Type	Item description
database	C	Name of database used as the source of the data 8008; mine, 8000
name	C	name of deposit or mine
grade	F	grade of deposit (grams per tonne)
tcg	F	total gold endowment as Tonnes Contained Gold (TCG)
oreton	F	ore tonnage (tonnes) for largest resource quoted
x_coord	F	deposit location; Easting (AMG84, metres)
y_coord	F	deposit location; Northing (AMG84, metres)

D.9 Metamorphic Grade

A metamorphic-grade map was prepared from a combination of maps by Binns *et al.* (1976) and Witt (1993). Scanned images of the maps, which covered different parts of the Kalgoorlie study area, were digitized in ArcView. Boundaries of the metamorphic domains were adjusted slightly so that they matched the crustal-scale faults and shear zones of the solid geology map of the study area. Areas that were categorized as shear zone lithologies were reclassified by assigning the areas equally to the metamorphic facies on either side of the shear zone. The attributes for the metamorphic layer are shown in Table D.13 below.

Table D.13: Data dictionary for metamorphic grade layer, *l45_Lmeta* for the Kalgoorlie study area.

Grid name: <i>l45_Lmeta</i>		
Grid parameters: cell size = 100 m, rows = 1140, columns = 1100, grid type = float		
Item names	Type	Item description
0	I	granitoid (no metamorphic facies assigned)
1	I	amphibolite
2	I	upper greenschist
3	I	lower greenschist

D.10 Favourable Contact-Type Data

Data and calculations used to create the favourable contact-type layers

l44_favcont25_pr0110-200.mat, *l44_favcont25_pxtcg0110-200.mat*) are shown in Table D.14 below. Fuzzy membership values indicating the degree of favourability are based on a statistic which is generated by multiplying the probability that cells contain a known deposit (for which $\text{TCG} \geq 1000$ kg) by the total gold resource per cell; i.e. $P(D) \times \text{TCG}/\text{cell}$.

Table D.14: Data and results of calculations used to create favourable contact-type (fuzzy membership) layers based on P(D).

Contact Code	Contact Abbrev.	Rock Type 1	Rock Type 2	No. of cells	No. of deps ¹	TCG kg	TCG/cell kg/10 ⁴ m ²	P(deposit) × 10 ³	Fuzzy M/ship ²	Fuzzy M/ship ³
119	PFUs	Feldspar Porphyry	Serpentine	139	3	25862.4	186.061	21.583	1.000	1.000
116	MdMdq	Dolerite	Quartz Dolerite	303	3	1251764.8	4131.237	9.901	1.000	1.000
76	MdShcc	Dolerite	Carbonaceous Shale	585	3	32997.0	56.405	5.128	1.000	1.000
92	laSvg	Andesite (even grained)	Volcanogenic Sediments	207	1	3312.0	16.000	4.831	1.000	1.000
74	GtMd	Granitoid	Dolerite	670	2	15938.4	23.789	2.985	1.000	1.000
23	PfShcc	Feldspar Porphyry	Carbonaceous Shale	1172	2	4303.1	3.672	1.706	1.000	1.000
49	MdPf	Dolerite	Feldspar Porphyry	1212	2	14232.5	11.743	1.650	1.000	1.000
63	FvMd	Undivided Felsic Volcanic	Dolerite	625	1	2306.7	3.691	1.600	0.970	0.973
54	ScU	Conglomerate	Undivided Ultramafic Rocks	626	1	1513.0	2.417	1.597	0.968	0.971
37	PmdU	Proterozoic dolerite	Undivided Ultramafic Rocks	647	1	1419.4	2.194	1.546	0.937	0.943
38	MbPmd	Basalt	Proterozoic dolerite	814	1	1168.0	1.435	1.229	0.745	0.770
40	MbMd	Basalt	Dolerite	5126	6	151484.2	29.552	1.171	0.710	0.739
11	MgShcc	Gabbro	Carbonaceous Shale	1764	2	208511.7	118.204	1.134	0.687	0.719
2	GtU	Granitoid	Undivided Ultramafic Rocks	9512	10	38309.7	4.028	1.051	0.637	0.673
32	MbPf	Basalt	Feldspar Porphyry	3349	3	20570.1	6.142	0.896	0.543	0.589
15	MbShcc	Basalt	Carbonaceous Shale	4514	4	19669.7	4.357	0.886	0.537	0.583
17	ShccU	Carbonaceous Shale	Undivided Ultramafic Rocks	7105	5	59340.2	8.352	0.704	0.427	0.484
55	PFU	Feldspar Porphyry	Undivided Ultramafic Rocks	2930	2	2706.9	0.924	0.683	0.414	0.473
51	MmbShcc	Magnesian Basalt	Carbonaceous Shale	1807	1	3231.0	1.788	0.553	0.335	0.402
39	MdU	Dolerite	Undivided Ultramafic Rocks	2009	1	4404.0	2.192	0.498	0.302	0.372
25	PFsvg	Feldspar Porphyry	Volcanogenic Sediments	17247	7	31542.9	1.829	0.406	0.246	0.321
7	MgMmb	Gabbro	Magnesian Basalt	8926	3	17121.4	1.918	0.336	0.204	0.283
29	MbMmb	Basalt	Magnesian Basalt	9187	3	9476.1	1.031	0.327	0.198	0.278
18	SvgU	Volcanogenic Sediments	Undivided Ultramafic Rocks	15300	4	14185.0	0.927	0.261	0.158	0.242
10	MgSsvg	Gabbro	Volcanogenic Sediments	17209	4	31972.6	1.858	0.232	0.141	0.227
50	MdMmb	Dolerite	Magnesian Basalt	4422	1	1073.0	0.243	0.226	0.137	0.223
14	MbU	Basalt	Undivided Ultramafic Rocks	14440	3	14374.1	0.995	0.208	0.126	0.213
60	ScSsvg	Conglomerate	Volcanogenic Sediments	5384	1	38394.0	7.131	0.186	0.113	0.201
66	SSvg	Undiv. Sedimentary Rock ⁵	Volcanogenic Sediments	5545	1	1190.4	0.215	0.180	0.109	0.198

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Table D.14: *continued*

Contact Code	Contact Abbrev.	Rock Type 1	Rock Type 2	No. of cells	No. of deps ¹	TCG kg	TCG/cell kg/10 ⁴ m ²	P(deposit) ×10 ³	Fuzzy M/ship ²	Fuzzy M/ship ³
42	MmbU	Magnesian Basalt	Undivided Ultramafic Rocks	23698	3	33535.0	1.415	0.127	0.077	0.169
69	MgS	Gabbro	Undiv. Sedimentary Rock	8114	1	13979.0	1.723	0.123	0.075	0.167
19	ShccSvg	Carbonaceous Shale	Volcanogenic Sediments	9312	1	29253.5	3.141	0.107	0.065	0.158
3	MgU	Gabbro	Undivided Ultramafic Rocks	9764	1	3946.3	0.404	0.102	0.062	0.156
6	GtMb	Granitoid	Basalt	13215	1	2779.7	0.210	0.076	0.046	0.141
48	MbSvg	Basalt	Volcanogenic Sediments	15656	1	7654.0	0.489	0.064	0.039	0.135
1	GtHm	Granitoid	Amphibolite (undivided)	6765	0	0	0.000	0.000	0.000	0.100
4	HmU	Amphibolite (undivided)	Undivided Ultramafic Rocks	485	0	0	0.000	0.000	0.000	0.100
5	GtPmd	Granitoid	Proterozoic dolerite	349	0	0	0.000	0.000	0.000	0.100
8	MgPf	Gabbro	Feldspar Porphyry	362	0	0	0.000	0.000	0.000	0.100
9	MmbPf	Magnesian Basalt	Feldspar Porphyry	1268	0	0	0.000	0.000	0.000	0.100
12	HmMb	Amphibolite (undivided)	Basalt	4002	0	0	0.000	0.000	0.000	0.100
13	GtMmb	Granitoid	Magnesian Basalt	3315	0	0	0.000	0.000	0.000	0.100
16	HmPmd	Amphibolite (undivided)	Proterozoic dolerite	80	0	0	0.000	0.000	0.000	0.100
20	FvGt	Undivided Felsic Volcanic	Granitoid	1235	0	0	0.000	0.000	0.000	0.100
21	GtMg	Granitoid	Gabbro	2165	0	0	0.000	0.000	0.000	0.100
22	FvMg	Undivided Felsic Volcanic	Gabbro	3657	0	0	0.000	0.000	0.000	0.100
24	FvHm	Undivided Felsic Volcanic	Amphibolite (undivided)	831	0	0	0.000	0.000	0.000	0.100
26	MgPmd	Gabbro	Proterozoic dolerite	455	0	0	0.000	0.000	0.000	0.100
27	FvMb	Undivided Felsic Volcanic	Basalt	3590	0	0	0.000	0.000	0.000	0.100
28	FvPmd	Undivided Felsic Volcanic	Proterozoic dolerite	134	0	0	0.000	0.000	0.000	0.100
30	HmMmb	Amphibolite (undivided)	Magnesian Basalt	1600	0	0	0.000	0.000	0.000	0.100
31	MbMg	Basalt	Gabbro	13117	0	0	0.000	0.000	0.000	0.100
33	FvIv	Undivided Felsic Volcanic	Undiv. Int. Volcanic Rock	255	0	0	0.000	0.000	0.000	0.100
34	IvPmd	Undivided Int. Volc. Rock	Proterozoic dolerite	11	0	0	0.000	0.000	0.000	0.100
35	IvMg	Undivided Int. Volc. Rock	Gabbro	562	0	0	0.000	0.000	0.000	0.100
36	FvU	Undivided Felsic Volcanic	Undivided Ultramafic Rocks	2265	0	0	0.000	0.000	0.000	0.100
41	HmMg	Amphibolite (undivided)	Gabbro	65	0	0	0.000	0.000	0.000	0.100
43	MmbPmd	Magnesian Basalt	Proterozoic dolerite	512	0	0	0.000	0.000	0.000	0.100
44	FvMmb	Undivided Felsic Volcanic	Magnesian Basalt	1135	0	0	0.000	0.000	0.000	0.100

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Table D.14: *continued*

Contact Code	Contact Abbrev.	Rock Type 1	Rock Type 2	No. of cells	No. of deps ¹	TCG kg	TCG/cell kg/10 ⁴ m ²	P (deposit) ×10 ³	Fuzzy M/ship ²	Fuzzy M/ship ³
45	PmdShcc	Proterozoic dolerite	Carbonaceous Shale	158	0	0	0.000	0.000	0.000	0.100
46	n/a ⁴			1	0	0	0.000	0.000	0.000	0.100
47	PmdSvg	Proterozoic dolerite	Volcanogenic Sediments	848	0	0	0.000	0.000	0.000	0.100
52	MdMg	Dolerite	Gabbro	954	0	0	0.000	0.000	0.000	0.100
53	GtPf	Granitoid	Feldspar Porphyry	558	0	0	0.000	0.000	0.000	0.100
56	MmbSc	Magnesian Basalt	Conglomerate	30	0	0	0.000	0.000	0.000	0.100
57	MbSc	Basalt	Conglomerate	161	0	0	0.000	0.000	0.000	0.100
58	MgSc	Gabbro	Conglomerate	188	0	0	0.000	0.000	0.000	0.100
59	MdPmd	Dolerite	Proterozoic dolerite	114	0	0	0.000	0.000	0.000	0.100
61	PmdS	Proterozoic dolerite	Undiv. Sedimentary Rock	289	0	0	0.000	0.000	0.000	0.100
62	MbS	Basalt	Undiv. Sedimentary Rock	8620	0	0	0.000	0.000	0.000	0.100
64	PmdSc	Proterozoic dolerite	Conglomerate	40	0	0	0.000	0.000	0.000	0.100
65	SSc	Undiv. Sedimentary Rock	Conglomerate	5843	0	0	0.000	0.000	0.000	0.100
67	PfPmd	Feldspar Porphyry	Proterozoic dolerite	53	0	0	0.000	0.000	0.000	0.100
68	GtSvg	Granitoid	Volcanogenic Sediments	4435	0	0	0.000	0.000	0.000	0.100
70	FvS	Undivided Felsic Volcanic	Undiv. Sedimentary Rock	162	0	0	0.000	0.000	0.000	0.100
71	HmSvg	Amphibolite (undivided)	Volcanogenic Sediments	227	0	0	0.000	0.000	0.000	0.100
72	SU	Undiv. Sedimentary Rock	Undivided Ultramafic Rocks	4449	0	0	0.000	0.000	0.000	0.100
73	MmbSvg	Magnesian Basalt	Volcanogenic Sediments	7420	0	0	0.000	0.000	0.000	0.100
75	FvSvg	Undivided Felsic Volcanic	Volcanogenic Sediments	1124	0	0	0.000	0.000	0.000	0.100
77	MdSvg	Dolerite	Volcanogenic Sediments	9717	0	0	0.000	0.000	0.000	0.100
78	PS	Feldspar Porphyry	Undiv. Sedimentary Rock	202	0	0	0.000	0.000	0.000	0.100
79	FvSc	Undivided Felsic Volcanic	Conglomerate	670	0	0	0.000	0.000	0.000	0.100
80	PSc	Feldspar Porphyry	Conglomerate	345	0	0	0.000	0.000	0.000	0.100
81	PmdUtc	Proterozoic dolerite	Talc-Chlorite U/mafic Rock	2	0	0	0.000	0.000	0.000	0.100
82	ShccUtc	Carbonaceous Shale	Talc-Chlorite U/mafic Rock	592	0	0	0.000	0.000	0.000	0.100
83	UUtc	Undivided Ultramafic Rocks	Talc-Chlorite U/mafic Rock	842	0	0	0.000	0.000	0.000	0.100
84	PFUtc	Feldspar Porphyry	Talc-Chlorite U/mafic Rock	8	0	0	0.000	0.000	0.000	0.100
85	MgUs	Gabbro	Serpentine	2452	0	0	0.000	0.000	0.000	0.100
86	MmbS	Magnesian Basalt	Undiv. Sedimentary Rock	3228	0	0	0.000	0.000	0.000	0.100

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Table D.14: *continued*

Contact Code	Contact Abbrev.	Rock Type 1	Rock Type 2	No. of cells	No. of deps ¹	TCG kg	TCG/cell kg/10 ⁴ m ²	P (deposit) ×10 ³	Fuzzy M/ship ²	Fuzzy M/ship ³
87	SUtc	Undiv. Sedimentary Rock	Talc-Chlorite U/mafic Rock	40	0	0	0.000	0.000	0.000	0.100
88	MbUtc	Basalt	Talc-Chlorite U/mafic Rock	44	0	0	0.000	0.000	0.000	0.100
89	FvPf	Undivided Felsic Volcanic	Feldspar Porphyry	426	0	0	0.000	0.000	0.000	0.100
90	MbUs	Basalt	Serpentinite	560	0	0	0.000	0.000	0.000	0.100
91	MdUs	Dolerite	Serpentinite	606	0	0	0.000	0.000	0.000	0.100
93	IaShcc	Andesite (even grained)	Carbonaceous Shale	82	0	0	0.000	0.000	0.000	0.100
94	IaPf	Andesite (even grained)	Feldspar Porphyry	318	0	0	0.000	0.000	0.000	0.100
95	MdS	Dolerite	Undiv. Sedimentary Rock	551	0	0	0.000	0.000	0.000	0.100
96	SUs	Undiv. Sedimentary Rock	Serpentinite	1667	0	0	0.000	0.000	0.000	0.100
97	IvS	Undivided Int. Volcanic	Undiv. Sedimentary Rock	91	0	0	0.000	0.000	0.000	0.100
98	SvgUs	Undivided Int. Volcanic	Serpentinite	2089	0	0	0.000	0.000	0.000	0.100
99	n/a ⁴	Volcanogenic Sediments		1	0	0	0.000	0.000	0.000	0.100
100	n/a ⁴			1	0	0	0.000	0.000	0.000	0.100
101	UUs	Undivided Ultramafic Rocks	Serpentinite	2453	0	0	0.000	0.000	0.000	0.100
102	MmbUs	Magnesian Basalt	Serpentinite	1881	0	0	0.000	0.000	0.000	0.100
103	IaSc	Andesite (even grained)	Conglomerate	88	0	0	0.000	0.000	0.000	0.100
104	PmdUs	Proterozoic dolerite	Serpentinite	8	0	0	0.000	0.000	0.000	0.100
105	MdSc	Dolerite	Conglomerate	20	0	0	0.000	0.000	0.000	0.100
106	GtUs	Granitoid	Serpentinite	669	0	0	0.000	0.000	0.000	0.100
107	IaMg	Andesite (even grained)	Gabbro	23	0	0	0.000	0.000	0.000	0.100
108	GtZls	Granitoid	Undiff. Felsic Schist	49	0	0	0.000	0.000	0.000	0.100
109	MbZls	Basalt	Undiff. Felsic Schist	51	0	0	0.000	0.000	0.000	0.100
110	n/a ⁴			1	0	0	0.000	0.000	0.000	0.100
111	n/a ⁴			1	0	0	0.000	0.000	0.000	0.100
112	IaMd	Andesite (even grained)	Dolerite	372	0	0	0.000	0.000	0.000	0.100
113	SSHcc	Undiv. Sedimentary Rock	Carbonaceous Shale	247	0	0	0.000	0.000	0.000	0.100
114	n/a ⁴			1	0	0	0.000	0.000	0.000	0.100
115	MdqMg	Quartz Dolerite	Gabbro	8	0	0	0.000	0.000	0.000	0.100
117	MbMdq	Basalt	Quartz Dolerite	179	0	0	0.000	0.000	0.000	0.100
118	n/a ⁴			1	0	0	0.000	0.000	0.000	0.100

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Table D.14: *continued*

Contact Code	Contact Abbrev.	Rock Type 1	Rock Type 2	No. of cells	No. of deps ¹	TCG kg	TCG/cell kg/10 ⁴ m ²	P (deposit) ×10 ³	Fuzzy M/ship ²	Fuzzy M/ship ³
120	FvUs	Undivided Felsic Volcanic	Serpentinite	1019	0	0	0.000	0.000	0.000	0.100
121	MdqUs	Quartz Dolerite	Serpentinite	2	0	0	0.000	0.000	0.000	0.100
122	MdqMmb	Quartz Dolerite	Magnesian Basalt	4	0	0	0.000	0.000	0.000	0.100
123	ScUs	Conglomerate	Serpentinite	30	0	0	0.000	0.000	0.000	0.100
124	FvShcc	Undivided Felsic Volcanic	Carbonaceous Shale	32	0	0	0.000	0.000	0.000	0.100
125	MdqPf	Quartz Dolerite	Feldspar Porphyry	2	0	0	0.000	0.000	0.000	0.100
126	ShccUs	Carbonaceous Shale	Serpentinite	103	0	0	0.000	0.000	0.000	0.100
127	MdqS	Quartz Dolerite	Undiv. Sedimentary Rock	6	0	0	0.000	0.000	0.000	0.100
128	Gts	Granitoid	Undiv. Sedimentary Rock	964	0	0	0.000	0.000	0.000	0.100
129	HpqhPf	Si-rich Hornfels	Feldspar Porphyry	188	0	0	0.000	0.000	0.000	0.100
130	HpqbSvsg	Si-rich Hornfels	Volcanogenic Sediments	246	0	0	0.000	0.000	0.000	0.100
131	MgUtc	Gabbro	Talc-Chlorite U/mafic Rock	203	0	0	0.000	0.000	0.000	0.100
132	MmbUtc	Magnesian Basalt	Talc-Chlorite U/mafic Rock	100	0	0	0.000	0.000	0.000	0.100
133	GtsShcc	Granitoid	Carbonaceous Shale	70	0	0	0.000	0.000	0.000	0.100
134	MmbMmb	Magnesian Basalt	Magnesian Basalt	10	0	0	0.000	0.000	0.000	0.100
Total			Total	339982	89	2113521.8				

¹deps = deposits²Fuzzy membership value set to 0.0 for cells where distance > 1300 m from the nearest contact.³Fuzzy membership value set to 0.1 for cells where distance > 200 m from the nearest contact.⁴A lithological boundary corresponding to this numerical code is not present in study area. The number of cells was set from zero to one in order to avoid divide by zero errors during processing.⁵Abbreviations: int. = intermediate, undiv. = undivided, u/mafic = ultramafic, undiff. = undifferentiated, volc. = volcanic.

Data and calculations used to create the favourable contact-type layers *l44-favcont25-pr-1300m.mat* and *l44-favcont25-ptcg-1300m.mat*) are shown in Table D.15 below. Fuzzy membership values indicating the degree of favourability are based on ranking the contact types in order of the probability that cells, for which the nearest contact-type has a certain value, contain one of the known deposits (TCG *ge* 1000 kg) multiplied by the total contained gold per 100 metre cell ($P(D)*TCG/cell$).

Table D.15: Data and results of calculations used to create favourable contact-type (fuzzy membership) layers based on $P(D) \times TCG/cell$.

Contact Code	Contact Abbrev.	Rock Type 1	Rock Type 2	No. of cells	No. of deps ¹	TCG kg	TCG/cell $kg/10^4 m^2$	$P(Dep) \times TCG/cell$ (10^3)	Fuzzy $M/ship^2$	Fuzzy $M/ship^3$
116	MdMdg	Dolerite	Quartz Dolerite	303	3	1251765	4131.237	40903.338	1.000	1.000
119	PfUs	Feldspar Porphyry	Serpentine	139	3	25862	186.061	4015.699	1.000	1.000
76	MdShcc	Dolerite	Carbonaceous Shale	585	3	32997	56.405	289.257	1.000	1.000
11	MgShcc	Gabbro	Carbonaceous Shale	1764	2	208512	118.204	134.018	1.000	1.000
92	IaSvg	Andesite (even grained)	Volcanogenic Sediments	207	1	3312	16.000	77.295	1.000	1.000
74	GtMd	Granitoid	Dolerite	670	2	15938	23.789	71.011	1.000	1.000
40	MbMd	Basalt	Dolerite	5126	6	151484	29.552	34.591	1.000	1.000
49	MdPf	Dolerite	Feldspar Porphyry	1212	2	14233	11.743	19.378	1.000	1.000
23	PfShcc	Feldspar Porphyry	Carbonaceous Shale	1172	2	4303	3.672	6.265	0.323	0.391
63	FvMd	Undivided Felsic Volcanic	Dolerite	625	1	2307	3.691	5.905	0.305	0.374
17	ShccU	Carbonaceous Shale	Undivided Ultramafic Rocks	7105	5	59340	8.352	5.877	0.303	0.373
32	MbPf	Basalt	Feldspar Porphyry	3349	3	20570	6.142	5.502	0.284	0.356
2	GtU	Granitoid	Undivided Ultramafic Rocks	9512	10	38310	4.028	4.234	0.218	0.297
15	MbShcc	Basalt	Carbonaceous Shale	4514	4	19670	4.357	3.861	0.199	0.279
54	ScU	Conglomerate	Undivided Ultramafic Rocks	626	1	1513	2.417	3.861	0.199	0.279
37	PmdU	Proterozoic dolerite	Undivided Ultramafic Rocks	647	1	1419	2.194	3.391	0.175	0.257
38	MbPmd	Basalt	Proterozoic dolerite	814	1	1168	1.435	1.763	0.091	0.182
60	ScSvg	Conglomerate	Volcanogenic Sediments	5384	1	38394	7.131	1.325	0.068	0.162
39	MdU	Dolerite	Undivided Ultramafic Rocks	2009	1	4404	2.192	1.091	0.056	0.151
51	MmbShcc	Magnesian Basalt	Carbonaceous Shale	1807	1	3231	1.788	0.990	0.051	0.146
25	PfSvg	Feldspar Porphyry	Volcanogenic Sediments	17247	7	31543	1.829	0.742	0.038	0.134
7	MgMmb	Gabbro	Magnesian Basalt	8926	3	17121	1.918	0.645	0.033	0.130
55	PfU	Feldspar Porphyry	Undivided Ultramafic Rocks	2930	2	2707	0.924	0.631	0.033	0.129
10	MgSvg	Gabbro	Volcanogenic Sediments	17209	4	31973	1.858	0.432	0.022	0.120
19	ShccSvg	Carbonaceous Shale	Volcanogenic Sediments	9312	1	29253	3.141	0.337	0.017	0.116
29	MbMmb	Basalt	Magnesian Basalt	9187	3	9476	1.031	0.337	0.017	0.116
18	SvgU	Volcanogenic Sediments	Undivided Ultramafic Rocks	15300	4	14185	0.927	0.242	0.012	0.111
69	MgS	Gabbro	Undiv. Sedimentary Rock	8114	1	13979	1.723	0.212	0.011	0.110
14	MbU	Basalt	Undivided Ultramafic Rocks	14440	3	14374	0.995	0.207	0.011	0.110
42	MmbU	Magnesian Basalt	Undivided Ultramafic Rocks	23698	3	33535	1.415	0.179	0.009	0.108

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Table D.15: *continued*

Contact Code	Contact Abbrev.	Rock Type 1	Rock Type 2	No. of cells	No. of deps ¹	TCG kg	TCG/cell kg/10 ⁴ m ²	P(Dep)× TCG/cell (10 ³)	Fuzzy M/ship ²	Fuzzy M/ship ³
50	MdMmb	Dolerite	Magnesian Basalt	4422	1	1073	0.243	0.055	0.003	0.103
3	MgU	Gabbro	Undivided Ultramafic Rocks	9764	1	3946	0.404	0.041	0.002	0.102
66	SSvg	Undiv. Sedimentary Rock	Volcanogenic Sediments	5545	1	1190	0.215	0.039	0.002	0.102
48	MbSvyg	Basalt	Volcanogenic Sediments	15656	1	7654	0.489	0.031	0.002	0.101
6	GtMb	Granitoid	Basalt	13215	1	2780	0.210	0.016	0.001	0.101
1	GtHm	Granitoid	Amphibolite (undivided)	6765	0	0	0.000	0.000	0.000	0.100
4	HmU	Amphibolite (undivided)	Undivided Ultramafic Rocks	485	0	0	0.000	0.000	0.000	0.100
5	GtPmd	Granitoid	Proterozoic dolerite	349	0	0	0.000	0.000	0.000	0.100
8	MgPf	Gabbro	Feldspar Porphyry	362	0	0	0.000	0.000	0.000	0.100
9	MmbPf	Magnesian Basalt	Feldspar Porphyry	1268	0	0	0.000	0.000	0.000	0.100
12	HmMb	Amphibolite (undivided)	Basalt	4002	0	0	0.000	0.000	0.000	0.100
13	GtMmb	Granitoid	Magnesian Basalt	3315	0	0	0.000	0.000	0.000	0.100
16	HmPmd	Amphibolite (undivided)	Proterozoic dolerite	80	0	0	0.000	0.000	0.000	0.100
20	FvGt	Undivided Felsic Volcanic	Granitoid	1235	0	0	0.000	0.000	0.000	0.100
21	GtMg	Granitoid	Gabbro	2165	0	0	0.000	0.000	0.000	0.100
22	FvMg	Undivided Felsic Volcanic	Gabbro	3657	0	0	0.000	0.000	0.000	0.100
24	FvHm	Undivided Felsic Volcanic	Amphibolite (undivided)	831	0	0	0.000	0.000	0.000	0.100
26	MgPmd	Gabbro	Proterozoic dolerite	455	0	0	0.000	0.000	0.000	0.100
27	FvMb	Undivided Felsic Volcanic	Basalt	3590	0	0	0.000	0.000	0.000	0.100
28	FvPmd	Undivided Felsic Volcanic	Proterozoic dolerite	134	0	0	0.000	0.000	0.000	0.100
30	HmMmb	Amphibolite (undivided)	Magnesian Basalt	1600	0	0	0.000	0.000	0.000	0.100
31	MbMg	Basalt	Gabbro	13117	0	0	0.000	0.000	0.000	0.100
33	FvIv	Undivided Felsic Volcanic	Undivided Int. Volcanic	255	0	0	0.000	0.000	0.000	0.100
34	IvPmd	Undivided Int. Volcanic	Proterozoic dolerite	11	0	0	0.000	0.000	0.000	0.100
35	IvMg	Undivided Int. Volcanic	Gabbro	562	0	0	0.000	0.000	0.000	0.100
36	FvU	Undivided Felsic Volcanic	Undivided Ultramafic Rocks	2265	0	0	0.000	0.000	0.000	0.100
41	HmMg	Amphibolite (undivided)	Gabbro	65	0	0	0.000	0.000	0.000	0.100
43	MmbPmd	Magnesian Basalt	Proterozoic dolerite	512	0	0	0.000	0.000	0.000	0.100
44	FvMmb	Undivided Felsic Volcanic	Magnesian Basalt	1135	0	0	0.000	0.000	0.000	0.100
45	PmdShcc	Proterozoic dolerite	Carbonaceous Shale	158	0	0	0.000	0.000	0.000	0.100
46	n/a ³			1	0	0	0.000	0.000	0.000	0.100

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Table D.15: *continued*

Contact Code	Contact Abbrev.	Rock Type 1	Rock Type 2	No. of cells	No. of deps ¹	TCG kg	TCG/cell kg/10 ⁴ m ²	P(Dep)× TCG/cell (10 ³)	Fuzzy M/ship ²	Fuzzy M/ship ³
47	PmdSvg	Proterozoic dolerite	Volcanogenic Sediments	848	0	0	0.000	0.000	0.000	0.100
52	MdMg	Dolerite	Gabbro	954	0	0	0.000	0.000	0.000	0.100
53	GtPf	Granitoid	Feldspar Porphyry	558	0	0	0.000	0.000	0.000	0.100
56	MmbSc	Magnesian Basalt	Conglomerate	30	0	0	0.000	0.000	0.000	0.100
57	MbSc	Basalt	Conglomerate	161	0	0	0.000	0.000	0.000	0.100
58	MgSc	Gabbro	Conglomerate	188	0	0	0.000	0.000	0.000	0.100
59	MdPmd	Dolerite	Proterozoic dolerite	114	0	0	0.000	0.000	0.000	0.100
61	PmdS	Proterozoic dolerite	Undiv. Sedimentary Rock	289	0	0	0.000	0.000	0.000	0.100
62	MbS	Basalt	Undiv. Sedimentary Rock	8620	0	0	0.000	0.000	0.000	0.100
64	PmdSc	Proterozoic dolerite	Conglomerate	40	0	0	0.000	0.000	0.000	0.100
65	SSc	Undiv. Sedimentary Rock	Conglomerate	5843	0	0	0.000	0.000	0.000	0.100
67	PfPmd	Feldspar Porphyry	Proterozoic dolerite	53	0	0	0.000	0.000	0.000	0.100
68	GtSvg	Granitoid	Volcanogenic Sediments	4435	0	0	0.000	0.000	0.000	0.100
70	FvS	Undivided Felsic Volcanic	Undiv. Sedimentary Rock	162	0	0	0.000	0.000	0.000	0.100
71	HmSvg	Amphibolite (undivided)	Volcanogenic Sediments	227	0	0	0.000	0.000	0.000	0.100
72	SU	Undiv. Sedimentary Rock	Undivided Ultramafic Rocks	4449	0	0	0.000	0.000	0.000	0.100
73	MmbSvg	Magnesian Basalt	Volcanogenic Sediments	7420	0	0	0.000	0.000	0.000	0.100
75	FvSvg	Undivided Felsic Volcanic	Volcanogenic Sediments	1124	0	0	0.000	0.000	0.000	0.100
77	MdSvg	Dolerite	Volcanogenic Sediments	9717	0	0	0.000	0.000	0.000	0.100
78	PfS	Feldspar Porphyry	Undiv. Sedimentary Rock	202	0	0	0.000	0.000	0.000	0.100
79	FvSc	Undivided Felsic Volcanic	Conglomerate	670	0	0	0.000	0.000	0.000	0.100
80	PfSc	Feldspar Porphyry	Conglomerate	345	0	0	0.000	0.000	0.000	0.100
81	PmdUtc	Proterozoic dolerite	Talc-Chlorite U/mafic Rock	2	0	0	0.000	0.000	0.000	0.100
82	ShccUtc	Carbonaceous Shale	Talc-Chlorite U/mafic Rock	592	0	0	0.000	0.000	0.000	0.100
83	UUtc	Undivided Ultramafic Rocks	Talc-Chlorite U/mafic Rock	842	0	0	0.000	0.000	0.000	0.100
84	PfUtc	Feldspar Porphyry	Talc-Chlorite U/mafic Rock	8	0	0	0.000	0.000	0.000	0.100
85	MgUs	Gabbro	Serpentine	2452	0	0	0.000	0.000	0.000	0.100
86	MmbS	Magnesian Basalt	Undiv. Sedimentary Rock	3228	0	0	0.000	0.000	0.000	0.100
87	SUtc	Undiv. Sedimentary Rock	Talc-Chlorite U/mafic Rock	40	0	0	0.000	0.000	0.000	0.100
88	MbUtc	Basalt	Talc-Chlorite U/mafic Rock	44	0	0	0.000	0.000	0.000	0.100
89	FvPf	Undivided Felsic Volcanic	Feldspar Porphyry	426	0	0	0.000	0.000	0.000	0.100

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Table D.15: *continued*

Contact Code	Contact Abbrev.	Rock Type 1	Rock Type 2	No. of cells	No. of deps ¹	TCG kg	TCG/cell kg/10 ⁴ m ²	P(Dep)× TCG/cell (10 ³)	Fuzzy M/ship ²	Fuzzy M/ship ³
90	MbUs	Basalt	Serpentinite	560	0	0	0.000	0.000	0.000	0.100
91	MdUs	Dolerite	Serpentinite	606	0	0	0.000	0.000	0.000	0.100
93	IaShcc	Andesite (even grained)	Carbonaceous Shale	82	0	0	0.000	0.000	0.000	0.100
94	IaPf	Andesite (even grained)	Feldspar Porphyry	318	0	0	0.000	0.000	0.000	0.100
95	MdS	Dolerite	Undiv. Sedimentary Rock	551	0	0	0.000	0.000	0.000	0.100
96	SUs	Undiv. Sedimentary Rock	Serpentinite	1667	0	0	0.000	0.000	0.000	0.100
97	IvS	Undiv. Int. Volcanic	Undiv. Sedimentary Rock	91	0	0	0.000	0.000	0.000	0.100
98	SvgUs	Volcanogenic Sediments	Serpentinite	2089	0	0	0.000	0.000	0.000	0.100
99	n/a ³			1	0	0	0.000	0.000	0.000	0.100
100	n/a ³			1	0	0	0.000	0.000	0.000	0.100
101	UUs	Undivided Ultramafic Rocks	Serpentinite	2453	0	0	0.000	0.000	0.000	0.100
102	MmbUs	Magnesian Basalt	Serpentinite	1881	0	0	0.000	0.000	0.000	0.100
103	IaSc	Andesite (even grained)	Conglomerate	88	0	0	0.000	0.000	0.000	0.100
104	PmdUs	Proterozoic dolerite	Serpentinite	8	0	0	0.000	0.000	0.000	0.100
105	MdSc	Dolerite	Conglomerate	20	0	0	0.000	0.000	0.000	0.100
106	GtUs	Granitoid	Serpentinite	669	0	0	0.000	0.000	0.000	0.100
107	IaMg	Andesite (even grained)	Gabbro	23	0	0	0.000	0.000	0.000	0.100
108	GtZls	Granitoid	Undiff. Felsic Schist	49	0	0	0.000	0.000	0.000	0.100
109	MbZls	Basalt	Undiff. Felsic Schist	51	0	0	0.000	0.000	0.000	0.100
110	n/a ³			1	0	0	0.000	0.000	0.000	0.100
111	n/a ³			1	0	0	0.000	0.000	0.000	0.100
112	IaMd	Andesite (even grained)	Dolerite	372	0	0	0.000	0.000	0.000	0.100
113	SSHcc	Undiv. Sedimentary Rock	Carbonaceous Shale	247	0	0	0.000	0.000	0.000	0.100
114	n/a ³			1	0	0	0.000	0.000	0.000	0.100
115	MdqMg	Quartz Dolerite	Gabbro	8	0	0	0.000	0.000	0.000	0.100
117	MbMdq	Basalt	Quartz Dolerite	179	0	0	0.000	0.000	0.000	0.100
118	n/a ³			1	0	0	0.000	0.000	0.000	0.100
120	FvUs	Undivided Felsic Volcanic	Serpentinite	1019	0	0	0.000	0.000	0.000	0.100
121	MdqUs	Quartz Dolerite	Serpentinite	2	0	0	0.000	0.000	0.000	0.100
122	MdqMmb	Quartz Dolerite	Magnesian Basalt	4	0	0	0.000	0.000	0.000	0.100
123	ScUs	Conglomerate	Serpentinite	30	0	0	0.000	0.000	0.000	0.100

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Table D.15: *continued*

Contact Code	Contact Abbrev.	Rock Type 1	Rock Type 2	No. of cells	No. of deps ¹	TCG kg	TCG/cell kg/10 ⁴ m ²	P(Dep)× TCG/cell (10 ³)	Fuzzy M/ship ²	Fuzzy M/ship ³
124	FvShcc	Undivided Felsic Volcanic	Carbonaceous Shale	32	0	0	0.000	0.000	0.000	0.100
125	MdqPf	Quartz Dolerite	Feldspar Porphyry	2	0	0	0.000	0.000	0.000	0.100
126	ShccUs	Carbonaceous Shale	Serpentinite	103	0	0	0.000	0.000	0.000	0.100
127	MdqS	Quartz Dolerite	Undiv. Sedimentary Rock	6	0	0	0.000	0.000	0.000	0.100
128	GtS	Granitoid	Undiv. Sedimentary Rock	964	0	0	0.000	0.000	0.000	0.100
129	HpqhPf	Si-rich Hornfels	Feldspar Porphyry	188	0	0	0.000	0.000	0.000	0.100
130	HpqhSvsg	Si-rich Hornfels	Volcanogenic Sediments	246	0	0	0.000	0.000	0.000	0.100
131	MgUtc	Gabbro	Talc-Chlorite U/mafic Rock	203	0	0	0.000	0.000	0.000	0.100
132	MmbUtc	Magnesian Basalt	Talc-Chlorite U/mafic Rock	100	0	0	0.000	0.000	0.000	0.100
133	GtShcc	Granitoid	Carbonaceous Shale	70	0	0	0.000	0.000	0.000	0.100
134	MmbMmb	Magnesian Basalt	Magnesian Basalt	10	0	0	0.000	0.000	0.000	0.100
Total			Total	339982	89	2113522				

¹ deps = deposits² Fuzzy membership value set to 0.0 for cells where distance > 1300 m from the nearest contact.³ Fuzzy membership value set to 0.1 for cells where distance > 200 m from the nearest contact.⁴ A lithological boundary corresponding to this numerical code is not present in study area. The number of cells was set from zero to one in order to avoid divide by zero errors during processing.⁵ Abbreviations: int. = intermediate, undiv. = undivided, u/mafic = ultramafic, undiff. = undifferentiated, volc. = volcanic.

D.11 Favourable Lithology Data

Data and calculations used to create the favourable lithology layer (*l1_favgeol25_pr0110.mat*) is shown in Table D.16 below. Fuzzy membership values indicating the degree of favourability are based on the probability of a deposit (> 1000 kg TCG).

Table D.16: Data and results of calculations used to create favourable lithology GIS layer based on P(Deposit).

Rock Code	Rock Abbrev.	Rock Type	No. of cells	No. of deps ¹	TCG kg	TCG/cell kg/10 ⁴ m ²	P(deposit) × 10 ³	Fuzzy M/ship ²
20	Mdq	Quartz Dolerite	117	1	2103	17.973	8.547	1.000
15	Ia	Andesite, even-grained	923	1	3312	3.588	1.083	1.000
13	Md	Dolerite	15161	14	1459023	96.235	0.923	1.000
10	Pf	Feldspar Porphyry	14998	7	28064	1.871	0.467	1.000
4	U	Undiv. Ultramafic Rock	95067	27	160518	1.688	0.284	0.647
7	Sc	Conglomerate	8530	2	39907	4.678	0.234	0.551
6	Shcc	Carbonaceous Shale	22755	5	55689	2.447	0.220	0.524
3	Mb	Basalt	117529	25	143460	1.221	0.213	0.510
19	Us	Serpentine	15489	3	25862	1.670	0.194	0.474
5	Mg	Gabbro	56944	10	263371	4.625	0.176	0.439
9	Mmb	Magnesian Basalt	49249	6	29945	0.608	0.122	0.335
12	Fv	Undiv. Felsic Volcanic	18131	1	2307	0.127	0.055	0.206
11	Svg	Volcanogenic Sediments	167123	9	31738	0.190	0.054	0.204
8	S	Undiv. Sedimentary Rock	56462	2	2802	0.050	0.035	0.167
1	Gt	Granitoid	331673	7	43497	0.131	0.021	0.140
2	Hm	Amphibolite (undivided)	11346	0	0	0.000	0.000	0.100
14	Iv	Undiv. Int. Volc. Rock	384	0	0	0.000	0.000	0.100
16	n/a ³		1	0	0	0.000	0.000	0.100
17	?	Unknown / unclassified	217	0	0	0.000	0.000	0.100
18	Utc	Talc-Chl. U/mafic Rock	589	0	0	0.000	0.000	0.100
21	Hpqh	Si-rich Hornfels	139	0	0	0.000	0.000	0.100
22	n/a ³		1	0	0	0.000	0.000	0.100
23	n/a ³		1	0	0	0.000	0.000	0.100
24	Zls	Undiff. Felsic Schist	15	0	0	0.000	0.000	0.100
25	Zu	Ultramafic schist	2	0	0	0.000	0.000	0.100
Total			982843	120	2291599			

¹Abbreviations: deps = deposits, int. = intermediate, undiv. = undivided, u/mafic = ultramafic, undiff. = undifferentiated, volc. = volcanic.

²Fuzzy membership value set to 0.1 for definitely unfavourable host rock types.

³Rock type with this code not found in study area. Number of cells changed from 0 to 1 to avoid divide by zero errors.

Data and calculations used to create the favourable lithology layer (*l1-favgeol-prtcg.mat*) is shown in Table D.17 below. Fuzzy membership values indicating the degree of favourability are based on ranking the lithologies according to the index calculated as the probability of the lithology containing one of the known deposits (TCG *ge* 1000 kg) multiplied by the total contained gold per 100 metre cell ($P(D) \times \text{TCG/cell}$).

Table D.17: Data and results of calculations used to create favourable lithology GIS layer based on $P(D) \times TCG/cell$.

Rock Code	Rock Abbrev.	Rock Type	No. of cells	No. of deposits	TCG kg	TCG/cell $kg/10^4 m^2$	P(deposit) $\times 10^3$	P(Dep) $\times TCG/cell$ (10^3)	Fuzzy M/ship ²
20	Mdq	Quartz Dolerite	1	1	2103	17.973	8.547	153.615	1.000
13	Md	Dolerite	14	14	1459023	96.235	0.923	88.866	1.000
15	Ia	Andesite, even-grained	1	1	3312	3.588	1.083	3.888	1.000
7	Sc	Conglomerate	2	2	39907	4.678	0.234	1.097	1.000
10	Pf	Feldspar Porphyry	7	7	28064	1.871	0.467	0.873	1.000
5	Mg	Gabbro	10	10	263371	4.625	0.176	0.812	0.930
6	Shcc	Carbonaceous Shale	5	5	55689	2.447	0.220	0.538	0.616
4	U	Undivided Ultramafic Rocks	27	27	160518	1.688	0.284	0.480	0.550
19	Us	Serpentinite	3	3	25862	1.670	0.194	0.323	0.370
3	Mb	Basalt	25	25	143460	1.221	0.213	0.260	0.298
9	Mmb	Magnesian Basalt	6	6	29945	0.608	0.122	0.074	0.085
11	Svg	Volcanogenic Sediments	9	9	31738	0.190	0.054	0.010	0.011
12	Fv	Undivided Felsic Volcanic	1	1	2307	0.127	0.055	0.007	0.008
1	Gt	Granitoid	7	7	43497	0.131	0.021	0.003	0.003
8	S	Undiv. Sedimentary Rock ¹	2	2	2802	0.050	0.035	0.002	0.002
2	Hm	Amphibolite (undivided)	0	0	0	0.000	0.000	0.000	0.000
14	Iv	Undiv. Int. Volc. Rock	0	0	0	0.000	0.000	0.000	0.000
16	n/a ³		0	0	0	0.000	0.000	0.000	0.000
17	?	Unknown / unclassified	0	0	0	0.000	0.000	0.000	0.000
18	Utc	Talc-Chl. U/mafic Rock	0	0	0	0.000	0.000	0.000	0.000
21	Hpqh	Si-rich Hornfels	0	0	0	0.000	0.000	0.000	0.000
22	n/a ³		0	0	0	0.000	0.000	0.000	0.000
23	n/a ³		0	0	0	0.000	0.000	0.000	0.000
24	Zls	Undiff. Felsic Schist	0	0	0	0.000	0.000	0.000	0.000
25	Zu	Ultramafic schist	0	0	0	0.000	0.000	0.000	0.000
Total					2291599				

¹Abbreviations: chl. = chlorite, int. = intermediate, undiv. = undivided, u/mafic = ultramafic, undiff. = undifferentiated, volc. = volcanic.

²Fuzzy membership value set to 0.1 for definitely unfavourable host rock types.

³Rock type with this code not found in study area. Number of cells changed from 0 to 1 to avoid divide by zero errors.

Appendix E

Summary of Data Processing used in the Tenterfield Pilot Study

E.1 Data Processing Procedure used in Pilot Study, Chp. 4

E.1.1 Pre-processing

Step 1. Convert all vector and image files to grid format.

GIS layers were prepared using the software package GEODIPS Jusmady & Taylor (1997) and ARC/INFO. Depending on the initial format one of the following steps are taken;

1. Remove file header. This is necessary if, for example, file has been exported from GEODIPS.
2. Convert ARC/INFO coverages to grids using *polygrid* command
3. Convert ARC/INFO images to grids using *imagegrid* command
4. Convert ARC/INFO grids to an ASCII grid using *gridascii* command

Step 2. Convert GIS layers to vectors

Run program, **merge_sls**, to merge GIS database layers into a list of vectors. Program also scales, labels and sorts output into multiple files. Table E.1 shows the input and outputs for program **merge_sls** below.

Table E.1: Inputs and outputs for program, *merge_sls*

Inputs:	
File name	Description
<i>geology</i>	Geology grid cell values ^a
<i><input#2></i>	Airborne magnetic layer: grid cell values
<i><input#3></i>	Uranium channel, gamma-ray survey data: grid cell values
<i><input#4></i>	Thorium channel, gamma-ray survey data: grid cell values
<i><input#5></i>	Potassium channel, gamma-ray survey data: grid cell values
<i><input#6></i>	Total count channel, gamma-ray survey data: grid cell values
<i><input#7></i> ^b	Proximity to nearest fault: grid cell values
<i>deposits</i>	Deposit occurrence data (binary): grid cell values ^c
Outputs:	
File name	Description
<i>log_merge</i>	Count of vectors read and processed
<i>rawvec</i>	Unscaled vectors without 1-of-n coding of geology
<i>rawvecd</i>	Unscaled deposit vectors
<i>rawvecn</i>	Unscaled non-deposit vectors
<i>vectorsall</i>	Vectors (scaled, geology 1-of-n coded)
<i>vectorsd</i>	Deposit vectors (scaled, geology in 1-of-n code)
<i>vecn1</i>	Non-deposit vectors (scaled, geology in 1-of-n code)
<i>vecn15</i>	Vectors with geology codes 1 to 15

^aFirst layer *must* be the geology layer^bWith minor modifications, the program can handle up to 30 user-specified input files^cLast layer *must* be the deposit occurrence layer

Step 3. Randomly select training data

Run program, **rand_select**, to create training, training-stop and test data sets by randomly selecting feature vectors from an input file containing either all the deposit or all the non-deposit feature vectors from the GIS map grid. Deposit and non-deposit feature vectors are selected separately. Table E.2 shows the input and outputs for program **rand_select** below.

Table E.2: Inputs and outputs for program, *rand_select*

Inputs:	
File name	Description
<file#1>	Name of user specified file containing vectors; i.e., <i>vectors</i> or <i>vectorsd</i> ^a from step two
<parameter#1>	Number of vectors to randomly select ($\leq$ total no. of vectors in file)
<parameter#2>	Number of output files to create; usually the 3 files listed below
Outputs:	
File name	Description
<file#n >	Name of 1 to 24 user specified files to store user specified number of vectors each
<i>log_rand</i>	Count of vectors read and processed

^aThe file containing all the deposit vectors, *vectorsd*, is processed in a separate run

E.1.2 Neural Network Training

Step 4. Train neural network

Run program, *bpWin* using command, *bp* <template file> <startup file> to train a neural network using training data sets produced in steps above. The program is a multilayer feedforward neural network simulation and is a 32-bit version of the *bp* program created by by McClelland & Rumellhart (1988). The program and ancillary input files listed below are contained in the *network* directory on the CD-ROM (vol. 1) submitted with the thesis (refer to Table B.1 on page 512). Table E.3 shows the input and outputs for program *bpWin* below.

Training involves alternately processing the input feature vector file (*1.pat* using the command *ptrain*, then changing the input file to the training-stop data set, (*2.pat*), using the command, *get patterns 2.pat*, and testing the partially trained network using the command, *tall*; i.e., “test all”. Test runs were performed initially every 100 epochs and then more frequently, reducing from every ten to every two epochs, as the number of epochs approached the minimum Total Sum of Squares (TSS) error.

Table E.3: Inputs and outputs for program, *bpWin*

Inputs:	
File name	Description
<i>1821.tem</i>	Template file; specifies data displayed on screen during program execution
<i>1821.str</i>	Start file which specifies;
	Network file name (<i>1821.net</i>)
	Input file names (<i>1.pat</i>)
	Global display level (<i>dlevel</i> = 3 then, when the display is updated, all templates with display level ≤ 3 are displayed
	<i>lflag</i> = 1. If flag variable $\neq 0$ learning occurs and weights are updated.
	Learning rate (0.50)
	Momentum (0.00)
	Weight-update frequency. If set to <i>pattern</i> then weights updated after every input pattern.
	Initial mode of program operation (<i>tall</i> = test all patterns in input file)
<i>1821.net</i>	File defines network topology; i.e., 18-2-1
	<i>ecrit</i> = 0.04; If the total sum of squares (<i>TSS</i>) falls below <i>ecrit</i> then training stops
	<i>nepochs</i> = 50; i.e., the no. of cycles of training performed when <i>ptrain</i> command is issued
1.pat	Training pattern file (contains a list of input feature vectors)
2.pat	Training-stop pattern file (contains a list of input feature vectors)
Outputs:	
File name	Description
10a.wts	Initial random connection weights. This file is created as the first step after starting <i>bpWin</i>
10atrain.wts	Trained connection weights. The number and letter denote the training run
Parameters:	
Name	Description
learning rate	0.5
momentum	0.0
pattern order	Patterns presented in permuted order if command <i>ptrain</i> is used
weight update	Stochastic (i.e. after each pattern). This is set using the commands <i>set mode</i> , <i>lgrain</i> = <i>epoch</i>
weight range	$[-0.5, +0.5]$
topology	18 input, 2 hidden and 1 output unit. The number of hidden units were varied from 0 to 9. The <i>.net</i> and <i>.str</i> files were modified accordingly.

In order to recognize the minimum TSS error, the training TSS error and the number of epochs of training were recorded before each test together with the TSS error for the training-stop data set. Training is stopped at the number of epochs corresponding to the minimum TSS error for the training data set. The trained weights are saved in a file; e.g., *10atrain.wts*. The training procedure is repeated for up to ten sets of random initial weights in order to avoid the possibility of the network converging to a local minimum in weight space. The network with the best performance on the test data set was selected to process the entire map grid.

Step 5. Test neural network

Run program *bpWin* using the test data set *3.pat* as the input file. The TSS error for this data set gives an indication of the generalization ability of the network. Table E.4 shows the input and outputs for *bpWin*, in test mode, below.

Table E.4: Inputs and outputs for program, *bpWin*, for testing the generalization ability of the trained network

Inputs:	
File name	Description
<i>1821.tem</i>	Template file; specifies data displayed on screen during program execution
<i>1821.str</i>	Start file. See Table E.3
<i>1821.net</i>	Defines network topology, <i>ecrit</i> = 0.04, and <i>nepochs</i> = 50
<i>3.pat</i>	Test pattern file (contains a list of input feature vectors)
Parameters:	
Name	Description
TSS	Total Sum of Squares (TSS) error for the test data set

Step 6. Process map grid using the trained network

Run program, *bpWin* using the file containing the feature vectors corresponding to the entire map grid as input. Connection weights that result from training are saved in a file in the previous step. In production mode, this trained-weights file becomes an input file. Table E.5 shows the input and outputs for *bpWin*, in production mode, below.

Table E.5: Inputs and outputs for program, *bpWin*, in production mode. The weights that were modified as a result of training are used to process vectors for the entire GIS map grid.

Inputs:	
File name	Description
<i>prodn.tem</i>	Template file; to speed processing only minimal data are displayed on screen in production mode
<i>prodn.str</i>	Start file. The pattern file is set to <i>4.pat</i> . See Table E.3
<i>1821.net</i>	Defines network topology, <i>ecrit</i> = 0.04, and <i>nepochs</i> = 50
<i>4.pat</i>	Feature vectors corresponding to the entire study area
<i>10atrain.wts</i>	Trained connection weights, derived from training in step 4 above, are loaded into the network
Outputs:	
File Name	Description
<i>log_tnet</i>	log file records the output activation values for the trained network

E.1.3 Post-processing

Step 7. Convert continuous output of network to map classes

Run program, **map_class**. This program is used to classify the raw output of a neural network into a set of prospectivity-map class values. Output activation values are in the approximate range [0.05, 0.95]. Mineral prospectivity maps with 9 classes were prepared in the pilot study described in Chapter 4. Table E.6 shows the input and outputs for **map_class**, in production mode, below.

Table E.6: Inputs and outputs for program, *map_class*, which converts the raw output of a trained network into a user specified number of prospectivity map classes.

Inputs:	
File name	Description
<i>log_tnet</i>	Output activation values for the trained network; user specified file name
Parameter	Description
<i>new_max</i>	New maximum value used to scale the data set
<i>new_min</i>	New minimum value used to scale the data set
<i>n_rows</i>	Number of rows in the output grid files: <i>scaled</i> and <i>classed</i>

continued on next page

Table E.6: *continued*

Inputs:	
File name	Description
n_cols	Number of columns in the output grid files: <i>scaled</i> and <i>classed</i>
Outputs:	
File Name	Description
<i>log_class</i>	Count of values processed
<i>scaled</i>	File containing scaled data in grid format
<i>classed</i>	File containing integers representing map classes

Step 8. Calculate map quality statistics

Run program **map_qstats** to calculate the chi-squared statistic and Spearman's and Kendall's rank correlation coefficients as measures of prospectivity map quality for a single map. Table E.7 shows the input and outputs for *deposit_locns* below.

Table E.7: Inputs and outputs for program *map_qstats* which calculates the chi-squared statistic and Spearman's and Kendall's rank correlation coefficients as measures of prospectivity map quality.

Inputs:	
File name	Description
<i>classed</i>	File containing integers representing map classes; i.e. a prospectivity map file
<i>deposits</i>	Deposit occurrence file (binary): grid cell values
Outputs:	
File Name	Description
<i>log_qstats</i>	Count of the number of values read and total number of deposits
<map file name> <i>stats.txt</i>	Map file name with <i>stats.txt</i> appended to it; contains map quality statistics and intermediate results

E.1.4 Miscellaneous

Step 9. Calculate number of grid cell and deposit for each rock unit

Run program **deposit_locns** to counts the number of grid cells and deposits in each geological unit in an input ASCII grid file corresponding to the geology GIS database layer. The file *<map file name> stats.txt* obtained from step 8 is used to calculate the probability-based measures of map quality described in Chapter 4. Table E.8 shows the input and outputs for *deposit_locns* below.

Table E.8: Inputs and outputs for program *deposit_locns* which calculates statistics on the number of grid cells and deposits for each geological unit.

Inputs:	
File name	Description
<i>4.pat</i>	File containing list of vectors for map grid covering the entire study area; user specified file name
Outputs:	
File Name	Description
<i>log_dep_stats</i>	Count of vectors read and processed
<i>stats</i>	Numbers of cells and deposits contained in each geology map class

Appendix F

Summary of Matlab Scripts used in Kalgoorlie Case Study

The code for all functions and scripts shown in Table F.1 is contained on the CD-ROM (vol. 1) that accompanies the thesis.

Table F.1: Summary of MATLAB functions and scripts.

Script/Function Name	Application
Creating Derived Input Layers	
fault_density	Calculate total length of faults in a 5 x 5 km window and assign that value to the central cell. Based on simplified geology legend containing 25 rock types.
favcontact25_pr0110	Create a fuzzy membership layer for favourable contact type based on P(D) by reclassifying a contact type layer.
favcontact25_pxtcg0110	Create a fuzzy membership layer for favourable contact type based on P(D)*TCG/cell by reclassifying a contact type layer.
favgeol25_pr0110	Create a fuzzy membership layer for favourable rock type based on P(D) by reclassifying a solid geology layer.
litho_diversity	Calculate the number of lithological contacts in a 5x5 km window surrounding cell.

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Table F.1: *continued*

Script/Function Name	Application
geolcodes_kal	Reclassify rock type codes in a geology input layer to form a contiguous sequence (required as a preliminary step to create 1-of-n coded solid geology input layer).
Importing GIS Layers	
strip_hdr	Remove the header from an ArcView ASCII export file in order to load the ASCII file into MATLAB.
Formating Input GIS Layers	
makearray	Format an non-grid formatted ASCII file into rows of length for loading into Matlab. Used to correct formatting errors in GEODIPS ASCII export files for Tenterfield project area.
Evaluation of Input Layers	
chi_wts3	Plots, prints and saves cumulative chi-squared and weights contrast versus distance plots using a vectorized algorithm to avoid for FOR loops.
j_function_dist	Plot bivariate J-function for the distance relationship between deposit points and the distance to the linear or point features represented in the input grid.
j_function_degrees	Plot bivariate J-function for input layers representing strike angles.
j_function15_step_wise_dist	Plot step-wise version of bivariate J-function for input layers representing distance.
j_function_step_wise_10deg	Plot step-wise version of bivariate J-function for input layers representing strike angles.
ks3	Plot and calculate D-statistic for Kolmogorov-Smirnov test.
ave_vec_dist	Calculate the average, maximum and minimum distance between vectors in an input array in which the vectors correspond to columns. Used to determine the value of <i>spread</i> for a probabilistic neural network.
median_dist	Calculate median distance to nearest fault or lithological contact. The average distance <i>between</i> faults is 2 x this value.

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Table F.1: *continued*

Script/Function Name	Application
rescale_big_is_fav	Convert input array values to "distance" from maximum value. This function converts grids containing parameters like chemical reactivity, in which large values are favourable, into a grid in which small values are favourable by calculating the difference between each cell value and the maximum value in the grid.
xchi	Plots a bar graph of the function, $y = (O - E)/E$ for the relationship between deposit points and some linear or point feature in an input grid at intervals of 200 metres (distance layers) or for 25 equal intervals, where O = observed number of deposits in interval and E = expected number of deposits (assuming a uniform random distribution).
xchi_degrees	Version of function <i>xchi</i> above for input layers representing strikes of faults or shear zones.
Pre-processing Input Layers	
add_geol1ofn	Convert the input pattern array (containing the rock type in the first column) to 1-of-n coded geology.
inv_layer	Convert distances values input to the inverse of distance (i.e. $1/x$) whilst preserving <i>Nodata</i> = -9999 values.
inv_scale_batch_vec2vec	Batch job to transform neural network input layers that represent distance using the function, <i>inv_layer</i> .
log_invx10to5_layer	Convert distance input layers. Calculate $\log_{10}(1/x \times 10^5)$ of each cell value whilst preserving <i>Nodata</i> = -9999 values.
log_invx10to5_scale_bat_vec2vec	Batch job to transform neural network input layers that represent distance using the function, <i>log_invx10to5_layer</i> .
reclass_dist_contrast_nrow_buf	Batch job to reclassify input layers containing rheological and chemical contrasts so that beyond a particular distance to the lithological contact, the contrast is set to zero.
reclass_dist_strike_wide_buf	Batch job, as above to reclassify input layers containing strike angles and distances. For distances to nearest e.g., fault exceeding a distance limit, the strike is set to the mean strike value and distance is set to the maximum value. Distance limits vary for each layer and represent upper limits based on $(O - E)/E$ bar graphs (see Section 6.2.6 in Chapter 5).
reclass_dist_strike_nrow_buf	As above but distance limits represent lower limits.

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Table F.1: *continued*

Script/Function Name	Application
scalemat	Scale elements of an input map array to user defined limits. Output is an array of the same dimensions as the input array.
scalemat_batch_vec2vec	Batch job to scale neural network input layers to range [0,1] and target deposit values to range [0.1,0.9].
Creating Training Sets	
add_noise_equal	Create a set of larger neural network training data sets by adding random noise to training input pattern & target sets. Equal number of patterns created for each rock type. Uniform and normally distributed random noise can be selected by user.
add_noise_propn	Create a set of larger neural network training data sets by adding random noise to training input pattern & target sets. Numbers of patterns from each rock type proportional to number of deposits in each rock type. Uniform and normally distributed random noise can be selected by user.
bin2arr_selctdgeol.bat	Batch job to convert the output binary files, r1_1 and r1_2, r2_1 and r2_2 etc created by functions that randomly select non-deposit 1-of-n coded patterns (<i>selectgeol_1ofn_vecbinvec</i> and <i>selectgeol_1ofn_vecbinvec</i>) into mat-arrays.
join_selected_deps_batch	Concatenate the separate deposit files d1_1 and d1_2, d2_1 and d2_2, etc. These files were created because the 1-of-n coded geology pattern files were too large to process as mat-arrays. This problem was solved by splitting the patterns into 2 halves.
join_selected_geol_batch	Concatenate the separate non-deposit files r1_1 and r1_2, r2_1 and r2_2, etc.
make_train_batch	Convert a set of input layers into neural network training sets; <i>train</i> , <i>valid</i> , <i>test</i> .
make_train_batch_1ofn	Convert a set of input layers, including the 1-of-n coded geology, into neural network training sets; <i>train</i> , <i>valid</i> , <i>test</i> .
make_train_batch_som	Create training set for an SOFM neural network.
make_train_batch_som_noise	Create a noise-augmented training set for an SOFM neural network.

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Table F.1: *continued*

Script/Function Name	Application
make_train_Ndeps	Create train, training-stop and test data sets of patterns from deposit and non-deposit Matlab arrays so that the train data set is based on Ndeps deposits. For example, if Ndeps = 5 then the train data set is based on 5 deposits and the remaining $120 - 5 = 115$ deposits are used to create the valid and test data sets.
make_som_selected_train_set	Create training set based on non-deposit patterns that have been classified into 22 classes by an SOFM neural network.
merge_cat_10	Combine 10 grids (mat-files) to produce an array of pattern column vectors excluding geology. The geology code in patterns is the 22 rock-code contiguous code, which is converted to 1-of-n coding in a separate step.
merge_fuzzy_10_cat	Combine 10 fuzzy membership input grids (mat-files) selected as the best representatives of each evidence type to produce an array of pattern column vectors.
merge_fuzzy_17_cat	Combine 17 fuzzy membership input grids (mat-files) selected as the best representatives of each evidence type to produce an array of pattern column vectors.
merge_fuzzy_10_dda	Combine 10 fuzzy membership input grids (mat-files) to produce an array of pattern column vectors. Selection of layers: top 10 layers ranked by $D \times D/A$, where D = % of deposits & A = % of total area.
merge_fuzzy_17_dda	Combine 17 fuzzy membership input grids (mat-files) to produce an array of pattern column vectors. Selection of layers: top 10 layers ranked by $D \times D/A$, where D = % of deposits & A = % of total area.
merge_fuzzygeol_10_cat	Combine 10 input grids (mat-files) selected as the best representatives of each evidence type to produce an array of pattern column vectors. Geology is represented as <i>favourable geology</i> using fuzzy membership values.
merge_fuzzygeol_10_DA	Combine 10 input grids (mat-files) to produce an array of pattern column vectors. Geology is represented as <i>favourable geology</i> using fuzzy membership values. Selection of layers: top 10 layers ranked by D/A AND $D \geq \sim 20\%$.

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Table F.1: *continued*

Script/Function Name	Application
merge_fuzzygeol_10_DDA	Combine 10 input grids (mat-files) to produce an array of pattern column vectors. Geology is represented as <i>favourable geology</i> using fuzzy membership values. Selection of layers: top 10 layers ranked by $D \times (D/A)$.
merge_fuzzygeol_10_DDA2	Combine 10 input grids (mat-files) to produce an array of pattern column vectors. Geology is represented as <i>favourable geology</i> using fuzzy membership values. Selection of layers: top 10 layers ranked by $D \times (D/A)$ AND $D \geq \sim 20\%$ AND $D/A \geq 3$.
merge_fuzzygeol_17_cat	Combine 17 layers chosen using “category ” criteria. (See <i>merge_fuzzygeol_10_cat</i> above.)
merge_fuzzygeol_17_DA	Combine 17 layers chosen using “D/A ” criteria. (See <i>merge_fuzzygeol_10_DA</i> above.)
merge_fuzzygeol_17_DDA	Combine 17 layers chosen using “DDA ” criteria. (See <i>merge_fuzzygeol_10_DDA</i> above.)
merge_fuzzygeol_17_DDA2	Combine 17 layers chosen using “DDA2 ” criteria. (See <i>merge_fuzzygeol_10_DDA2</i> above.)
merge_fuzzygeol_25	Combine 25 layers included in all selections of layers used above.
merge_geolsubs_14	Combine 14 layers including substitutes for solid geology. The following layers are used in place of solid geology; rock mechanical properties L2.l.rh5 = uniaxial compressive strength, L2.l.rh7 = fracture toughness, L2.l.rh4 = Young’s Modulus, and sulphidation and oxidation ratio layers; L3.l.ch2 = Fe(total wt%) oxides $\times$ Fe/(Fe+Mg+Ca), and L3.l.ch3 = $\text{Fe}_2\text{O}_3/(\text{Fe}_2\text{O}_3+\text{FeO})$.
noiseNorm	Randomly modify an input scalar by a normally distributed random number with mean = 1, variance = 1 and standard distribution = 1. Used to augment neural network training data sets by randomly adding or subtracting noise.
noiseUni	Randomly modify an input scalar by a percentage of its value specified by parameter “percent” (uniform random noise). Used to augment neural network training data sets by randomly adding or subtracting noise.
randselect_batch	Calls function <i>randselect_vec</i> to create train, training-stop and test data sets of patterns from deposit and non-deposit MATLAB arrays.

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Table F.1: *continued*

Script/Function Name	Application
<code>randselect_batch_som_all</code>	Version of <i>randselect_batch</i> to select patterns that have been classified into 22 classes by an SOFM network.
<code>randselect_batch_som_cntr_edge</code>	Version of <i>randselect_batch</i> to select patterns that have been classified into 22 classes by an SOFM network and which fall into the upper or lower 25 percentile of <i>distancetocentroidofdepositfeaturevectors</i> .
<code>randselect_1ofn_batch</code>	Version of <i>randselect_batch</i> to select patterns in which the rock type is coded in 1-of-n format.
<code>randselect_vec_1</code>	Randomly select one set of N patterns from a input MATLAB array consisting of rows of patterns. N is specified in the function call.
<code>randselect_vec</code>	Create 3 sets of deposits patterns from a input MATLAB array consisting of rows of patterns. Used to create training sets with different numbers of deposits.
<code>rowpats2colpt</code>	Split mat-arrays containing training, test, and training-stop patterns into separate pattern and target arrays (and cell arrays), P, T, and a structure containing the training-stop patterns and target values (V.P, and V.P). The patterns are also converted from row = patterns to columns = patterns.
<code>rowpats2colpt_train</code>	Version of the function above used to create P, T training sets for SOFM 1x9 selected training sets for patterns close to centre of the class centroids (CENTRE) and, in a separate step, for patterns at the edge of the cluster (EDGE).
<code>rowpats2colpt_valid_test</code>	Version of the function above used to create training-stop (VV) and test (TV) sets for SOFM 1x9 selected training sets for patterns close to centre of the class centroids (CENTRE) and, in a separate step, for patterns at the edge of the cluster (EDGE).
<code>selectdeps_1ofn_vecbinvec</code>	Select deposit patterns from a mat-array containing all training patterns and create separate files for patterns corresponding to each rock type. Use for training patterns in which geology is represented by 1-of-n codes values.
<code>selectdeps_fuzzy_vecbinvec</code>	Split a mat-array containing training patterns into separate deposit arrays per rock type or SOFM class resulting in files; d1, d2,...d22.

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Table F.1: *continued*

Script/Function Name	Application
<code>selectdeps_fuzzy_som_pctnl2</code>	Split deposit patterns from a mat-array containing all training patterns into separate deposit arrays per SOFM class resulting in files; d1, d2,...d22.
<code>selectgeol_1ofn_vecbinvec</code>	As <i>selectdeps_1ofn_vecbinvec</i> above but selects non-deposit patterns.
<code>selectgeol_fuzzy_vecbinvec</code>	As <i>selectdeps_fuzzy_vecbinvec</i> above but selects non-deposit patterns.
<code>selectgeol_fuzzy_som_pctnl2</code>	As <i>selectdeps_fuzzy_som_pctnl2</i> above but selects non-deposit patterns.
<code>select_trainset_10</code>	Select the 10th split of training patterns into training, training-stop, and test data sets.
<code>select_trainset_10_1ofN</code>	Version of script above for 1-of-n coded geology training patterns.
Neural Network Training	
<code>newpnn_purelin</code>	Modification of MATLAB function, <i>newpnn</i> , which creates a new probabilistic neural network. The modified version produces probability values as outputs instead of a classification of the inputs in the form of a class label; e.g. 1 = deposit and 2 = non-deposit.
<code>pnn_find_best_sigma2</code>	Determine optimal value of spread (= sigma) for radial basis functions used in a PNN network by plotting the performance for the test data set versus spread over a large range of values.
<code>pnn_test3</code>	Test a modified version of a PNN with linear outputs.
<code>som_class_batch1x9</code>	Run a trained SOFM neural network (with a 1×9 output layer to classify an input array consisting of rows of map pattern vectors.
<code>som_class_batch1x22</code>	Run a trained SOFM neural network (with a 1×22 output layer to classify an input array consisting of rows of map pattern vectors.
<code>som_train_batch1x9</code>	Train a SOFM neural network with an output layer with a 1×9 topology in order to classify an input array containing feature vectors.
<code>som_classifn_test</code>	Run a test example (hard-coded) showing how a set of feature vectors can be classified using a SOFM neural network using the training algorithm <i>trainr</i> .
<code>som_make_train_pproc_batch</code>	Create training set, train, produce a 22-class prospectivity map and assess the quality of the map for 10 SOFM networks.

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Table F.1: *continued*

Script/Function Name	Application
som_train_batch1x22	Train a SOFM neural network with an output layer with a 1×22 topology in order to classify an input array containing feature vectors.
som_train_batch1x9	Train a SOFM neural network with an output layer with a 1×9 topology in order to classify an input array containing feature vectors.
train_mlp_gd_10_20_1	Train an 10-20-1 MLP neural network with <i>traingd</i> algorithm; loads input arrays, sets and prints parameter values and saves trained network weights. Versions of this function exist for each network topology used.
train_mlp_gdx_10_20_1	Train an 10-20-1 MLP neural network with <i>traingdx</i> algorithm (see above).
train_mlp_lm_10_20_1	Train an 10-20-1 MLP neural network with <i>trainlm</i> algorithm (see above).
train_pnn	Train an PNN neural network (see above).
train_post_proc_batch	Train network and assess map quality of resultant mineral prospectivity map for 10 networks per training data set.
Post-processing	
act2map	Create map from a row vector of neural network output activations.
add_nodata	Add <i>Nodata</i> values from geology to prospectivity map.
mapclass	Convert input array (mat-file) containing fuzzy membership values or network output activations to 9 classes of mineral prospectivity. The classes represent equal intervals.
mapclass_eucdist	Convert input array (mat-file) containing Euclidean distances of grid cell vectors to the centroid of the deposit vector class or most deposit-like class. For example, the SOFM prospectivity map, <i>som_dist_nclass9</i> , contains cell values representing the distance to the neuron representing class 9 (i.e. class containing the most deposits or class with the highest P(D)). This function converts the input map to a conventional 9-class prospectivity map.
add_depdata_2_pat	Add deposit name, Easting, Northing, X, Y, TCG to training pattern vectors to produce an array structures.

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Table F.1: *continued*

Script/Function Name	Application
post_proc_batch	Batch job to convert a trained MLP network and an array containing input patterns and target values into a prospectivity map. The script also analyses the quality of the map.
post_proc_batch_1ofn	Version of batch job described above for network using a 1-of-n coded lithology input.
post_proc_batch_fuzzy	Version of batch job described above for network using fuzzy membership values as inputs.
post_proc_batch_pnn	Batch job to convert a trained PNN network and an array containing input patterns and target values into a prospectivity map. The script also analyses the quality of the map.
reclass_som_class_map	Reclassify the values in a map that has been classified using a 1x22 SOFM network so that the class numbers represent increasing prospectivity.
scalemat09vec	Scale array containing neural network activations prior to producing a 9-class prospectivity map.
training_set_perf	Calculate the performance of a trained network on the training, training-stop and test data sets. Calculate overall percentage of patterns correct, and percentages of deposits and non-deposits correct based on an activation threshold of 0.5.
training_set_perf	Version of function above for neural networks with fuzzy membership inputs.
Fuzzy Systems - Creating Input Layers	
batch_layer2fav_0110_500	Batch job to reclassify input layers to fuzzy membership values using trapezoidal fuzzy membership functions. Fuzzy membership value of 0.1 was assigned to all cells where distance to nearest lithological contact ≥ 500 metres.
batch_layer2fav_0510_500	As above but fuzzy membership value of 0.5 was assigned to all cells where distance to nearest lithological contact ≥ 500 metres.
check_maxmin_fuzzy_batch	Batch job to check the result of converting input layers to fuzzy membership values by calculating and displaying the max. and min. value for all layers used as inputs to a fuzzy logic prospectivity analysis.

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Table F.1: *continued*

Script/Function Name	Application
check_contact_type_fuzzy_vals	Check fuzzy m/ship values assigned to each contact type in a fuzzy contact-type layer.
check_litho_fuzzy_vals	Check fuzzy m/ship values assigned to each rock type in a fuzzy lithology-type layer.
deps_cont_type	Calculate number of cells, deposits, TCG, D/A, TCG/A, TCG/cell, and $P(D/C_k) \times TCG/cell$ for each contact type within a mboxdistance $\leq$ LIMIT from the nearest lithological contact.
deps_litho	Calculate number of cells, deposits, TCG, D/A and $P(D/C_k) \times TCG/cell$ for each lithology type (see above).
favcontact25_pr0110	Create a fuzzy membership layer for favourable contact type based on TCG by reclassifying a contact type layer. Fuzzy membership value of 0.1 was assigned to all cells where distance to nearest lithological contact $\geq$ 500 m.
favcontact25_pr0510	As above but fuzzy membership value of 0.5 was assigned to all cells where distance to nearest lithological contact $\geq$ 500 m.
favcontact25_pxtcg0110	Create a fuzzy membership layer for favourable contact type based on $P(D/C_k) \times TCG/cell$ by reclassifying a contact type layer. Fuzzy membership value of 0.1 was assigned to all cells where distance to nearest lithological contact $\geq$ 500 m.
favcontact25_pxtcg0510	As above but fuzzy membership value of 0.5 was assigned to all cells where distance to nearest lithological contact $\geq$ 500 m.
favgeol25_pr0110	Create a fuzzy membership layer for favourable geology (based on P(D)) by reclassifying a geology GIS layer. Rocks types that do not contain known deposits were assigned a fuzzy membership value of 0.1.
favgeol25_pr0510	As above but rocks types that do not contain known deposits were assigned a fuzzy membership value of 0.5.
layer2fav_batch	Batch job to Reclassify an input layer to fuzzy membership values.
layer2fav	Reclassify an input layer to fuzzy membership values using trapezoidal fuzzy membership functions.
trap	Convert values of an input vector into fuzzy membership values using a trapezoidal fuzzy membership function.

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Table F.1: *continued*

Script/Function Name	Application
traplhs	Asymmetric trapezoidal fuzzy membership function—as above but with fuzzy membership function starts with low values of X set to a fuzzy membership = 1.0 and at an inflection point decreases linearly to a second inflection point where $Y = 0.0$ or 0.1 .
traprhs	Asymmetric trapezoidal fuzzy membership function—as above but with fuzzy membership function starts with low values of X set to a fuzzy membership = 0.0 or 0.1 and at an inflection point increases linearly to a second inflection point where $Y = 1.0$.
Fuzzy Systems - Making Prospectivity Maps	
fuzzy_make_analyze_map_batch	Batch job to create fuzzy systems prospectivity maps using calls to function <i>fuzzy_maps_gamma2</i> (see below).
fuzzy_maps_gamma2	Creates a series of prospectivity maps for a particular set of input layers (10 or 17) using a range of gamma values as well as AND, OR, product and sum. Output are classed and map quality statistics are calculated and written to an ASCII log file.
Prospectivity Map Analysis	
act2histo_nodata	Plot an histogram of output activations from a trained neural network (exclude <i>Nodata</i> map areas).
kendalls	Calculate Kendall's rank correlation coefficient for data in two input vectors.
map-quality	Calculate map quality statistics and produce plots used to assess the quality of a map.
map-quality_som_class_map	Calculate map quality statistics and produce plots used to assess the quality of a the map, <i>som_reclass_map</i> , classified by an SOFM using a 1×9 output layer.
mapstats	Calculate statistics used to compare input layers and output maps as predictors of the mineral deposits.
mapstats.binary	Version of <i>mapstats</i> used for binary input layers where the favourable zones = 1 and the rest = 0.
map2histo_nodata	Plots histogram of raw neural network or fuzzy systems map cell values.

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Table F.1: *continued*

Script/Function Name	Application
maxmin_actmap	Calculate the maximum and minimum output values for raw neural network or fuzzy system prospectivity map.
roc_curve	Plot Receiver Operating Characteristic (ROC) curves.
roc_curve_pnn	Version of function above for maps created with probabilistic networks.
roc_curve_som_class	Version of function above for maps created with SOFM networks.
run_net_2_make_actmap	Run a trained network to produce an output activation map and save it.
run_net_2_make_actmap_batch	Batch job to run a trained network to produce an output activation map (see above).
spearman	Calculate Spearman's rank correlation coefficient for data in two input vectors. Called by function, <i>mapsstats</i> to calculate statistic for the relationship between the classes in a mineral prospectivity map and the probability of a known deposit occurring in the area corresponding to a particular map class.
training_set_perf	Calculate the performance of a trained network on the training, training-stop and test data sets. Calculate overall percentage of patterns correct, and percentages of deposits and non-deposits correct based on an activation threshold of 0.5.
training_set_perf_fuzzy	Version of function <i>training_set_perf</i> for fuzzy systems maps.
training_set_perf_pnn	Version of function <i>training_set_perf</i> for PNN maps.
Figure Preparation	
batch_add_nodata	adds <i>Nodata</i> values to raw neural network output activation and fuzzy systems fuzzy-membership maps and converts resultant maps to ASCII format prior to importing maps into the software package, GEOSOFT <i>Oasis Montaj</i> .
batch_change_fig_props	Changes Matlab figure properties; e.g. axis labels & font size and exports new file to Postscript format for a group of figures listed in a file.
fig_logistic	Create plot of sigmoidal logistic activation function.

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Table F.1: *continued*

Script/Function Name	Application
fig_parzen	Batch job to create a perspective plot of spherical Gaussian radial basis functions used in Parzen window PDF. Calls functions <i>parzen2</i> and <i>set_up_plot</i> .
parzen2	Calculate spherical Gaussian radial basis function used in the Parzen PDF estimator.
plot_run_traind_nn_roc_figs	Batch job to run trained neural networks to create ROC curves, and histogram of nn output activations. Raw output activation maps are also created and saved.
plot_som_reclass_deps_vs_class	Plots a histogram of frequency of deposits for each of the 9 or 22 classes of feature vectors defined by using an SOFM to classify the patterns corresponding to all the grid locations in the map. SOFM class labels are first reclassified so they are in order of increasing $P(\text{deposit} \rightarrow \text{class})$.
plot_som_reclass_PD_vs_class	Plot histogram of $\Pr(D \rightarrow \text{class})$ vs SOFM class after reclassifying the input map, <i>som_class_map</i> to give <i>som_reclass_map</i> .
post_proc_batch_fuzzy_final_fig	Creates fuzzy prospectivity maps, calculates map quality statistics and plots ROC graphs. Called by <i>plot_run_traind_nn_roc_figs</i> .
post_proc_batch_nn_final_fig	as above: for neural network maps.
print_setup	Sets printing options prior to printing a figure.
setup_parzen_plot	Set up <i>Plot Aspect Ratio</i> in function, <i>fig_parzen</i> .
Utilities	
array2bin	Convert mat-file in memory to stored binary file. Data is written as double precision floating point format (32-bit).
array2bin_batch	Batch job to save Matlab arrays as binary files. Use for 10, 17 fuzzy neural network inputs.
array2bin_lge	Convert .mat file in memory to stored binary file. Data is written as double precision floating point format (32-bit) for very large arrays ($> 17 \times 1254000$ double precision floating point values).
ascii2array	Reads an ASCII file containing a single line header with 2 integers, indicating the number of columns and the number of lines, into a Matlab array.

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Table F.1: *continued*

Script/Function Name	Application
batch_mat2ascii	Batch job to convert a series of mat-files (prospectivity maps) to ASCII files with ARCVIEW headers suitable for importing into ArcView GIS.
bin2array	Convert float32 binary file to a Matlab array file.
bin2array_lines	Convert float32 very large binary files ($> 17 \times 1254000$ double precision floating point values) to a Matlab array file.
count_data	Count data cells in a map grid (mat-array).
histo	Plot a histogram of elements stored in a row vector.
mat_ft_x_10002arc	Convert mat-array file containing floating point values to an ASCII file containing a header suitable for importing into ARCVIEW. Values in the MATLAB file are multiplied by 1000 prior to rounding because ArcView can only import integer ASCII grid files.
mat_int2arc	Convert mat-array containing integer values to file suitable for importing into ARCVIEW.
maxmin	Calculate maximum and minimum value of an array with and without <i>Nodata</i> = -9999 values.
maxmin_noprint	Version of <i>maxmin</i> that does not print results to screen; called from within other functions.
readbin_1stline	Read first pattern in a binary file containing float32 data and display it on the screen.
reclass	Reclassify the values in an input grid.

Appendix G

Evaluation of GIS Input Layers: Kalgoorlie Case Study

G.1 Graphs used to evaluate spatial relationships in GIS layers

(a) Contrast, C_W

(b) Bivariate J-function (cumulative)

(c) Chi-squared

(d) Bivariate J-function (interval-based)

(e) Kolmogorov-Smirnov test

(f) $(O - E)/E$

Figure G.1. Plots used to examine the relationship between deposits and favourable lithology in layer *lfavgeol25pr*. The layer contains fuzzy membership values. The empirical curve is shown in blue in b), d) & e). The theoretical curve is shown in red in b) & e) and as grey bars in d). The X-axis parameter in graphs a), b), c) & d) was transformed to create a new parameter representing the difference between the maximum and the original parameter value; i.e., $x = X_{max} - x$.

(a) Contrast, C_W

(b) Bivariate J-function (cumulative)

(c) Chi-squared

(d) Bivariate J-function (interval-based)

(e) Kolmogorov-Smirnov test

(f) $(O - E)/E$

Figure G.2. Plots used to examine the relationship between deposits and subjective (fuzzy) rock competency in the layer, *l2.Lrh1b*. The empirical curve is shown in blue in b), d) & e). The theoretical curve is shown in red in b) & e) and as grey bars in d). The X-axis parameter in graphs a), b) & c) was transformed to create a new parameter representing the difference between the maximum and the original parameter value; i.e., $x = X_{max.} - x$.

(a) Contrast, C_W

(b) Bivariate J-function (cumulative)

(c) Chi-squared

(d) Bivariate J-function (interval-based)

(e) Kolmogorov-Smirnov test

(f) $(O - E)/E$

Figure G.3. Plots used to examine the relationship between deposits and subjective (classes) rock competency in the layer, *l2_lrh2b*. The empirical curve is shown in blue in b), d) & e). The theoretical curve is shown in red in b) & e) and as grey bars in d). The X-axis parameter in graphs a), b) & c) was transformed to create a new parameter representing the difference between the maximum and the original parameter value; i.e., $x = X_{max.} - x$.

(a) Contrast, C_W

(b) Bivariate J-function (cumulative)

(c) Chi-squared

(d) Bivariate J-function (interval-based)

(e) Kolmogorov-Smirnov test

(f) $(O - E)/E$

Figure G.4. Plots used to examine the relationship between deposits and rock strength using Young's Modulus compiled from Hatheway & Kiersch (1989) in the layer, *l2_Lrh3*. The empirical curve is shown in blue in b), d) & e). The theoretical curve is shown in red in b) & e) and as grey bars in d). The X-axis parameter in graphs a), b) & c) was transformed to create a new parameter representing the difference between the maximum and the original parameter value; i.e., $x = X_{max} - x$.

(a) Contrast, C_W

(b) Bivariate J-function (cumulative)

(c) Chi-squared

(d) Bivariate J-function (interval-based)

(e) Kolmogorov-Smirnov test

(f) $(O - E)/E$

Figure G.5. Plots used to examine the relationship between deposits and rock strength using Young's Modulus compiled from Lee (2000) in the layer, *l2_Lrh4*. The empirical curve is shown in blue in b), d) & e). The theoretical curve is shown in red in b) & e) and as grey bars in d). The X-axis parameter in graphs a), b) & c) was transformed to create a new parameter representing the difference between the maximum and the original parameter value; i.e., $x = X_{max.} - x$.

(a) Contrast, C_W

(b) Bivariate J-function (cumulative)

(c) Chi-squared

(d) Bivariate J-function (interval-based)

(e) Kolmogorov-Smirnov test

(f) $(O - E)/E$

Figure G.6. Plots used to examine the relationship between deposits and rock strength using uniaxial compressive strength in the layer, *l2_Lrh5*. The empirical curve is shown in blue in b), d) & e). The theoretical curve is shown in red in b) & e) and as grey bars in d). The X-axis parameter in graphs a), b) & c) was transformed to create a new parameter representing the difference between the maximum and the original parameter value; i.e., $x = X_{max} - x$.

(a) Contrast, C_W

(b) Bivariate J-function (cumulative)

(c) Chi-squared

(d) Bivariate J-function (interval-based)

(e) Kolmogorov-Smirnov test

(f) $(O - E)/E$

Figure G.7. Plots used to examine the relationship between deposits and rock strength using uniaxial compressive strength in the layer, *l2_Lrh6*. The empirical curve is shown in blue in b), d) & e). The theoretical curve is shown in red in b) & e) and as grey bars in d). The X-axis parameter in graphs a), b) & c) was transformed to create a new parameter representing the difference between the maximum and the original parameter value; i.e., $x = x_{max} - x$.

(a) Contrast, C_W

(b) Bivariate J-function (cumulative)

(c) Chi-squared

(d) Bivariate J-function (interval-based)

(e) Kolmogorov-Smirnov test

(f) $(O - E)/E$

Figure G.8. Plots used to examine the relationship between deposits and rock strength using fracture toughness in the layer, *l2_Lrh7*. The empirical curve is shown in blue in b), d) & e). The theoretical curve is shown in red in b) & e) and as grey bars in d). The X-axis parameter in graphs a), b) & c) was transformed to create a new parameter representing the difference between the maximum and the original parameter value; i.e., $x = X_{max} - x$.

(a) Contrast, C_W

(b) Bivariate J-function (cumulative)

(c) Chi-squared

(d) Bivariate J-function (interval-based)

(e) Kolmogorov-Smirnov test

(f) $(O - E)/E$

Figure G.9. Plots used to examine the relationship between deposits and sulphidation index, $Fe_{tot}/(Fe_{tot}+Mg+Ca)$ in the layer, *l3_Lch1*. The empirical curve is shown in blue in b), d) & e). The theoretical curve is shown in red in b) & e) and as grey bars in d). The X-axis parameter in graphs a), b) & c) was transformed to create a new parameter representing the difference between the maximum and the original parameter value; i.e., $x = X_{max.} - x$.

(a) Contrast, C_w

(b) Bivariate J-function (cumulative)

(c) Chi-squared

(d) Bivariate J-function (interval-based)

(e) Kolmogorov-Smirnov test

(f) $(O - E)/E$

Figure G.10. Plots used to examine the relationship between deposits and sulphidation index, $Fe_{tot}(wt\%) \times Fe_{tot} / (Fe_{tot} + Mg + Ca)$ in the layer, *l3_Lch2*. The empirical curve is shown in blue in b), d) & e). The theoretical curve is shown in red in b) & e) and as grey bars in d). The X-axis parameter in graphs a), b) & c) was transformed to create a new parameter representing the difference between the maximum and the original parameter value; i.e., $x = X_{max} - x$.

(a) Contrast, C_W

(b) Bivariate J-function (cumulative)

(c) Chi-squared

(d) Bivariate J-function (interval-based)

(e) Kolmogorov-Smirnov test

(f) $(O - E)/E$

Figure G.11. Plots used to examine the relationship between deposits and oxidation index, $\text{Fe}_2\text{O}_3/(\text{Fe}_2\text{O}_3+\text{FeO})$ in the layer, *l3_Lch3*. The empirical curve is shown in blue in b), d) & e). The theoretical curve is shown in red in b) & e) and as grey bars in d). The X-axis parameter in graphs a), b) & c) was transformed to create a new parameter representing the difference between the maximum and the original parameter value; i.e., $x = X_{max.} - x$.

(a) Contrast, C_W

(b) Bivariate J-function (cumulative)

(c) Chi-squared

(d) Bivariate J-function (interval-based)

(e) Kolmogorov-Smirnov test

(f) $(O - E)/E$

Figure G.12. Plots used to examine the relationship between deposits and oxidation index, $\text{Fe}_2\text{O}_3/(\text{FeO})$ in the layer, *l3_lch4*. The empirical curve is shown in blue in b), d) & e). The theoretical curve is shown in red in b) & e) and as grey bars in d).

(a) Contrast, C_W

(b) Bivariate J-function (cumulative)

(c) Chi-squared

(d) Bivariate J-function (interval-based)

(e) Kolmogorov-Smirnov test

(f) $(O - E)/E$

Figure G.13. Plots used to examine the relationship between deposits and oxidation index, Fe^{2+}/Fe^{3+} in the layer, *l3_Lch5*. The empirical curve is shown in blue in b), d) & e). The theoretical curve is shown in red in b) & e) and as grey bars in d).

(a) Contrast, C_W

(b) Bivariate J-function (cumulative)

(c) Chi-squared

(d) Bivariate J-function (interval-based)

(e) Kolmogorov-Smirnov test

(f) $(O - E)/E$

Figure G.14. Plots used to examine the relationship between deposits and distance to felsic porphyritic intrusions in the layer, *l4-l_pf_dist*. The empirical curve is shown in blue in b), d) & e). The theoretical curve is shown in red in b) & e) and as grey bars in d).

(a) Contrast, C_W

(b) Bivariate J-function (cumulative)

(c) Chi-squared

(d) Bivariate J-function (interval-based)

(e) Kolmogorov-Smirnov test

(f) $(O - E)/E$

Figure G.15. Plots used to examine the relationship between deposits and airborne total magnetic intensity in the layer, *l5-m-rtp*. The empirical curve is shown in blue in b), d) & e). The theoretical curve is shown in red in b) & e) and as grey bars in d).

(a) Contrast, C_W

(b) Bivariate J-function (cumulative)

(c) Chi-squared

(d) Bivariate J-function (interval-based)

(e) Kolmogorov-Smirnov test

(f) $(O - E)/E$

Figure G.16. Plots used to examine the relationship between deposits and Bouguer gravity anomalies in the layer, *l12_grav*. The X-axis parameter in graphs a), b), c) & d) was transformed to create a new parameter representing the difference between the maximum and the original parameter value; i.e., $x = X_{max.} - x$. The empirical curve is shown in blue in b), d) & e). The theoretical curve is shown in red in b) & e) and as grey bars in d).

(a) Contrast, C_W

(b) Bivariate J-function (cumulative)

(c) Chi-squared

(d) Bivariate J-function (interval-based)

(e) Kolmogorov-Smirnov test

(f) $(O - E)/E$

Figure G.17. Plots used to examine the relationship between deposits and distance to positive magnetic anomalies, where the z-score, $Z \geq 1$, in the layer, *l14_mz1_dist*. In b), d) & e), the empirical curve is blue and the theoretical curve is red.

(a) Contrast, C_W

(b) Bivariate J-function (cumulative)

(c) Chi-squared

(d) Bivariate J-function (interval-based)

(e) Kolmogorov-Smirnov test

(f) $(O - E)/E$

Figure G.18. Plots used to examine the relationship between deposits and distance to positive magnetic anomalies, where the z-score, $Z \geq 2$, in the layer, *l14_mz2_dist*. In b), d) & e), the empirical curve is blue and the theoretical curve is red.

(a) Contrast, C_W

(b) Bivariate J-function (cumulative)

(c) Chi-squared

(d) Bivariate J-function (interval-based)

(e) Kolmogorov-Smirnov test

(f) $(O - E)/E$

Figure G.19. Plots used to examine the relationship between deposits and distance to negative magnetic anomalies, where the z-score, $Z \leq 1$, in the layer, *l14_mz-1_dist*. In b), d) & e), the empirical curve is blue and the theoretical curve is red.

(a) Contrast, C_W

(b) Bivariate J-function (cumulative)

(c) Chi-squared

(d) Bivariate J-function (interval-based)

(e) Kolmogorov-Smirnov test

(f) $(O - E)/E$

Figure G.20. Plots used to examine the relationship between deposits and distance to crustal-scale faults and shear zones in the layer, *l20_f1_dist*. The empirical curve is shown in blue in b), d) & e). The theoretical curve is shown in red in b) & e) and as grey bars in d).

(a) Contrast, C_W

(b) Bivariate J-function (cumulative)

(c) Chi-squared

(d) Bivariate J-function (interval-based)

(e) Kolmogorov-Smirnov test

(f) $(O - E)/E$

Figure G.21. Plots used to examine the relationship between deposits and distance to NNW-trending regional-scale faults and shear zones in the layer, *l21-f2-dist*. The empirical curve is shown in blue in b), d) & e). The theoretical curve is shown in red in b) & e) and as grey bars in d).

(a) Contrast, C_W

(b) Bivariate J-function (cumulative)

(c) Chi-squared

(d) Bivariate J-function (interval-based)

(e) Kolmogorov-Smirnov test

(f) $(O - E)/E$

Figure G.22. Plots used to examine the relationship between deposits and distance to NE-trending regional faults and shear zones in the layer, *l22_d3_dist*. The empirical curve is shown in blue in b), d) & e). The theoretical curve is shown in red in b) & e) and as grey bars in d).

(a) Contrast, C_W

(b) Bivariate J-function (cumulative)

(c) Chi-squared

(d) Bivariate J-function (interval-based)

(e) Kolmogorov-Smirnov test

(f) $(O - E)/E$

Figure G.23. Plots used to examine the relationship between deposits and distance to E-trending regional faults and shear zones in the layer, *l23_d4_dist*. The empirical curve is shown in blue in b), d) & e). The theoretical curve is shown in red in b) & e) and as grey bars in d).

(a) Contrast, C_W

(b) Bivariate J-function (cumulative)

(c) Chi-squared

(d) Bivariate J-function (interval-based)

(e) Kolmogorov-Smirnov test

(f) $(O - E)/E$

Figure G.24. Plots used to examine the relationship between deposits and the strike of crustal-scale shear zones in the layer *l28_s_strf1*. The strike angles have been reduced to a range 0–179°. The empirical curve is shown in blue in b), d) & e). The theoretical curve is shown in red in b) & e) and as grey bars in d).

(a) Contrast, C_W

(b) Bivariate J-function (cumulative)

(c) Chi-squared

(d) Bivariate J-function (interval-based)

(e) Kolmogorov-Smirnov test

(f) $(O - E)/E$

Figure G.25. Plots used to examine the relationship between deposits and strike of NNW-trending regional-scale faults and shear zones in the layer, *l29_sf2*. The strike angles have been reduced to a range 0–179°. The empirical curve is shown in blue in b), d) & e). The theoretical curve is shown in red in b) & e) and as grey bars in d).

(a) Contrast, C_W

(b) Bivariate J-function (cumulative)

(c) Chi-squared

(d) Bivariate J-function (interval-based)

(e) Kolmogorov-Smirnov test

(f) $(O - E)/E$

Figure G.26. Plots used to examine the relationship between deposits and strike of NE-trending regional-scale faults and shear zones in the layer, *l30.sf3*. The strike angles have been reduced to a range 0–179°. The empirical curve is shown in blue in b), d) & e). The theoretical curve is shown in red in b) & e) and as grey bars in d).

(a) Contrast, C_W

(b) Bivariate J-function (cumulative)

(c) Chi-squared

(d) Bivariate J-function (interval-based)

(e) Kolmogorov-Smirnov test

(f) $(O - E)/E$

Figure G.27. Plots used to examine the relationship between deposits and strike of E-trending regional-scale faults and shear zones in the layer, *l31.sf4*. The strike angles have been reduced to a range 0–179°. The empirical curve is shown in blue in b), d) & e). The theoretical curve is shown in red in b) & e) and as grey bars in d).

(a) Contrast, C_W

(b) Bivariate J-function (cumulative)

(c) Chi-squared

(d) Bivariate J-function (interval-based)

(e) Kolmogorov-Smirnov test

(f) $(O - E)/E$

Figure G.28. Plots used to examine the relationship between deposits and distance to the intersection of the nearest regional-scale faults and shear zones in the layer, *l34_s_f23pdst*. The empirical curve is shown in blue in b), d) & e). The theoretical curve is shown in red in b) & e) and as grey bars in d).

(a) Contrast, C_W

(b) Bivariate J-function (cumulative)

(c) Chi-squared

(d) Bivariate J-function (interval-based)

(e) Kolmogorov-Smirnov test

(f) $(O - E)/E$

Figure G.29. Plots used to examine the relationship between deposits and subjective (fuzzy) rheological contrast in the layer, *l36_Lrh11k*. The empirical curve is shown in blue in b), d) & e). The theoretical curve is shown in red in b) & e) and as grey bars in d). The X-axis parameter in graphs a), b) & c) was transformed to create a new parameter representing the difference between the maximum and the original parameter value; i.e., $x = X_{max} - x$.

(a) Contrast, C_W

(b) Bivariate J-function (cumulative)

(c) Chi-squared

(d) Bivariate J-function (interval-based)

(e) Kolmogorov-Smirnov test

(f) $(O - E)/E$

Figure G.30. Plots used to examine the relationship between deposits and subjective (classes) rheological contrast in the layer, *l36_lrh21k*. The empirical curve is shown in blue in b), d) & e). The theoretical curve is shown in red in b) & e) and as grey bars in d). The X-axis parameter in graphs a), b) & c) was transformed to create a new parameter representing the difference between the maximum and the original parameter value; i.e., $x = X_{max} - x$.

(a) Contrast, C_W

(b) Bivariate J-function (cumulative)

(c) Chi-squared

(d) Bivariate J-function (interval-based)

(e) Kolmogorov-Smirnov test

(f) $(O - E)/E$

Figure G.31. Plots used to examine the relationship between deposits and rheological contrast using Young's Modulus compiled from Hatheway & Kiersch (1989) in the layer, *l36_Lrh31k*. The empirical curve is shown in blue in b), d) & e). The theoretical curve is shown in red in b) & e) and as grey bars in d). The X-axis parameter in graphs a), b) & c) was transformed to create a new parameter representing the difference between the maximum and the original parameter value; i.e., $x = X_{max} - x$.

(a) Contrast, C_W

(b) Bivariate J-function (cumulative)

(c) Chi-squared

(d) Bivariate J-function (interval-based)

(e) Kolmogorov-Smirnov test

(f) $(O - E)/E$

Figure G.32. Plots used to examine the relationship between deposits and rheological contrast using Young's Modulus compiled from Lee (2000) in the layer, *l36_lrh41k*. The empirical curve is shown in blue in b), d) & e). The theoretical curve is shown in red in b) & e) and as grey bars in d). The X-axis parameter in graphs a), b) & c) was transformed to create a new parameter representing the difference between the maximum and the original parameter value; i.e., $x = X_{max.} - x$.

(a) Contrast, C_W

(b) Bivariate J-function (cumulative)

(c) Chi-squared

(d) Bivariate J-function (interval-based)

(e) Kolmogorov-Smirnov test

(f) $(O - E)/E$

Figure G.33. Plots used to examine the relationship between deposits and rheological contrast using uniaxial compressive strength in the layer, *l36_Lrh51k*. The empirical curve is shown in blue in b), d) & e). The theoretical curve is shown in red in b) & e) and as grey bars in d). The X-axis parameter in graphs a), b) & c) was transformed to create a new parameter representing the difference between the maximum and the original parameter value; i.e., $x = X_{max.} - x$.

(a) Contrast, C_W

(b) Bivariate J-function (cumulative)

(c) Chi-squared

(d) Bivariate J-function (interval-based)

(e) Kolmogorov-Smirnov test

(f) $(O - E)/E$

Figure G.34. Plots used to examine the relationship between deposits and rheological contrast using uniaxial compressive strength in the layer, *l36_Lrh61k*. The empirical curve is shown in blue in b), d) & e). The theoretical curve is shown in red in b) & e) and as grey bars in d). The X-axis parameter in graphs a), b) & c) was transformed to create a new parameter representing the difference between the maximum and the original parameter value; i.e., $x = X_{max.} - x$.

(a) Contrast, C_W

(b) Bivariate J-function (cumulative)

(c) Chi-squared

(d) Bivariate J-function (interval-based)

(e) Kolmogorov-Smirnov test

(f) $(O - E)/E$

Figure G.35. Plots used to examine the relationship between deposits and rheological contrast using fracture toughness in the layer, *l36-Lrh71k*. The empirical curve is shown in blue in b), d) & e). The theoretical curve is shown in red in b) & e) and as grey bars in d). The X-axis parameter in graphs a), b) & c) was transformed to create a new parameter representing the difference between the maximum and the original parameter value; i.e., $x = X_{max.} - x$.

(a) Contrast, C_W

(b) Bivariate J-function (cumulative)

(c) Chi-squared

(d) Bivariate J-function (interval-based)

(e) Kolmogorov-Smirnov test

(f) $(O - E)/E$

Figure G.36. Plots used to examine the relationship between deposits and chemical contrast, $Fe_{tot}/(Fe_{tot} + Mg + Ca)$ (sulphidation index) in the layer, *l37_Lch11k*. The empirical curve is shown in blue in b), d) & e). The theoretical curve is shown in red in b) & e) and as grey bars in d). The X-axis parameter in graphs a), b) & c) was transformed to create a new parameter representing the difference between the maximum and the original parameter value; i.e., $x = X_{max.} - x$.

(a) Contrast, C_W

(b) Bivariate J-function (cumulative)

(c) Chi-squared

(d) Bivariate J-function (interval-based)

(e) Kolmogorov-Smirnov test

(f) $(O - E)/E$

Figure G.37. Plots used to examine the relationship between deposits and chemical contrast, $Fe_{tot}(wt\%) * Fe_{tot}/(Fe_{tot} + Mg + Ca)$ (sulphidation index) in the layer, *l37-L.ch21k*. The empirical curve is shown in blue in b), d) & e). The theoretical curve is shown in red in b) & e) and as grey bars in d). The X-axis parameter in graphs a), b) & c) was transformed to create a new parameter representing the difference between the maximum and the original parameter value; i.e., $x = X_{max.} - x$.

(a) Contrast, C_W

(b) Bivariate J-function (cumulative)

(c) Chi-squared

(d) Bivariate J-function (interval-based)

(e) Kolmogorov-Smirnov test

(f) $(O - E)/E$

Figure G.38. Plots used to examine the relationship between deposits and chemical contrast, $\text{Fe}_2\text{O}_3/(\text{Fe}_2\text{O}_3 + \text{FeO})$ (oxidation index) in the layer, *l37-Lch31k*. The empirical curve is shown in blue in b), d) & e). The theoretical curve is shown in red in b) & e) and as grey bars in d). The X-axis parameter in graphs a), b) & c) was transformed to create a new parameter representing the difference between the maximum and the original parameter value; i.e., $x = X_{max.} - x$.

(a) Contrast, C_W

(b) Bivariate J-function (cumulative)

(c) Chi-squared

(d) Bivariate J-function (interval-based)

(e) Kolmogorov-Smirnov test

(f) $(O - E)/E$

Figure G.39. Plots used to examine the relationship between deposits and chemical contrast, $\text{Fe}_2\text{O}_3/(\text{FeO})$ (oxidation index) in the layer, *l37_Lch41k*. The empirical curve is shown in blue in b), d) & e). The theoretical curve is shown in red in b) & e) and as grey bars in d). The X-axis parameter in graphs a), b) & c) was transformed to create a new parameter representing the difference between the maximum and the original parameter value; i.e., $x = X_{max} - x$.

(a) Contrast, C_w

(b) Bivariate J-function (cumulative)

(c) Chi-squared

(d) Bivariate J-function (interval-based)

(e) Kolmogorov-Smirnov test

(f) $(O - E)/E$

Figure G.40. Plots used to examine the relationship between deposits and chemical contrast, $Fe_2O/(Fe_2O_3)$ (oxidation index) in the layer, *l37_Lch51k*. The empirical curve is shown in blue in b), d) & e). The theoretical curve is shown in red in b) & e) and as grey bars in d). The X-axis parameter in graphs a), b) & c) was transformed to create a new parameter representing the difference between the maximum and the original parameter value; i.e., $x = X_{max} - x$.

(a) Contrast, C_W

(b) Bivariate J-function (cumulative)

(c) Chi-squared

(d) Bivariate J-function (interval-based)

(e) Kolmogorov-Smirnov test

(f) $(O - E)/E$

Figure G.41. Plots used to examine the relationship between deposits and strike of lithological contacts in the layer *l38_c_str1k*. The strike angles have been reduced to a range 0–179°. The empirical curve is shown in blue in b), d) & e). The theoretical curve is shown in red in b) & e) and as grey bars in d).

(a) Contrast, C_W

(b) Bivariate J-function (cumulative)

(c) Chi-squared

(d) Bivariate J-function (interval-based)

(e) Kolmogorov-Smirnov test

(f) $(O - E)/E$

Figure G.42. Plots used to examine the relationship between deposits and distance to nearest lithological contact in the layer *l39_c.dist*. The empirical curve is shown in blue in b), d) & e). The theoretical curve is shown in red in b) & e) and as grey bars in d).

(a) Contrast, C_W

(b) Bivariate J-function (cumulative)

(c) Chi-squared

(d) Bivariate J-function (interval-based)

(e) Kolmogorov-Smirnov test

(f) $(O - E)/E$

Figure G.43. Plots used to examine the relationship between deposits and density of regional NNW- and NE- trending faults in layer *l42-f123-density*. The length of faults in a 5×5 km window was assigned to the central cell. The empirical curve is shown in blue in b), d) & e). The theoretical curve is shown in red in b) & e) and as grey bars in d). The X-axis parameter in graphs a), b) & c) was transformed to create a new parameter representing the difference between the maximum and the original parameter value; i.e., $x = X_{max} - x$.

(a) Contrast, C_W

(b) Bivariate J-function (cumulative)

(c) Chi-squared

(d) Bivariate J-function (interval-based)

(e) Kolmogorov-Smirnov test

(f) $(O - E)/E$

Figure G.44. Plots used to examine the relationship between deposits and density of lithological contacts in layer *l43_lith_diversity*. The number of lithological boundaries in horizontal and vertical directions in a 5×5 km window is used as a relative measure of lithological complexity. The empirical curve is shown in blue in b), d) & e). The theoretical curve is shown in red in b) & e) and as grey bars in d). In graphs a), b) & c), a new variable x' was created to represent the difference between the maximum and the original variable; i.e. $x' = X_{max} - x$.

(a) Contrast, C_W

(b) Bivariate J-function (cumulative)

(c) Chi-squared

(d) Bivariate J-function (interval-based)

(e) Kolmogorov-Smirnov test

(f) $(O - E)/E$

Figure G.45. Plots used to examine the relationship between deposits and favourable lithological contacts in layer $l_{44favcnt25pr}$. The layer contains fuzzy membership values. The empirical curve is shown in blue in b), d) & e). The theoretical curve is shown in red in b) & e) and as grey bars in d). In graphs a), b), c) & d) a new variable x' was created to represent the difference between the maximum and the original variable; i.e. $x' = X_{max} - x$.

(a) Contrast, C_W

(b) Bivariate J-function (cumulative)

(c) Chi-squared

(d) Bivariate J-function (interval-based)

(e) Kolmogorov-Smirnov test

(f) $(O - E)/E$

Figure G.46. Plots used to examine the relationship between deposits and metamorphic grade in layer *l45_Lmeta*. There are four classes of rock in the metamorphic-grade map, which were assigned the numeric codes shown in brackets; granite (0), amphibolite (1), upper greenschist (2), and lower greenschist facies (3). The numeric codes were assigned so that the code increases with increasing favourability for gold deposits. The empirical curve is shown in blue in b), d) & e). The theoretical curve is shown in red in b) & e) and as grey bars in d). In graphs a), b) & c) a new variable x' was created to represent the difference between the maximum and the original variable; i.e. $x' = X_{max} - x$.

(a) Contrast, C_W

(b) Bivariate J-function (cumulative)

(c) Chi-squared

(d) Bivariate J-function (interval-based)

(e) Kolmogorov-Smirnov test

(f) $(O - E)/E$

Figure G.47. Plots used to examine the relationship between deposits and the distance to the ground trace of the nearest anticlinal axis in the layer, *l46-dist.anti*. The empirical curve is shown in blue in b), d) & e). The theoretical curve is shown in red in b) & e) and as grey bars in d).

(a) Contrast, C_W

(b) Bivariate J-function (cumulative)

(c) Chi-squared

(d) Bivariate J-function (interval-based)

(e) Kolmogorov-Smirnov test

(f) $(O - E)/E$

Figure G.48. Plots used to examine the relationship between deposits and the distance to the ground trace of the nearest synclinal axis in the layer, *l46-dist_sync*. The empirical curve is shown in blue in b), d) & e). The theoretical curve is shown in red in b) & e) and as grey bars in d).

G.2 Ranking of potential GIS input layers

Fifty-nine potential input GIS layers were ranked according to their ability to predict the known deposits in the study area. The best 10 and best 17 of these were selected as inputs to the neural networks used in experiments in Chapter 7. Four methods of ranking the GIS layers are presented in the following tables; Several criteria were used used to rank the layers;

1. best representatives of each evidence category (Table G.1)
2. D/A AND $D \geq \sim 20\%$ (Table G.2)
3. $D*D/A$ (Table G.3)
4. $D*D/A$ AND $D \geq \sim 20\%$ AND $D/A \geq \sim 3$, (Table G.4)

where D is the percentage of the deposits and A is the percentage of the map area. In each of the tables, the names of layers that belong to the 10-layer set are shown in dark grey and those belonging to 17-layer set are shown in light grey.

Table G.1: Ranking of potential GIS input layers. Layers are grouped according to categories of evidence. Within categories, layers with the highest value of D/A (for which $D \geq 20\%$) were selected. D = percentage of known deposits in binary favourable region and A = percentage of total map area occupied by favourable region.

Layer Type	GIS Layer	Favourable values	Deposits		Cells		Deposits (%)	Area (%)	D/A	D*(D/A)
			fav. zone	total	fav. zone	total				
Rock strength										
Young's modulus, CRC ⁷	l2_lrh3	80.1–95.2 GPa	16	120	16607	982843	13.33	1.69	7.89	105.21
Compressive Strength	l2_lrh5	187–250 MPa	89	120	322779	942843	74.17	34.23	2.17	160.68
Young's modulus, AMC ⁸	l2_lrh4	70.0–82.3 GPa	82	120	342602	982843	68.33	34.86	1.96	133.96
Fracture toughness	l2_lrh7	1.8–4.0 MPa	91	120	382172	982843	75.83	38.88	1.95	147.89
Tensile Strength	l2_lrh6	16.8–18.5 MPa	40	120	171630	942843	33.33	17.46	1.91	63.63
10 classes	l2_lrh2	7–9	72	120	599181	982843	60.00	60.96	0.98	59.05
Fuzzy membership	l2_lrh1	0.7–1.0	31	120	377225	982843	25.83	38.38	0.67	17.39
Chemical ratios										
Fe(wt%)*Fe/(Fe+Mg+Ca)	l3_lch2	4.3–4.8	14	120	15161	982843	11.67	1.54	7.56	88.24
Fe ₂ O ₃ /(Fe ₂ O ₃ +FeO)	l3_lch3	0.19–0.26	14	120	15326	982843	11.67	1.56	7.48	87.29
Fe ³⁺ /Fe ²⁺	l3_lch5	0.13–0.78	99	120	452329	982843	82.50	46.02	1.79	147.89
Fe ₂ O ₃ /FeO	l3_lch4	0.10–0.19	13	120	73799	982843	10.83	7.51	1.44	15.63
Fe/(Fe+Mg+Ca)	l3_lch1	0.39–0.44	32	120	211741	982843	26.67	21.54	1.24	33.01
Field strength data:										
Bouguer gravity anomaly	l12_grav	-560- -330 mGal	105	120	515590	980863	87.50	52.56	1.66	145.65
Magnetic intensity (RTP)	l5_m_rtp	58100-59000 nT	11	120	63196	981560	9.17	6.44	1.42	13.05
Distance to nearest:										
Porphyritic felsic intrusion	l4_l_pf_dist	0–400 m	32	120	48307	982843	26.67	4.92	5.43	144.68
Crustal-scale shear zone	l20_f1_dist	0–400 m	22	120	45742	982843	18.33	4.65	3.94	72.22
Porphyritic felsic intrusion	l4_l_pf_dist	0–1400 m	54	120	135252	982843	45.00	13.76	3.27	147.15
Anticlinal axes	l46_dist_anti	0–1800 m	65	120	174638	982843	54.17	17.77	3.05	165.12
Regional NE fault	l22_d3_dist	0–200 m	50	120	141130	982843	41.67	14.36	2.90	120.90
Reg. fault intersection	l34_s_f23pdst	0–1200 m	47	120	161988	982843	39.17	16.48	2.38	93.08

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Table G.1: *continued*

Layer Type	GIS Layer	Favourable values	Deposits		Cells		Deposits (%)	Area (%)	D/A	D*(D/A)
			fav. zone	total	fav. zone	total				
Crustal-scale shear zone	l20_f1_dist	0–1400 m	42	120	145691	982843	35.00	14.82	2.36	82.64
+ve mag. anomaly ($Z \geq 2$)	l14_mz2_dist	0–600 m	49	120	183351	982843	40.83	18.66	2.19	89.38
Lithological contact	l39_c_dist	0–200m	89	120	339982	982843	74.17	34.59	2.14	159.02
Regional NE fault	l22_d3_dist	0–800 m	92	120	405341	982843	76.67	41.24	1.86	142.52
+ve mag. anomaly ($Z \geq 2$)	l14_mz2_dist	0–1600 m	99	120	441094	982843	82.50	44.88	1.84	151.66
+ve mag. anomaly ($Z \geq 1$)	l14_mz1_dist	0–400 m	60	120	294446	982843	50.00	29.96	1.67	83.45
+ve mag. anomaly ($Z \geq 1$)	l14_mz1_dist	0–1200 m	107	120	590922	982843	89.17	60.12	1.48	132.24
Regional NNW fault	l21_f2_dist	0–1200m	75	120	439080	982843	62.50	44.67	1.40	87.44
Regional E fault	l23_d4_dist	0–400 m	13	120	81741	982843	10.83	8.32	1.30	14.11
Regional E fault	l23_d4_dist	0–800 m	23	120	157211	982843	19.17	16.00	1.20	22.97
Synclinal axes ⁹	l46_dist_sync	0–1000 m	1	120	64954	982843	0.83	6.61	0.13	0.11
Strike of nearest:										
Regional NW fault	l29_s_f2str	30–40°	9	120	6112	982843	7.50	0.62	12.06	90.45
Regional NE fault	l30_s_f3str	60–90, 140–180°	25	120	31086	982843	20.83	3.16	6.59	137.23
Regional E fault	l31_s_f4str	130–150°	10	120	25390	982843	8.33	2.58	3.23	26.88
Lithological contact	l38_c_str1k	30–50, 110–120°	24	120	62015	982843	20.00	6.31	3.17	63.39
Crustal-scale shear zone	l28_s_f1str	120–160°	43	120	132696	982843	35.83	13.50	2.65	95.10
Rheological contrast										
Compressive Strength (UCS)	l36_l_rh51k	148–169 MPa	5	120	2015	982843	4.17	0.21	20.32	84.68
Young's modulus ⁷	l36_l_rh31k	62.3–69.2 GPa	3	120	2067	982843	2.50	0.21	11.89	29.72
Young's modulus ⁸	l36_l_rh41k	32.1–37.5 GPa	15	120	18144	982843	12.50	1.85	6.77	84.64
Fuzzy	l36_l_rh11k	0.68–0.85	24	120	35887	982843	20.00	3.65	5.48	109.55
Fracture toughness	l36_l_rh71k	2.24–2.52	12	120	22064	982843	10.00	2.24	4.45	44.55
Tensile Strength (UTS)	l36_l_rh61k	5.88–7.35	15	120	45031	982843	12.50	4.58	2.73	34.10
10 classes	l36_l_rh21k	4–7	45	120	146535	982843	37.50	14.91	2.52	94.32
Chemical contrast										

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Table G.1: *continued*

Layer Type	GIS Layer	Favourable values	Deposits		Cells		Deposits (%)	Area (%)	D/A	D*(D/A)
			fav. zone	total	fav. zone	total				
Fe(wt%)*Fe/(Fe+Mg+Ca)	l37_lch21k	4.0–4.4	6	120	4611	982843	5.00	0.47	10.66	53.29
Fe ₂ O ₃ /FeO	l37_lch41k	1.7–2.8	21	120	33971	982843	17.50	3.46	5.06	88.60
Fe ³⁺ /Fe ²⁺	l37_lch51k	1.5–2.5	21	120	33971	982843	17.50	3.46	5.06	88.60
Fe ₂ O ₃ /(Fe ₂ O ₃ +FeO)	l37_lch31k	0.42–0.60	13	120	23443	982843	10.83	2.39	4.54	49.20
Fe/(Fe+Mg+Ca)	l37_lch11k	0.12–0.35	33	120	81085	982843	27.50	8.25	3.33	91.67
Density										
Lithological contact	l43_lith_diversity	710–1220	53	120	74491	982843	44.17	7.58	5.83	257.38
NNW & NE faults	l42_fl23_density	300–600	71	120	212581	982843	59.17	21.63	2.74	161.85
Fuzzy Membership Layers										
Rock contact, P _(deposit)	l44favcnt25pr ³	0–200 m	19	120	6186	982843	15.83	0.63	25.16	398.31
Rock contact, P _(dep.) *TCG	l44favcnt25ptg ⁴	0–200 m	22	120	10006	982843	18.33	1.02	18.01	330.15
Rock contact, P _(dep.)	l44fc25pl300 ⁵	0–1300 m	21	120	11993	982843	17.50	1.22	14.34	250.98
Rock contact, P _(dep.) *TCG	l44f25ptg1300 ⁶	0–1300 m	26	120	18777	982843	21.67	1.91	11.34	245.72
Host rock, P _(dep.)	l1favgeol25pr ¹	0.75–1.0	23	120	31199	982843	19.17	3.17	6.04	115.73
Host rock P _(dep.) *TCG	l1favgeol25ptg ²	0.75–1.0	35	120	96673	982843	29.17	9.84	2.97	86.49
Metamorphic grade	l45_lmeta	2–3	90	120	395604	982843	75.00	40.25	1.86	139.75

¹l1favgeol25pr (abbreviated name used in ArcView) = l1favgeolt25-pr0110 (name in text and Table 6.4 in Chapter 5 and in Matlab files, CD-ROM vol. 1).²l1favgeol25ptg (abbreviated name used in ArcView) = l1favgeolt25-ptg. See footnote above.³l44favcnt25pr (abbreviated name used in ArcView) = l1favcnt25-pr0110_200. See footnote above.⁴l44favcnt25ptg (abbreviated name used in ArcView) = l1favcnt25-ptg0110_200. See footnote above.⁵l44favc25pl300 (abbreviated name used in ArcView) = l1favcnt25-pr_1300. See footnote above.⁶l44favc25ptg1300 (abbreviated name used in ArcView) = l1favcnt25-ptg_1300. See footnote above.⁷CRC: Data from a compilation by Hatheway & Kiersch, 1989 (see Table 5.5 in Chapter 5).⁸AMC: Unpublished data provided by M. Lee, Australian Mining Consultants (AMC), 2000 (see Tables 5.5 & D.5 in Appendix D).⁹A negative association exists between deposits and the buffer zone for this layer. It was included for comparison with positive associations.

Table G.2: Ranking of potential GIS input layers using the statistic, D/A, where D = percentage of known deposits in binary favourable region and A = percentage of total map area occupied by favourable region. Layers with the highest value of D/A and $D \geq \sim 20\%$ were selected.

Layer Type	GIS Layer	Favourable values	Deposits		Cells		Deposits (%)	Area (%)	D/A	D*(D/A)
			fav. zone	total	fav. zone	total				
Fav. rock contact, $P_{(dep.)}$	l44favcnt25pr ³	0–200 m	19	120	6186	982843	15.83	0.63	25.16	398.31
Rheol. contrast: UCS	l36_lrh51k	148–169 MPa	5	120	2015	982843	4.17	0.21	20.32	84.68
Fav. rock contact, $P_{(dep.)} * TCG$	l44favcnt25ptg ⁴	0–200 m	22	120	10006	982843	18.33	1.02	18.01	330.15
Fav. rock contact, $P_{(dep.)}$	l44fc25p1300 ⁵	0–1300 m	21	120	11993	982843	17.50	1.22	14.34	250.98
Strike: regional NW fault	l29_s.f2str	30–40°	9	120	6112	982843	7.50	0.62	12.06	90.45
Rheol. contrast: Young's mod. ⁷	l36_lrh31k	62.3–69.2 MPa	3	120	2067	982843	2.50	0.21	11.89	29.72
Fav. rock contact, $P_{(dep.)} * TCG$	l44f25ptg1300 ⁶	0–1300 m	26	120	18777	982843	21.67	1.91	11.34	245.72
Chem. contrast: $Fe(wt\%) * Fe/(Fe+Mg+Ca)$	l37_lch21k	4.0–4.4	6	120	4611	982843	5.00	0.47	10.66	53.29
Young's modulus, CRC^7	l2_lrh3	80.1–95.2 GPa	16	120	16607	982843	13.33	1.69	7.89	105.21
$Fe(wt\%) * Fe/(Fe+Mg+Ca)$	l3_lch2	4.3–4.8	14	120	15161	982843	11.67	1.54	7.56	88.24
$Fe_2O_3/(Fe_2O_3+FeO)$	l3_lch3	0.19–0.26	14	120	15326	982843	11.67	1.56	7.48	87.29
Rheol. Contrast: Young's mod. ⁸	l36_lrh41k	32.1–37.5 MPa	15	120	18144	982843	12.50	1.85	6.77	84.64
Strike: regional NE fault	l30_s.f3str	60–90, 140–180°	25	120	31086	982843	20.83	3.16	6.59	137.23
Fav. host rock $P_{(deposit)}$	l1favgeol25pr ¹	0.75–1.0	23	120	31199	982843	19.17	3.17	6.04	115.73
Density: Lith. contact	l43_lith_diversity	710–1220	53	120	74491	982843	44.17	7.58	5.83	257.38
Rheol. contrast: Fuzzy	l36_lrh11k	0.68–0.85	24	120	35887	982843	20.00	3.65	5.48	109.55
Dist: Porphyritic felsic intrusion	l4_lpf.dist	0–400 m	32	120	48307	982843	26.67	4.92	5.43	144.68
Chem. contrast: Fe_2O_3/FeO	l37_lch41k	1.7–2.8	21	120	33971	982843	17.50	3.46	5.06	88.60
Chem. contrast: Fe^{3+}/Fe^{2+}	l37_lch51k	1.5–2.5	21	120	33971	982843	17.50	3.46	5.06	88.60
Chem. contrast: $Fe_2O_3/(Fe_2O_3+FeO)$	l37_lch31k	0.42–0.60	13	120	23443	982843	10.83	2.39	4.54	49.20
Rheol. contrast: Fract. tough.	l36_lrh71k	2.24–2.52	12	120	22064	982843	10.00	2.24	4.45	44.55
Dist: Crustal-scale shear zone	l20_fl_dist	0–400 m	22	120	45742	982843	18.33	4.65	3.94	72.22
Chem. contrast: $Fe/(Fe+Mg+Ca)$	l37_lch11k	0.12–0.35	33	120	81085	982843	27.50	8.25	3.33	91.67

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Table G.2: *continued*

Layer Type	GIS Layer	Favourable values	Deposits		Cells		Deposits (%)	Area (%)	D/A	D*(D/A)
			fav. zone	total	fav. zone	total				
Dist: Porphyritic felsic intrusion	l4_l_pf.dist	0–1400 m	54	120	135252	982843	45.00	13.76	3.27	147.15
Strike: regional E fault	l31_s.f4str	130–150°	10	120	25390	982843	8.33	2.58	3.23	26.88
Strike: Rock contacts	l38_c.str1k	30–50, 110–120°	24	120	62015	982843	20.00	6.31	3.17	63.39
Dist: anticlinal axes	l46_dist.anti	0–1800 m	65	120	174638	982843	54.17	17.77	3.05	165.12
Fav. host rock, $P_{(dep.)} * TCG$	l1favgeol25pxtg ²	0.75–1.0	35	120	96673	982843	29.17	9.84	2.97	86.49
Dist: regional NE fault	l22_d3.dist	0–200 m	50	120	141130	982843	41.67	14.36	2.90	120.90
Density: regional faults	l42_fl23_density	300–600	71	120	212581	982843	59.17	21.63	2.74	161.85
Rheol. contrast: UTS	l36_l_rh61k	5.88–7.35	15	120	45031	982843	12.50	4.58	2.73	34.10
Strike: Crustal-scale shear zone	l28_s.fl1str	120–160°	43	120	132696	982843	35.83	13.50	2.65	95.10
Rheol. contrast: 10 classes	l36_l_rh21k	4–7	45	120	146535	982843	37.50	14.91	2.52	94.32
Dist: Reg. fault intersection	l34_s.f23pdst	0–1200 m	47	120	161988	982843	39.17	16.48	2.38	93.08
Dist: crustal-scale shear zone	l20_fl_dist	0–1400 m	42	120	145691	982843	35.00	14.82	2.36	82.64
Dist: +ve mag. anomaly ($Z \geq 2$)	l14_mz2_dist	0–600 m	49	120	183351	982843	40.83	18.66	2.19	89.38
Compressive Strength (UCS)	l2_l_rh5	187–250 MPa	89	120	322779	942843	74.17	34.23	2.17	160.68
Dist: rock contact	l39_c.dist	0–200m	89	120	339982	982843	74.17	34.59	2.14	159.02
Young's modulus, AMC^8	l2_l_rh4	70.0–82.3 GPa	82	120	342602	982843	68.33	34.86	1.96	133.96
Fracture toughness	l2_l_rh7	1.8–4.0 MPa	91	120	382172	982843	75.83	38.88	1.95	147.89
Tensile Strength (UTS)	l2_l_rh6	16.8–18.5 MPa	40	120	171630	942843	33.33	17.46	1.91	63.63
Metamorphic grade	l45_l.meta	2–3	90	120	395604	982843	75.00	40.25	1.86	139.75
Dist: regional NE fault	l22_d3.dist	0–800 m	92	120	405341	982843	76.67	41.24	1.86	142.52
Dist: +ve mag. anomaly ($Z \geq 2$)	l14_mz2_dist	0–1600 m	99	120	441094	982843	82.50	44.88	1.84	151.66
Fe^{3+}/Fe^{2+}	l3_l_ch5	0.13–0.78	99	120	452329	982843	82.50	46.02	1.79	147.89
Dist: +ve mag. anomaly ($Z \geq 1$)	l14_mz1_dist	0–400 m	60	120	294446	982843	50.00	29.96	1.67	83.45
Bouguer gravity anomaly	l12_grav	–560––330 $mGal$	105	120	515590	980863	87.50	52.56	1.66	145.65
Dist: +ve mag. anomaly ($Z \geq 1$)	l14_mz1_dist	0–1200 m	107	120	590922	982843	89.17	60.12	1.48	132.24
$Fe_2O_3/+FeO$	l3_l_ch4	0.10–0.19	13	120	73799	982843	10.83	7.51	1.44	15.63
Magnetic intensity (RTP)	l5_m_rtp	58100–59000 nT	11	120	63196	981560	9.17	6.44	1.42	13.05
Dist: regional NNE fault	l21_f2_dist	0–1200m	75	120	439080	982843	62.50	44.67	1.40	87.44

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Table G.2: *continued*

Layer Type	GIS Layer	Favourable values	Deposits		Cells		Deposits (%)	Area (%)	D/A	D*(D/A)
			fav. zone	total	fav. zone	total				
Dist: regional E fault	l23_d4_dist	0–400 m	13	120	81741	982843	10.83	8.32	1.30	14.11
Fe/(Fe+Mg+Ca)	l3_l_ch1	0.39–0.44	32	120	211741	982843	26.67	21.54	1.24	33.01
Dist: regional E fault	l23_d4_dist	0–800 m	23	120	157211	982843	19.17	16.00	1.20	22.97
Rock strength (10 classes)	l2_l_rh2	7–9	72	120	599181	982843	60.00	60.96	0.98	59.05
Rock strength (fuzzy)	l2_l_rh1	0.7–1.0	31	120	377225	982843	25.83	38.38	0.67	17.39
Dist: synclinal axes ⁹	l46_dist_sync	0–1000 m	1	120	64954	982843	0.83	6.61	0.13	0.11

¹l1favgeol25pr (abbreviated name used in ArcView) = l1_favgeolt25_pr0110 (name in text and Table 6.4 in Chapter 5 and in Matlab files, CD-ROM vol. 1).

²l1favgeol25pxtg (abbreviated name used in ArcView) = l1_favgeolt25_pxtg. See footnote above.

³l44favcnt25pr (abbreviated name used in ArcView) = l1_favcnt25_pr0110_200. See footnote above.

⁴l44favcnt25ptg (abbreviated name used in ArcView) = l1_favcnt25_pxtg0110_200. See footnote above.

⁵l44favc25pl300 (abbreviated name used in ArcView) = l1_favcnt25_pr_l300. See footnote above.

⁶l44favc25ptg1300 (abbreviated name used in ArcView) = l1_favcnt25_pxtg_l300. See footnote above.

⁷Young's modulus, CRC: Data from a compilation by Hatheway & Kiersch, 1989 (see Table 5.5 in Chapter 5).

⁸Young's modulus, AMC: Unpublished data provided by M. Lee, Australian Mining Consultants (AMC), 2000 (see Tables 5.5 in Chapter 5 & D.5 in Appendix D).

⁹ A negative association exists between deposits and the buffer zone for this layer. It was included for comparison with positive associations.

Table G.3: Ranking of potential GIS input layers using the statistic, $D \times (D/A)$, where D = percentage of known deposits in binary favourable region and A = percentage of total map area occupied by favourable region. Layers with the highest value of $D \times (D/A)$ were selected.

Layer Type	GIS Layer	Favourable values	Deposits		Cells		Deposits (%)	Area (%)	D/A	D*(D/A)
			fav. zone	total	fav. zone	total				
Fav. rock contact $P_{(deposit)}$	l44favcnt25pr ³	0–200 m	19	120	6186	982843	15.83	0.63	25.16	398.31
Fav. rock contacts, $P_{(dep.)} * TCG$	l44favcnt25ptg ⁴	0–200 m	22	120	10006	982843	18.33	1.02	18.01	330.15
Density: rock contact	l43_lith_diversity	710–1220	53	120	74491	982843	44.17	7.58	5.83	257.38
Fav. rock contact, $P_{(deposit)}$	l44fc25p1300 ⁵	0–1300 m	21	120	11993	982843	17.50	1.22	14.34	250.98
Fav. rock contact, $P_{(dep.)} * TCG$	l44f25ptg1300 ⁶	0–1300 m	26	120	18777	982843	21.67	1.91	11.34	245.72
Dist: anticlinal axis	l46_dist_anti	0–1800 m	65	120	174638	982843	54.17	17.77	3.05	165.12
Density: regional faults	l42_fl23_density	300–600	71	120	212581	982843	59.17	21.63	2.74	161.85
Compressive strength	l2_l_rh5	187–250 MPa	89	120	322779	942843	74.17	34.23	2.17	160.68
Dist: rock contact	l39_c.dist	0–200m	89	120	339982	982843	74.17	34.59	2.14	159.02
Dist: +ve mag. anomaly ($Z \geq 2$)	l14_mz2.dist	0–1600 m	99	120	441094	982843	82.50	44.88	1.84	151.66
Fracture toughness	l2_l_rh7	1.8–4.0 MPa	91	120	382172	982843	75.83	38.88	1.95	147.89
Fe^{3+}/Fe^{2+}	l3_l_ch5	0.13–0.78	99	120	452329	982843	82.50	46.02	1.79	147.89
Dist: porphyritic felsic intrusion	l4_l_pf.dist	0–1400 m	54	120	135252	982843	45.00	13.76	3.27	147.15
Bouguer gravity anomaly	l12_grav	–560– –330 mGal	105	120	515590	980863	87.50	52.56	1.66	145.65
Dist: porphyritic felsic intrusion	l4_l_pf.dist	0–400 m	32	120	48307	982843	26.67	4.92	5.43	144.68
Dist: regional NE fault	l22_d3.dist	0–800 m	92	120	405341	982843	76.67	41.24	1.86	142.52
Metamorphic grade	l45_l_meta	2–3	90	120	395604	982843	75.00	40.25	1.86	139.75
Strike: regional NE fault	l30_s_f3str	60–90, 140–180°	25	120	31086	982843	20.83	3.16	6.59	137.23
Young's modulus, AMC ⁸	l2_l_rh4	70.0–82.3 GPa	82	120	342602	982843	68.33	34.86	1.96	133.96
Dist: +ve mag. anomaly ($Z \geq 1$)	l14_mz1.dist	0–1200 m	107	120	590922	982843	89.17	60.12	1.48	132.24
Dist: regional NE fault	l22_d3.dist	0–200 m	50	120	141130	982843	41.67	14.36	2.90	120.90
Fav. host rock, $P_{(deposit)}$	l1favgeol25pr ¹	0.75–1.0	23	120	31199	982843	19.17	3.17	6.04	115.73
Rheol. contrast: Fuzzy	l36_l_rh1lk	0.68–0.85	24	120	35887	982843	20.00	3.65	5.48	109.55
Young's modulus, CRC ⁷	l2_l_rh3	80.1–95.2 GPa	16	120	16607	982843	13.33	1.69	7.89	105.21
Strike: crustal-scale shear zone	l28_s_flstr	120–160°	43	120	132696	982843	35.83	13.50	2.65	95.10

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Table G.3: *continued*

Layer Type	GIS Layer	Favourable values	Deposits		Cells		Deposits (%)	Area (%)	D/A	D*(D/A)
			fav. zone	total	fav. zone	total				
Rheol. contrast: 10 classes	l36_lrh21k	4-7	45	120	146535	982843	37.50	14.91	2.52	94.32
Dist: intersection regional fault	l34_s.f23pdst	0-1200 m	47	120	161988	982843	39.17	16.48	2.38	93.08
Chem. contrast: Fe/(Fe+Mg+Ca)	l37_lch11k	0.12-0.35	33	120	81085	982843	27.50	8.25	3.33	91.67
Strike: regional NW fault	l29_s.f2str	30-40°	9	120	6112	982843	7.50	0.62	12.06	90.45
Dist: +ve mag. anomaly ($Z \geq 2$)	l14_mz2_dist	0-600 m	49	120	183351	982843	40.83	18.66	2.19	89.38
Chem. contrast: Fe ₂ O ₃ /FeO	l37_lch41k	1.7-2.8	21	120	33971	982843	17.50	3.46	5.06	88.60
Chem. contrast: Fe ³⁺ /Fe ²⁺	l37_lch51k	1.5-2.5	21	120	33971	982843	17.50	3.46	5.06	88.60
Fe(wt%)*Fe/(Fe+Mg+Ca)	l3_lch2	4.3-4.8	14	120	15161	982843	11.67	1.54	7.56	88.24
Dist: regional NNW fault	l21_f2_dist	0-1200m	75	120	439080	982843	62.50	44.67	1.40	87.44
Fe ₂ O ₃ /(Fe ₂ O ₃ +FeO)	l3_lch3	0.19-0.26	14	120	15326	982843	11.67	1.56	7.48	87.29
Fav. host rock, P _(dep.) *TCG	l1favgeol25pxtg ²	0.75-1.0	35	120	96673	982843	29.17	9.84	2.97	86.49
Rheol. contrast: UCS	l36_lrh51k	148-169 MPa	5	120	2015	982843	4.17	0.21	20.32	84.68
Rheol. contrast: Young's mod. ⁸	l36_lrh41k	32.1-37.5 MPa	15	120	18144	982843	12.50	1.85	6.77	84.64
Dist: +ve mag. anomaly ($Z \geq 1$)	l14_mz1_dist	0-400 m	60	120	294446	982843	50.00	29.96	1.67	83.45
Dist: crustal-scale shear zone	l20_fl_dist	0-1400 m	42	120	145691	982843	35.00	14.82	2.36	82.64
Dist: crustal-scale shear zone	l20_fl_dist	0-400 m	22	120	45742	982843	18.33	4.65	3.94	72.22
Tensile Strength	l2_lrh6	16.8-18.5 MPa	40	120	171630	942843	33.33	17.46	1.91	63.63
Strike: rock contacts	l38_c_str1k	30-50, 110-120°	24	120	62015	982843	20.00	6.31	3.17	63.39
Rock strength (10 classes)	l2_lrh2	7-9	72	120	599181	982843	60.00	60.96	0.98	59.05
Chem. contrast: Fe(wt%)*Fe/(Fe+Mg+Ca)	l37_lch21k	4.0-4.4	6	120	4611	982843	5.00	0.47	10.66	53.29
Chem. contrast: Fe ₂ O ₃ /(Fe ₂ O ₃ +FeO)	l37_lch31k	0.42-0.60	13	120	23443	982843	10.83	2.39	4.54	49.20
Rheol. contrast: Fract. tough.	l36_lrh71k	2.24-2.52	12	120	22064	982843	10.00	2.24	4.45	44.55
Rheol. contrast: UTS	l36_lrh61k	5.88-7.35	15	120	45031	982843	12.50	4.58	2.73	34.10
Fe/(Fe+Mg+Ca)	l3_lch1	0.39-0.44	32	120	211741	982843	26.67	21.54	1.24	33.01
Rheol. contrast: Young's mod. ⁷	l36_lrh31k	62.3-69.2 MPa	3	120	2067	982843	2.50	0.21	11.89	29.72
Strike: regional E fault	l31_s.f4str	130-150°	10	120	25390	982843	8.33	2.58	3.23	26.88

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Table G.3: *continued*

Layer Type	GIS Layer	Favourable values	Deposits		Cells		Deposits (%)	Area (%)	D/A	D*(D/A)
			fav. zone	total	fav. zone	total				
Dist: regional E fault	l23_d4_dist	0–800 m	23	120	157211	982843	19.17	16.00	1.20	22.97
Rock strength (fuzzy)	l2_lrh1	0.7–1.0	31	120	377225	982843	25.83	38.38	0.67	17.39
Fe ₂ O ₃ /Fe ₂ O ₃	l3_lch4	0.10–0.19	13	120	73799	982843	10.83	7.51	1.44	15.63
Dist: regional E faults	l23_d4_dist	0–400 m	13	120	81741	982843	10.83	8.32	1.30	14.11
Magnetic intensity (RTP)	l5_m_rtp	58100–59000 nT	11	120	63196	981560	9.17	6.44	1.42	13.05
Dist: synclinal axis ⁹	l46_dist_sync	0–1000 m	1	120	64954	982843	0.83	6.61	0.13	0.11

¹l1favgeol25pr (abbreviated name used in ArcView) = l1_favgeolt25_pr0110 (name in text and Table 6.4 in Chapter 5 and in Matlab files, CD-ROM vol. 1).

²l1favgeol25pxtg (abbreviated name used in ArcView) = l1_favgeolt25_pxtg. See footnote above.

³l44favcnt25pr (abbreviated name used in ArcView) = l1_favcont25_pr0110_200. See footnote above.

⁴l44favcnt25ptg (abbreviated name used in ArcView) = l1_favcont25_pxtg0110_200. See footnote above.

⁵l44favc25pl300 (abbreviated name used in ArcView) = l1_favcont25_pr_l300. See footnote above.

⁶l44favc25ptg1300 (abbreviated name used in ArcView) = l1_favcont25_pxtg_l300. See footnote above.

⁷Young's modulus, CRC: Data from a compilation by Hatheway & Kiersch, 1989 (see Table 5.5 in Chapter 5).

⁸Young's modulus, AMC: Unpublished data provided by M. Lee, Australian Mining Consultants (AMC), 2000 (see Tables 5.5 in Chapter 5 & D.5 in Appendix D).

⁹ A negative association exists between deposits and the buffer zone for this layer. It was included for comparison with positive associations.

Table G.4: Ranking of potential GIS input layers using a combination of statistics, i.e. $D \times D/A$, $AND\ D/A \geq \sim 3$, $AND\ D \geq \sim 20\%$, where D = percentage of known deposits in binary favourable region and A = percentage of total map area occupied by favourable region. Layers with the highest value of $D \times (D/A)$ where $and\ D/A \geq \sim 3$, $and\ D \geq \sim 20\%$ were selected.

Layer Type	GIS Layer	Favourable values	Deposits		Cells		Deposits (%)	Area (%)	D/A	D*(D/A)
			fav. zone	total	fav. zone	total				
Fav. rock contact, $P_{(deposit)}$	l44favcnt25pr ³	0-200 m	19	120	6186	982843	15.83	0.63	25.16	398.31
Fav. rock contact $P_{(dep.)} * TCG$	l44favcnt25ptg ⁴	0-200 m	22	120	10006	982843	18.33	1.02	18.01	330.15
Density: rock contacts	l43_lith_diversity	710-1220	53	120	74491	982843	44.17	7.58	5.83	257.38
Fav. rock contact, $P_{(deposit)}$	l44fc25p1300 ⁵	0-1300 m	21	120	11993	982843	17.50	1.22	14.34	250.98
Fav. rock contact $P_{(dep.)} * TCG$	l44f25ptg1300 ⁶	0-1300 m	26	120	18777	982843	21.67	1.91	11.34	245.72
Dist: anticlinal axis	l46_dist_anti	0-1800 m	65	120	174638	982843	54.17	17.77	3.05	165.12
Density: regional faults	l42_fl23_density	300-600	71	120	212581	982843	59.17	21.63	2.74	161.85
Compressive Strength	l2_l_rh5	187-250 MPa	89	120	322779	942843	74.17	34.23	2.17	160.68
Dist: rock contact	l39_c_dist	0-200m	89	120	339982	982843	74.17	34.59	2.14	159.02
Dist: +ve mag. anomaly ($Z \geq 2$)	l14_mz2_dist	0-1600 m	99	120	441094	982843	82.50	44.88	1.84	151.66
Fracture toughness	l2_l_rh7	1.8-4.0 MPa	91	120	382172	982843	75.83	38.88	1.95	147.89
Fe^{3+}/Fe^{2+}	l3_l_ch5	0.13-0.78	99	120	452329	982843	82.50	46.02	1.79	147.89
Dist: porphyritic felsic intrusion	l4_l_pf_dist	0-1400 m	54	120	135252	982843	45.00	13.76	3.27	147.15
Bouguer gravity anomaly	l12_grav	-560- -330 $mGal$	105	120	515590	980863	87.50	52.56	1.66	145.65
Dist: porphyritic felsic intrusions	l4_l_pf_dist	0-400 m	32	120	48307	982843	26.67	4.92	5.43	144.68
Dist: regional NE fault	l22_d3_dist	0-800 m	92	120	405341	982843	76.67	41.24	1.86	142.52
Metamorphic grade	l45_l_meta	2-3	90	120	395604	982843	75.00	40.25	1.86	139.75
Strike: regional NE fault	l30_s_f3str	60-90, 140-180°	25	120	31086	982843	20.83	3.16	6.59	137.23
Young's modulus, AMC^8	l2_l_rh4	70.0-82.3 GPa	82	120	342602	982843	68.33	34.86	1.96	133.96
Dist: +ve mag. anomaly ($Z \geq 1$)	l14_mz1_dist	0-1200 m	107	120	590922	982843	89.17	60.12	1.48	132.24
Dist: regional NE fault	l22_d3_dist	0-200 m	50	120	141130	982843	41.67	14.36	2.90	120.90
Fav. host rock, $P_{(deposit)}$	l1favgeol25pr ¹	0.75-1.0	23	120	31199	982843	19.17	3.17	6.04	115.73
Rheol. contrast Fuzzy	l36_l_rh1lk	0.68-0.85	24	120	35887	982843	20.00	3.65	5.48	109.55
Young's modulus, CRC^7	l2_l_rh3	80.1-95.2 GPa	16	120	16607	982843	13.33	1.69	7.89	105.21

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Table G.4: *continued*

Layer Type	GIS Layer	Favourable values	Deposits		Cells		Deposits (%)	Area (%)	D/A	D*(D/A)
			fav. zone	total	fav. zone	total				
Strike: crustal-scale shear zone	l28_s.flstr	120–160°	43	120	132696	982843	35.83	13.50	2.65	95.10
Rheol. contrast: 10 classes	l36_l.rh21k	4–7	45	120	146535	982843	37.50	14.91	2.52	94.32
Dist: intersection regional fault	l34_s.f23pdst	0–1200 m	47	120	161988	982843	39.17	16.48	2.38	93.08
Chem. contrast: Fe/(Fe+Mg+Ca)	l37_l.ch11k	0.12–0.35	33	120	81085	982843	27.50	8.25	3.33	91.67
Strike: regional NW fault	l29_s.f2str	30–40°	9	120	6112	982843	7.50	0.62	12.06	90.45
Dist: +ve mag. anomaly ($Z \geq 2$)	l14_mz2.dist	0–600 m	49	120	183351	982843	40.83	18.66	2.19	89.38
Chem. contrast: Fe ₂ O ₃ /Fe ₂ O ₃ +FeO	l37_l.ch41k	1.7–2.8	21	120	33971	982843	17.50	3.46	5.06	88.60
Chem. contrast: Fe ³⁺ /Fe ²⁺	l37_l.ch51k	1.5–2.5	21	120	33971	982843	17.50	3.46	5.06	88.60
Fe(wt%)*Fe/(Fe+Mg+Ca)	l3_l.ch2	4.3–4.8	14	120	15161	982843	11.67	1.54	7.56	88.24
Dist: regional NNW fault	l21_f2.dist	0–1200m	75	120	439080	982843	62.50	44.67	1.40	87.44
Fe ₂ O ₃ /(Fe ₂ O ₃ +FeO)	l3_l.ch3	0.19–0.26	14	120	15326	982843	11.67	1.56	7.48	87.29
Fav. host rock, $P_{(dep.)}$ *TCG	l1favgeol25pxtg ²	0.75–1.0	35	120	96673	982843	29.17	9.84	2.97	86.49
Rheol. contrast: UCS	l36_l.rh51k	148–169 MPa	5	120	2015	982843	4.17	0.21	20.32	84.68
Rheol. contrast: Young's mod. ⁸	l36_l.rh41k	32.1–37.5 MPa	15	120	18144	982843	12.50	1.85	6.77	84.64
Dist: +ve mag. anomaly ($Z \geq 1$)	l14_mz1.dist	0–400 m	60	120	294446	982843	50.00	29.96	1.67	83.45
Dist: crustal-scale shear zones	l20_fl.dist	0–1400 m	42	120	145691	982843	35.00	14.82	2.36	82.64
Dist: crustal-scale shear zone	l20_fl.dist	0–400 m	22	120	45742	982843	18.33	4.65	3.94	72.22
Uniaxial Tensile Strength	l2_l.rh6	16.8–18.5 MPa	40	120	171630	942843	33.33	17.46	1.91	63.63
Strike: rock contacts	l38_c.str1k	30–50, 110–120°	24	120	62015	982843	20.00	6.31	3.17	63.39
Rock strength (10 classes)	l2_l.rh2	7–9	72	120	599181	982843	60.00	60.96	0.98	59.05
Chem. contrast: Fe(wt%)*Fe/(Fe+Mg+Ca)	l37_l.ch21k	4.0–4.4	6	120	4611	982843	5.00	0.47	10.66	53.29
Chem. contrast: Fe ₂ O ₃ /FeO	l37_l.ch31k	0.42–0.60	13	120	23443	982843	10.83	2.39	4.54	49.20
Rheol. contrast: Fract. tough.	l36_l.rh71k	2.24–2.52	12	120	22064	982843	10.00	2.24	4.45	44.55
Rheol. contrast: UTS	l36_l.rh61k	5.88–7.35	15	120	45031	982843	12.50	4.58	2.73	34.10
Fe/(Fe+Mg+Ca)	l3_l.ch1	0.39–0.44	32	120	211741	982843	26.67	21.54	1.24	33.01
Rheol. contrast: Young's mod. ⁷	l36_l.rh31k	62.3–69.2 MPa	3	120	2067	982843	2.50	0.21	11.89	29.72
Strike: regional E fault	l31_s.f4str	130–150°	10	120	25390	982843	8.33	2.58	3.23	26.88

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Table G.4: *continued*

Layer Type	GIS Layer	Favourable values	Deposits		Cells		Deposits (%)	Area (%)	D/A	D*(D/A)
			fav. zone	total	fav. zone	total				
Dist: regional E fault	l23_d4_dist	0–800 m	23	120	157211	982843	19.17	16.00	1.20	22.97
Rock strength (fuzzy)	l2_lrh1	0.7–1.0	31	120	377225	982843	25.83	38.38	0.67	17.39
Fe ₂ O ₃ /FeO	l3_lch4	0.10–0.19	13	120	73799	982843	10.83	7.51	1.44	15.63
Dist: regional E faults	l23_d4_dist	0–400 m	13	120	81741	982843	10.83	8.32	1.30	14.11
Magnetic intensity (RTP)	l5_m_rtp	58100–59000 nT	11	120	63196	981560	9.17	6.44	1.42	13.05
Dist: synclinal axis ⁹	l46_dist_sync	0–1000 m	1	120	64954	982843	0.83	6.61	0.13	0.11

¹l1favgeol25pr (abbreviated name used in ArcView) = l1_favgeolt25_pr0110 (name in text and Table 6.4 in Chapter 5 and in Matlab files, CD-ROM vol. 1).

²l1favgeol25pxtg (abbreviated name used in ArcView) = l1_favgeolt25_pxtg. See footnote above.

³l44favcnt25pr (abbreviated name used in ArcView) = l1_favcont25_pr0110_200. See footnote above.

⁴l44favcnt25ptg (abbreviated name used in ArcView) = l1_favcont25_pxtg0110_200. See footnote above.

⁵l44favc25pl300 (abbreviated name used in ArcView) = l1_favcont25_pr_l300. See footnote above.

⁶l44favc25ptg1300 (abbreviated name used in ArcView) = l1_favcont25_pxtg_l300. See footnote above.

⁷Young's modulus, CRC: Data from a compilation by Hatheway & Kiersch, 1989 (see Table 5.5 in Chapter 5).

⁸Young's modulus, AMC: Unpublished data provided by M. Lee, Australian Mining Consultants (AMC), 2000 (see Tables 5.5 in Chapter 5 & D.5 in Appendix D).

⁹ A negative association exists between deposits and the buffer zone for this layer. It was included for comparison with positive associations.

Appendix H

Results of Neural Network Experiments: Kalgoorlie Case Study

Table H.1. MLP 10-5-1,(categories),traingdx, random split into 3 training pattern sets, same init. wts

Training set size		Training: 99 patterns (46 deposits, 53 barren), training-stop: = 88 (39 deposits, 49 barren), test = 81 (35 deposits, 46 barren)																	
Training set type		Randomly selected cells, approximately equal numbers of patterns from each rock type																	
Geology input format		Fuzzy membership values																	
Learn. Algorith.	l.r. Cycles	MSE	Train % correct			Stop % correct			Test % correct			Map % correct			Map statistics			D%*D%/A%	ROC
		Initial	Final	All	Deps	Non	All	Deps	Non	All	Deps	Non	All	Deps	Chi	rho	D%/A%		
traingdx	0.5 489	0.2838	0.0913	75.76	69.57	81.13	80.68	74.36	85.71	62.96	42.86	78.26	86.57	63.33	635.92	0.93	19.67	262.31	0.81
traingdx	0.5 341	0.2921	0.0936	78.79	71.74	84.91	65.91	71.79	61.22	60.49	48.57	69.57	64.28	65.00	246.22	0.95	11.64	155.13	0.72
traingdx	0.5 465	0.2819	0.1194	72.73	56.52	86.79	69.32	53.85	81.63	65.43	42.86	82.61	86.97	51.67	474.74	0.98	19.28	160.63	0.79
traingdx	0.5 210	0.3122	0.1248	70.71	71.74	69.81	59.09	48.72	67.35	64.20	51.43	73.91	71.03	58.33	92.70	0.44	0.00	0.00	0.70
traingdx	0.5 306	0.3052	0.1115	73.74	63.04	83.02	72.73	64.10	79.59	75.31	57.14	89.13	82.61	61.67	419.05	0.98	18.46	169.23	0.80
traingdx	0.5 239	0.2723	0.1469	63.64	71.74	56.60	50.00	64.10	38.78	51.85	71.43	36.96	41.68	69.17	10.40	-0.07	0.00	0.00	0.53
traingdx	0.5 285	0.2804	0.1263	68.69	52.17	83.02	62.50	38.46	81.63	72.84	48.57	91.30	89.65	46.67	430.35	0.98	15.35	179.08	0.71
traingdx	0.5 327	0.2637	0.1282	70.71	63.04	77.36	67.05	56.41	75.51	70.37	51.43	84.78	81.58	57.50	258.31	0.98	12.41	31.02	0.75
traingdx	0.5 418	0.2908	0.0778	83.84	78.26	88.68	75.00	56.41	89.80	74.07	62.86	82.61	83.73	66.67	496.58	0.98	14.71	208.40	0.81
traingdx	0.5 462	0.2910	0.0789	84.85	78.26	90.57	73.86	69.23	77.55	67.90	65.71	69.57	71.00	71.67	360.77	0.93	8.93	148.78	0.79
Average	354	0.2873	0.1099	74.35	67.61	80.19	67.61	59.74	73.88	66.54	54.29	75.87	75.91	61.17	342.50	0.81	12.04	131.46	0.74

Table H.2. MLP 10-5-1, 10 input layers, (categories), Effect of random selection of training patterns, Training pattern set 1

Training set size		Training: 99 patterns (46 deposits, 53 barren), training-stop: = 88 (39 deposits, 49 barren), test = 81 (35 deposits, 46 barren)																			
Training set type		Randomly selected cells, approximately equal numbers of patterns from each rock type																			
Geology input format		Fuzzy membership values																			
Learn. Algorith.	l.r. Cycles	MSE			Train % correct			Stop % correct			Test % correct			Map % correct			Map statistics			D%-D%/A%	ROC
		Initial	Final	All	Deps	Non	All	Deps	Non	All	Deps	Non	All	Deps	Non	Chi	rho	D%/A%			
traingd	0.5 11768	0.2838	0.0893	79.80	78.26	81.13	79.55	71.79	85.71	61.73	42.86	76.09	86.58	65.83	679.71	0.92	21.44	375.17	0.82		
traingd	0.5 1263	0.2808	0.1117	73.74	73.91	73.58	73.86	66.67	79.59	55.56	48.57	60.87	68.11	64.17	142.39	0.98	13.62	79.46	0.70		
traingd	0.5 1363	0.2692	0.1359	63.64	36.96	86.79	64.77	35.90	87.76	59.26	31.43	80.43	88.59	35.00	370.74	1.00	22.49	206.16	0.70		
traingd	0.5 8843	0.2037	0.0779	82.83	71.74	92.45	73.86	64.10	81.63	58.02	40.00	71.74	82.97	60.00	418.42	0.98	13.66	296.05	0.79		
traingd	0.5 8921	0.2172	0.0782	83.84	78.26	88.68	78.41	69.23	85.71	61.73	45.71	73.91	78.42	65.83	230.30	0.95	6.07	131.54	0.80		
traingd	0.5 1408	0.1533	0.1003	79.80	78.26	81.13	75.00	66.67	81.63	62.96	51.43	71.74	80.81	66.67	550.39	0.95	22.59	263.55	0.79		
traingd	0.5 2894	0.3009	0.0877	77.78	69.57	84.91	75.00	69.23	79.59	61.73	45.71	73.91	82.39	62.50	335.40	0.95	7.43	86.73	0.79		
traingd	0.5 6650	0.2343	0.0792	83.84	73.91	92.45	72.73	61.54	81.63	60.49	42.86	73.91	76.12	60.83	327.84	0.97	10.51	210.29	0.77		
traingd	0.5 5669	0.2468	0.0868	78.79	76.09	81.13	72.73	66.67	77.55	59.26	40.00	73.91	76.91	62.50	397.35	0.95	15.76	236.36	0.79		
traingd	0.5 6236	0.3612	0.0951	78.79	67.39	88.68	72.73	56.41	85.71	56.79	37.14	71.74	85.31	55.00	288.10	0.97	8.96	164.30	0.78		
Average	5502	0.2551	0.0942	78.29	70.44	85.09	73.86	62.82	82.65	59.75	42.57	72.83	80.62	59.83	374.06	0.96	14.25	204.96	0.77		

Table H.3. MLP 10-5-1, 10 input layers, (categories), Effect of random selection of training patterns, Training pattern set 2

Training set size		Training: 99 patterns (46 deposits, 53 barren), training-stop: = 88 (39 deposits, 49 barren), test = 81 (35 deposits, 46 barren)															
Training set type		Randomly selected cells, approximately equal numbers of patterns from each rock type															
Geology input format		Fuzzy membership values															
Learn. Algorith.	l.r. Cycles	MSE		Train % correct			Stop % correct			Test % correct			Map % correct		Map statistics		
		Initial	Final	All	Depos	Non	All	Depos	Non	All	Depos	Non	All	Depos	Chi	rho	D%/A% D%D%/A% ROC
traingd	0.5	2780		0.2921	0.0930	78.79	71.74	84.91	65.91	71.79	61.22	60.49	48.57	69.57	64.49	65.00	215.12 0.95 10.07 117.51 0.72
traingd	0.5	4615		0.3046	0.0844	79.80	76.09	83.02	72.73	79.49	67.35	64.20	57.14	69.57	70.53	71.67	807.84 0.98 38.76 516.79 0.79
traingd	0.5	3093		0.2915	0.0800	84.85	82.61	86.79	71.59	79.49	65.31	65.43	62.86	67.39	69.65	75.83	355.06 0.95 9.08 68.10 0.80
traingd	0.5	7433		0.3348	0.0894	79.80	73.91	84.91	68.18	79.49	59.18	59.26	57.14	60.87	60.07	70.83	424.61 0.78 20.37 271.57 0.75
traingd	0.5	4564		0.2571	0.0986	76.77	76.09	77.36	67.05	71.79	63.27	61.73	57.14	65.22	74.48	69.17	796.02 0.93 35.94 509.17 0.79
traingd	0.5	1372		0.1251	0.0894	79.80	69.57	88.68	70.45	71.79	69.39	65.43	54.29	73.91	65.39	65.83	102.54 0.92 4.27 42.69 0.72
traingd	0.5	2409		0.2581	0.0999	76.77	76.09	77.36	70.45	82.05	61.22	62.96	57.14	67.39	77.80	72.50	718.84 1.00 26.56 509.03 0.83
traingd	0.5	547		0.2291	0.1326	61.62	45.65	75.47	61.36	46.15	73.47	61.73	45.71	73.91	91.94	45.83	772.15 0.93 41.20 514.99 0.79
traingd	0.5	3529		0.3912	0.1004	76.77	65.22	86.79	68.18	56.41	77.55	64.20	40.00	82.61	78.60	55.00	376.48 0.98 17.42 275.79 0.73
traingd	0.5	1265		0.2835	0.1011	75.76	69.57	81.13	70.45	74.36	67.35	64.20	60.00	67.39	70.35	68.33	255.76 1.00 8.72 65.37 0.78
Average		3161		0.2767	0.0969	77.07	70.65	82.64	68.64	71.28	66.53	62.96	54.00	69.78	72.33	66.00	482.44 0.94 21.24 289.10 0.77

Table H.4. MLP 10-5-1, 10 input layers, (categories), Effect of random selection of training patterns, Training pattern set 3

Training set size		Training: 99 patterns (46 deposits, 53 barren), training-stop: = 88 (39 deposits, 49 barren), test = 81 (35 deposits, 46 barren)															
Training set type		Randomly selected cells, approximately equal numbers of patterns from each rock type															
Geology input format		Fuzzy membership values															
Learn. Algorith.	l.r. Cycles	MSE		Train % correct			Stop % correct			Test % correct			Map % correct		Map statistics		
		Initial	Final	All	Depos	Non	All	Depos	Non	All	Depos	Non	All	Depos	Chi	rho	D%/A% D%D%/A% ROC
traingd	0.5	9206		0.2819	0.1149	74.75	69.57	79.25	69.32	61.54	75.51	64.20	51.43	73.91	81.11	61.67	500.60 1.00 19.16 287.42 0.80
traingd	0.5	2929		0.3044	0.1105	76.77	71.74	81.13	67.05	66.67	67.35	72.84	68.57	76.09	79.19	69.17	499.38 0.98 15.25 25.42 0.80
traingd	0.5	1617		0.2969	0.1158	74.75	76.09	73.58	68.18	66.67	69.39	65.43	60.00	69.57	77.42	68.33	219.49 0.82 1.93 1.61 0.80
traingd	0.5	5280		0.3345	0.1238	71.72	56.52	84.91	69.32	66.67	71.43	69.14	57.14	78.26	88.58	60.00	589.26 0.95 6.68 11.14 0.80
traingd	0.5	8897		0.2227	0.1111	74.75	69.57	79.25	68.18	64.10	71.43	66.67	48.57	80.43	84.64	61.67	339.68 0.95 5.71 23.78 0.83
traingd	0.5	13		0.1611	0.1492	66.67	54.35	77.36	67.05	58.97	73.47	62.96	51.43	71.74	65.42	55.00	71.83 0.48 0.33 0.56 0.64
traingd	0.5	1633		0.2529	0.1275	69.70	56.52	81.13	76.14	66.67	83.67	64.20	45.71	78.26	88.86	56.67	595.91 0.47 0.00 0.00 0.85
traingd	0.5	4709		0.2067	0.1203	70.71	67.39	73.58	77.27	69.23	83.67	72.84	65.71	78.26	80.65	67.50	863.33 1.00 56.58 377.22 0.81
traingd	0.5	2984		0.3942	0.1345	67.68	56.52	77.36	64.77	66.67	63.27	64.20	65.71	63.04	75.87	62.50	466.41 0.98 21.50 89.57 0.78
traingd	0.5	4872		0.2508	0.1035	75.76	73.91	77.36	67.05	66.67	67.35	66.67	62.86	69.57	78.55	68.33	247.14 0.97 4.63 19.28 0.82
Average		4214		0.2712	0.1211	72.33	65.22	78.49	69.43	65.39	72.65	66.92	57.71	73.91	80.03	63.08	439.30 0.86 13.18 83.60 0.79

Table H.5. MLP 10-5-1, 10 input layers, (categories), Effect of random selection of training patterns, Training pattern set 4

Training set size		Training: 99 patterns (46 deposits, 53 barren), training-stop: = 88 (39 deposits, 49 barren), test = 81 (35 deposits, 46 barren)																				
Training set type		Randomly selected cells, approximately equal numbers of patterns from each rock type																				
Geology input format		Fuzzy membership values																				
Learn.	l.r.	Cycles	MSE			Train % correct			Stop % correct			Test % correct			Map % correct			Map statistics			D%*D%/A%	ROC
			Initial	Final	All	Depos	Non	All	Depos	Non	All	Depos	Non	All	Depos	Non	All	Chi	rho	D%/A%		
traingd	0.5	655	0.3122	0.1243	71.72	71.74	71.70	59.09	48.72	67.35	64.20	51.43	73.91	71.42	58.33	95.19	0.44	0.00	0.00	0.70		
traingd	0.5	760	0.3051	0.1118	73.74	67.39	79.25	63.64	53.85	71.43	70.37	54.29	82.61	89.11	59.17	754.33	0.95	29.53	369.16	0.78		
traingd	0.5	1794	0.2797	0.0939	78.79	78.26	79.25	64.77	51.28	75.51	70.37	48.57	86.96	88.16	60.83	551.33	0.95	9.12	53.20	0.82		
traingd	0.5	400	0.3601	0.1314	70.71	58.70	81.13	57.95	38.46	73.47	69.14	42.86	89.13	83.72	47.50	175.16	0.87	4.05	20.23	0.67		
traingd	0.5	3465	0.2378	0.0975	74.75	63.04	84.91	65.91	46.15	81.63	72.84	51.43	89.13	88.28	54.17	627.67	0.98	24.75	268.13	0.79		
traingd	0.5	163	0.1445	0.1209	70.71	63.04	77.36	68.18	48.72	83.67	69.14	51.43	82.61	73.99	55.00	97.00	0.87	1.75	5.83	0.70		
traingd	0.5	484	0.2615	0.1110	77.78	71.74	83.02	65.91	56.41	73.47	66.67	45.71	82.61	88.75	59.17	589.73	1.00	31.58	315.82	0.82		
traingd	0.5	427	0.2247	0.1270	67.68	58.70	75.47	56.82	33.33	75.51	58.02	40.00	71.74	90.22	45.00	695.13	0.98	47.32	473.20	0.77		
traingd	0.5	1841	0.3988	0.0993	78.79	69.57	86.79	61.36	43.59	75.51	71.60	51.43	86.96	82.95	55.83	794.35	0.98	22.06	459.58	0.78		
traingd	0.5	504	0.2891	0.1336	69.70	69.57	69.81	63.64	53.85	71.43	67.90	45.71	84.78	80.72	57.50	187.18	0.95	4.53	15.09	0.74		
Average		1049	0.2814	0.1151	73.44	67.18	78.87	62.73	47.44	74.90	68.03	48.29	83.04	83.73	55.25	456.71	0.90	17.47	198.02	0.76		

Table H.6. MLP 10-5-1, 10 input layers, (categories), Effect of random selection of training patterns, Training pattern set 5

Training set size	Training: 99 patterns (46 deposits, 53 barren), training-stop: = 88 (39 deposits, 49 barren), test = 81 (35 deposits, 46 barren)																							
Training set type	Randomly selected cells, approximately equal numbers of patterns from each rock type																							
Geology input format	Fuzzy membership values																							
Learn.	l.r.	Cycles	MSE			Train % correct			Stop % correct			Test % correct			Map % correct			Map statistics						
Algorith.			Initial	Final	All	Depos	Non	All	Depos	Non	All	Depos	Non	All	Depos	Non	All	Depos	Non	Chi	rho	D%/A%	D%-D%/A%	ROC
traingd	0.5	1864	0.3052	0.1106	73.74	63.04	83.02	72.73	64.10	79.59	75.31	57.14	89.13	82.40	61.67	417.97	0.98	19.08	174.90	0.80				
traingd	0.5	5270	0.3092	0.0883	79.80	80.43	79.25	75.00	76.92	73.47	72.84	68.57	76.09	73.36	75.83	358.08	0.95	6.07	45.50	0.82				
traingd	0.5	3555	0.2896	0.0815	81.82	82.61	81.13	72.73	69.23	75.51	71.60	62.86	78.26	80.87	72.50	280.98	0.97	7.90	72.40	0.82				
traingd	0.5	1854	0.3410	0.1228	71.72	54.35	86.79	64.77	53.85	73.47	74.07	60.00	84.78	91.06	55.83	639.47	0.98	9.58	55.88	0.77				
traingd	0.5	9497	0.2200	0.0835	82.83	80.43	84.91	69.32	74.36	65.31	70.37	68.57	71.74	77.44	75.00	297.01	0.97	6.98	116.41	0.83				
traingd	0.5	786	0.1649	0.1076	70.71	60.87	79.25	68.18	61.54	73.47	65.43	45.71	80.43	77.37	56.67	376.06	0.98	14.25	284.96	0.78				
traingd	0.5	512	0.2484	0.1218	73.74	65.22	81.13	67.05	58.97	73.47	67.90	62.86	71.74	83.54	62.50	332.38	0.98	8.77	14.62	0.83				
traingd	0.5	3687	0.2196	0.0806	81.82	80.43	83.02	69.32	64.10	73.47	76.54	68.57	82.61	68.44	71.67	194.48	0.98	7.98	73.18	0.78				
traingd	0.5	7923	0.4005	0.0774	83.84	78.26	88.68	72.73	64.10	79.59	70.37	60.00	78.26	79.16	68.33	232.47	1.00	8.14	95.00	0.81				
traingd	0.5	3004	0.2617	0.0843	81.82	76.09	86.79	65.91	66.67	65.31	66.67	60.00	71.74	80.71	68.33	232.15	1.00	6.21	31.04	0.82				
Average		3795	0.2760	0.0958	78.18	72.17	83.40	69.77	65.38	73.27	71.11	61.43	78.48	79.44	66.83	336.11	0.98	9.50	96.39	0.80				

Table H.7. MLP 10-5-1, 10 input layers, (categories), Effect of random selection of training patterns, Training pattern set 6

Training set size		Training: 99 patterns (46 deposits, 53 barren), training-stop: = 88 (39 deposits, 49 barren), test = 81 (35 deposits, 46 barren)															
Training set type		Randomly selected cells, approximately equal numbers of patterns from each rock type															
Geology input format		Fuzzy membership values															
Learn. Algorith.	l.r. Cycles	MSE		Train % correct			Stop % correct			Test % correct			Map % correct		Map statistics		
		Initial	Final	All	Deps	Non	All	Deps	Non	All	Deps	Non	All	Deps	Chi	rho	D%/A% D%*D%/A% ROC
traingd	0.5 894	0.2723	0.1469	63.64	71.74	56.60	50.00	64.10	38.78	50.62	68.57	36.96	41.64	68.33	12.45	-0.17	0.00 0.00 0.53
traingd	0.5 732	0.3043	0.1241	69.70	71.74	67.92	63.64	64.10	63.27	66.67	60.00	71.74	77.74	65.83	842.27	0.98	85.09 283.65 0.79
traingd	0.5 363	0.2952	0.1217	72.73	76.09	69.81	62.50	66.67	59.18	62.96	60.00	65.22	81.30	68.33	476.93	0.90	5.64 18.79 0.80
traingd	0.5 344	0.3576	0.1430	64.65	47.83	79.25	61.36	41.03	77.55	65.43	42.86	82.61	88.89	44.17	343.34	0.96	9.64 56.26 0.69
traingd	0.5 1247	0.2242	0.1287	66.67	54.35	77.36	59.09	41.03	73.47	71.60	57.14	82.61	87.48	50.83	344.83	0.98	13.63 170.42 0.81
traingd	0.5 15	0.1564	0.1455	65.66	54.35	75.47	65.91	53.85	75.51	64.20	45.71	78.26	67.29	51.67	58.97	0.50	0.37 0.62 0.65
traingd	0.5 306	0.2691	0.1387	66.67	45.65	84.91	65.91	46.15	81.63	71.60	48.57	89.13	90.77	46.67	632.92	0.40	0.00 0.00 0.81
traingd	0.5 6	0.1859	0.1859	55.56	30.43	77.36	52.27	35.90	65.31	55.56	31.43	73.91	72.28	32.50	30.27	0.32	2.53 2.11 0.57
traingd	0.5 2531	0.3934	0.1184	68.69	65.22	71.70	59.09	53.85	63.27	65.43	57.14	71.74	76.35	59.17	625.62	0.97	20.97 87.37 0.78
traingd	0.5 7771	0.2637	0.0609	88.89	89.13	88.68	68.18	64.10	71.43	79.01	71.43	84.78	79.24	75.83	372.27	1.00	10.32 206.45 0.84
Average	1421	0.2722	0.1314	68.29	60.65	74.91	60.80	53.08	66.94	65.31	54.29	73.70	76.30	56.33	373.99	0.68	14.82 82.57 0.73

Table H.8. MLP 10-5-1, 10 input layers, (categories), Effect of random selection of training patterns, Training pattern set 7

Training set size		Training: 99 patterns (46 deposits, 53 barren), training-stop: = 88 (39 deposits, 49 barren), test = 81 (35 deposits, 46 barren)															
Training set type		Randomly selected cells, approximately equal numbers of patterns from each rock type															
Geology input format		Fuzzy membership values															
Learn. Algorith.	l.r. Cycles	MSE		Train % correct			Stop % correct			Test % correct			Map % correct		Map statistics		
		Initial	Final	All	Deps	Non	All	Deps	Non	All	Deps	Non	All	Deps	Chi	rho	D%/A% D%*D%/A% ROC
traingd	0.5 1535	0.2804	0.1250	69.70	52.17	84.91	63.64	38.46	83.67	72.84	48.57	91.30	90.08	46.67	435.40	0.98	16.99 212.43 0.71
traingd	0.5 928	0.2979	0.1147	74.75	63.04	84.91	64.77	46.15	79.59	71.60	54.29	84.78	89.33	55.00	577.37	0.95	26.71 178.08 0.78
traingd	0.5 2341	0.2824	0.1025	78.79	73.91	83.02	68.18	51.28	81.63	70.37	68.57	71.74	82.94	65.00	491.33	0.92	8.94 81.94 0.81
traingd	0.5 702	0.3786	0.1377	65.66	50.00	79.25	63.64	35.90	85.71	69.14	54.29	80.43	89.47	46.67	301.67	0.98	13.87 138.68 0.69
traingd	0.5 3019	0.2052	0.0994	77.78	65.22	88.68	59.09	33.33	79.59	70.37	45.71	89.13	89.55	49.17	448.59	0.93	15.59 168.86 0.74
traingd	0.5 2036	0.1614	0.0968	81.82	73.91	88.68	73.86	58.97	85.71	69.14	54.29	80.43	82.69	63.33	595.71	0.98	25.71 321.34 0.79
traingd	0.5 1836	0.2534	0.1033	77.78	67.39	86.79	63.64	38.46	83.67	71.60	42.86	93.48	89.43	50.83	556.36	0.93	25.04 333.90 0.80
traingd	0.5 424	0.2163	0.1332	67.68	52.17	81.13	56.82	23.08	83.67	71.60	51.43	86.96	89.19	42.50	510.94	0.98	37.89 221.04 0.71
traingd	0.5 1631	0.3896	0.1154	76.77	65.22	86.79	71.59	56.41	83.67	64.20	51.43	73.91	83.18	58.33	556.18	1.00	25.86 344.77 0.77
traingd	0.5 6065	0.2737	0.0972	75.76	65.22	84.91	69.32	58.97	77.55	71.60	68.57	73.91	83.29	64.17	403.85	0.98	15.43 154.34 0.80
Average	2052	0.2700	0.1100	74.65	62.83	84.91	65.46	44.10	82.45	70.25	54.00	82.61	86.92	54.17	487.74	0.96	21.20 215.54 0.76

Table H.9. MLP 10-5-1, 10 input layers, (categories), Effect of random selection of training patterns, Training pattern set 8

Training set size		Training: 99 patterns (46 deposits, 53 barren), training-stop: = 88 (39 deposits, 49 barren), test = 81 (35 deposits, 46 barren)																						
Training set type		Randomly selected cells, approximately equal numbers of patterns from each rock type																						
Geology input format		Fuzzy membership values																						
Learn.	l.r.	Cycles	MSE		Train % correct			Stop % correct			Test % correct			Map % correct		Map statistics			D%*D%/A%	ROC				
			Initial	Final	All	Deps	Non	All	Deps	Non	All	Deps	Non	All	Deps	Chi	rho	D%/A%						
traingd	0.5	2255	0.2637	0.1278	70.71	63.04	77.36	67.05	56.41	75.51	70.37	51.43	84.78	81.90	57.50	264.20	0.98	12.69	31.73	0.75				
traingd	0.5	3853	0.3098	0.1173	71.72	65.22	77.36	71.59	69.23	73.47	72.84	65.71	78.26	83.42	66.67	585.73	0.45	0.00	0.00	0.83				
traingd	0.5	5956	0.3017	0.1019	78.79	76.09	81.13	73.86	66.67	79.59	85.19	77.14	91.30	81.96	73.33	489.13	0.98	21.28	230.51	0.83				
traingd	0.5	1049	0.3189	0.1398	68.69	45.65	88.68	61.36	30.77	85.71	75.31	45.71	97.83	90.71	40.83	270.69	0.65	11.26	46.92	0.66				
traingd	0.5	3144	0.2286	0.1152	76.77	69.57	83.02	68.18	61.54	73.47	74.07	60.00	84.78	83.72	64.17	298.69	0.88	1.71	2.86	0.81				
traingd	0.5	13	0.1620	0.1526	61.62	43.48	77.36	61.36	56.41	65.31	71.60	45.71	91.30	68.47	48.33	55.12	0.47	0.33	0.55	0.64				
traingd	0.5	4626	0.2412	0.0928	80.81	76.09	84.91	69.32	61.54	75.51	74.07	60.00	84.78	80.37	66.67	310.38	0.98	12.64	115.89	0.81				
traingd	0.5	5053	0.1962	0.1110	79.80	71.74	86.79	64.77	53.85	73.47	64.20	48.57	76.09	78.45	59.17	182.70	0.97	11.14	46.42	0.72				
traingd	0.5	3121	0.3992	0.1402	61.62	36.96	83.02	63.64	33.33	87.76	64.20	28.57	91.30	94.66	33.33	501.55	0.98	30.86	308.58	0.72				
traingd	0.5	8396	0.2606	0.0724	85.86	82.61	88.68	75.00	71.79	77.55	77.78	68.57	84.78	71.96	75.00	198.58	0.97	4.01	56.82	0.80				
Average		3747	0.2682	0.1171	73.64	63.05	82.83	67.61	56.15	76.74	72.96	55.14	86.52	81.56	58.50	315.68	0.83	10.59	84.03	0.76				

Table H.10. MLP 10-5-1, 10 input layers, (categories), Effect of random selection of training patterns, Training pattern set 9

Training set size		Training: 99 patterns (46 deposits, 53 barren), training-stop: = 88 (39 deposits, 49 barren), test = 81 (35 deposits, 46 barren)																							
Training set type		Randomly selected cells, approximately equal numbers of patterns from each rock type																							
Geology input format		Fuzzy membership values																							
Learn.	l.r.	Cycles	MSE		Train % correct				Stop % correct				Test % correct				Map % correct				Map statistics				ROC
			Initial	Final	All	Deps	Non	All	Deps	Non	All	Deps	Non	All	Deps	Non	All	Deps	Chi	rho	D%/A%	D*D%/A%			
traingd	0.5	2255	0.2637	0.1278	70.71	63.04	77.36	67.05	56.41	75.51	70.37	51.43	84.78	81.90	57.50	264.20	0.98	12.69	31.73	0.75					
traingd	0.5	3853	0.3098	0.1173	71.72	65.22	77.36	71.59	69.23	73.47	72.84	65.71	78.26	83.42	66.67	585.73	0.45	0.00	0.00	0.83					
traingd	0.5	5956	0.3017	0.1019	78.79	76.09	81.13	73.86	66.67	79.59	85.19	77.14	91.30	81.96	73.33	489.13	0.98	21.28	230.51	0.83					
traingd	0.5	1049	0.3189	0.1398	68.69	45.65	88.68	61.36	30.77	85.71	75.31	45.71	97.83	90.71	40.83	270.69	0.65	11.26	46.92	0.66					
traingd	0.5	3144	0.2286	0.1152	76.77	69.57	83.02	68.18	61.54	73.47	74.07	60.00	84.78	83.72	64.17	298.69	0.88	1.71	2.86	0.81					
traingd	0.5	13	0.1620	0.1526	61.62	43.48	77.36	61.36	56.41	65.31	71.60	45.71	91.30	68.47	48.33	55.12	0.47	0.33	0.55	0.64					
traingd	0.5	4626	0.2412	0.0928	80.81	76.09	84.91	69.32	61.54	75.51	74.07	60.00	84.78	80.37	66.67	310.38	0.98	12.64	115.89	0.81					
traingd	0.5	4626	0.2412	0.0928	80.81	76.09	84.91	69.32	61.54	75.51	74.07	60.00	84.78	80.37	66.67	310.38	0.98	12.64	115.89	0.81					
traingd	0.5	5168	0.2317	0.0943	77.78	73.91	81.13	67.05	48.72	81.63	62.96	48.57	73.91	87.12	58.33	766.76	1.00	38.45	448.61	0.81					
traingd	0.5	7290	0.4011	0.0801	79.80	78.26	81.13	72.73	64.10	79.59	65.43	60.00	69.57	65.07	68.33	131.07	0.98	4.78	35.85	0.74					
traingd	0.5	5984	0.2903	0.0818	82.83	82.61	83.02	71.59	53.85	85.71	67.90	62.86	71.74	72.70	67.50	261.14	0.97	7.58	69.52	0.78					
Average		3997	0.2718	0.1088	75.48	68.18	81.82	68.49	57.34	77.36	72.16	57.92	83.00	79.62	61.67	340.30	0.85	11.22	99.85	0.77					

Table H.11. MLP 10-5-1, 10 input layers, (categories), Effect of random selection of training patterns, Training pattern set 10

Training set size		Training: 99 patterns (46 deposits, 53 barren), training-stop: = 88 (39 deposits, 49 barren), test = 81 (35 deposits, 46 barren)																	
Training set type		Randomly selected cells, approximately equal numbers of patterns from each rock type																	
Geology input format		Fuzzy membership values																	
Learn. Algorith.	l.r. Cycles	MSE			Train % correct			Stop % correct			Test % correct			Map % correct			Map statistics		
		Initial	Final	All	All	Depos	Non	All	Depos	Non	All	Depos	Non	All	Depos	Chi	rho	D%/A%	D%D%/A%
traingd	0.5	7694	0.2910	0.0789	83.84	82.61	84.91	70.45	71.79	69.39	66.67	71.43	63.04	67.46	75.83	347.10	0.98	10.15	202.91
traingd	0.5	10975	0.3221	0.0941	78.79	80.43	77.36	73.86	76.92	71.43	66.67	74.29	60.87	67.93	77.50	721.73	0.97	36.51	395.57
traingd	0.5	11497	0.2995	0.0845	83.84	82.61	84.91	75.00	69.23	79.59	61.73	68.57	56.52	69.38	74.17	561.78	0.98	23.99	339.85
traingd	0.5	3831	0.3495	0.1169	71.72	56.52	84.91	69.32	53.85	81.63	69.14	54.29	80.43	87.83	55.00	660.18	0.98	21.64	342.69
traingd	0.5	19171	0.2432	0.0697	87.88	82.61	92.45	77.27	71.79	81.63	62.96	60.00	65.22	73.48	72.50	180.11	0.90	3.49	64.04
traingd	0.5	1999	0.1637	0.1078	74.75	73.91	75.47	77.27	71.79	81.63	66.67	65.71	67.39	74.06	70.83	694.40	0.95	27.52	206.36
traingd	0.5	5176	0.2425	0.0940	81.82	78.26	84.91	78.41	74.36	81.63	62.96	68.57	58.70	72.39	74.17	529.60	1.00	20.25	354.45
traingd	0.5	3258	0.2359	0.1108	76.77	76.09	77.36	70.45	64.10	75.51	67.90	71.43	65.22	71.96	70.83	1660.90	0.98	154.86	1161.45
traingd	0.5	15676	0.4019	0.0844	79.80	80.43	79.25	78.41	82.05	75.51	67.90	77.14	60.87	68.25	80.00	415.48	0.93	14.87	185.87
traingd	0.5	5021	0.2826	0.0863	78.79	80.43	77.36	65.91	64.10	67.35	69.14	77.14	63.04	67.45	74.17	348.71	0.98	17.58	73.23
Average		8430	0.2832	0.0927	79.80	77.39	81.89	73.64	70.00	76.53	66.17	68.86	64.13	72.02	72.50	612.00	0.97	33.09	332.64

Table H.12. MLP 10-5-1, 10 input layers, (categories), Swap VV and TV

Training set size		Training: 99 patterns (46 deposits, 53 barren), training-stop: = 88 (39 deposits, 49 barren), test = 81 (35 deposits, 46 barren)																	
Training set type		Randomly selected cells, approximately equal numbers of patterns from each rock type																	
Geology input format		Fuzzy membership values																	
Learn. Algorith.	l.r. Cycles	MSE			Train % correct			Stop % correct			Test % correct			Map % correct			Map statistics		
		Initial	Final	All	All	Depos	Non	All	Depos	Non	All	Depos	Non	All	Depos	Chi	rho	D%/A%	D%D%/A%
traingd	0.5	409	0.2838	0.1481	59.60	52.17	66.04	53.09	37.14	65.22	56.82	48.72	63.27	62.99	46.67	28.10	0.02	0.00	0.59
traingd	0.5	787	0.3004	0.1138	75.76	65.22	84.91	62.96	48.57	73.91	71.59	61.54	79.59	89.12	59.17	1048.93	0.83	57.42	669.88
traingd	0.5	3211	0.2863	0.0872	82.83	84.78	81.13	64.20	42.86	80.43	75.00	61.54	85.71	84.04	65.00	392.68	0.97	11.70	126.76
traingd	0.5	535	0.3269	0.1308	69.70	56.52	81.13	62.96	34.29	84.78	67.05	51.28	79.59	89.77	48.33	461.27	0.92	11.15	83.60
traingd	0.5	439	0.2356	0.1429	63.64	47.83	77.36	59.26	40.00	73.91	65.91	51.28	77.55	89.98	46.67	235.02	0.90	7.53	12.56
traingd	0.5	13	0.1485	0.1390	63.64	50.00	75.47	58.02	45.71	67.39	70.45	56.41	81.63	66.71	50.83	49.40	0.47	0.35	0.58
traingd	0.5	540	0.2710	0.1161	75.76	60.87	88.68	62.96	45.71	76.09	77.27	64.10	87.76	87.86	57.50	570.98	0.98	22.39	335.87
traingd	0.5	359	0.2275	0.1369	68.69	45.65	88.68	62.96	40.00	80.43	67.05	48.72	81.63	92.39	45.00	893.61	0.93	60.22	652.42
traingd	0.5	328	0.4035	0.1504	57.58	63.04	52.83	58.02	42.86	69.57	51.14	51.28	51.02	54.61	53.33	4.94	0.76	1.04	16.51
traingd	0.5	1517	0.2888	0.1186	70.71	58.70	81.13	66.67	57.14	73.91	68.18	56.41	77.55	85.42	57.50	817.29	0.97	42.25	281.64
Average		814	0.2772	0.1284	68.79	58.48	77.74	61.11	43.43	74.56	67.05	55.13	76.53	80.29	53.00	450.22	0.77	21.40	217.98

Table H.13. MLP 10-20-1, 10 input layers (categories), Ndeps = 5, Set 1

Training set size		Training: 10 patterns (5 deposits, 5 barren), training-stop: = 10 (5 deposits, 5 barren), test = 220 (110 deposits, 110 barren)																		
Training set type		Randomly selected cells, approximately equal numbers of patterns from each rock type																		
Geol. input format		Fuzzy membership values																		
Learn.	l.r.	Cyc.	MSE		Train % correct			Stop % correct			Test % correct			Map % correct		Map statistics				
			Initial	Final	All	Depos	Non	All	Depos	Non	All	Depos	Non	All	Depos	Non	Chi	rho	D%/A%	D%*D%/A%
trainlm	0.0	10	0.2188	0.0000	100.00	100.00	100.00	70.00	80.00	60.00	51.36	51.82	50.91	43.21	55.00	58.60	0.12	0.90	18.66	0.45
trainlm	0.0	7	0.2397	0.0068	100.00	100.00	100.00	40.00	60.00	20.00	45.00	43.64	46.36	51.73	46.67	15.54	-0.02	0.42	3.12	0.46
trainlm	0.0	6	0.3938	0.3938	30.00	0.00	60.00	50.00	20.00	80.00	53.64	32.73	74.55	88.15	30.83	130.42	0.92	15.59	51.98	0.70
trainlm	0.0	9	0.3950	0.0034	100.00	100.00	100.00	60.00	80.00	40.00	49.09	69.09	29.09	17.47	70.83	40.51	-0.45	0.73	17.67	0.42
trainlm	0.0	7	0.1027	0.0189	100.00	100.00	100.00	60.00	100.00	20.00	52.73	93.64	11.82	3.90	94.17	79.90	-0.05	0.55	21.03	0.35
trainlm	0.0	7	0.1055	0.0008	100.00	100.00	100.00	50.00	60.00	40.00	51.36	61.82	40.91	19.06	63.33	41.02	-0.87	0.44	7.27	0.36
trainlm	0.0	6	0.1768	0.0024	100.00	100.00	100.00	70.00	40.00	100.00	50.91	48.18	53.64	47.85	50.00	34.99	0.02	2.41	46.20	0.55
trainlm	0.0	7	0.3481	0.1906	60.00	20.00	100.00	70.00	60.00	80.00	49.55	33.64	65.45	58.41	34.17	8.42	-0.55	1.11	4.64	0.46
trainlm	0.0	8	0.2905	0.0000	100.00	100.00	100.00	60.00	80.00	40.00	47.73	60.00	35.45	26.87	62.50	72.41	-0.58	1.34	48.05	0.46
trainlm	0.0	7	0.2571	0.0017	100.00	100.00	100.00	50.00	60.00	40.00	47.73	73.64	21.82	12.35	74.17	61.76	-0.68	0.59	10.74	0.39
Average		7	0.2528	0.0619	89.00	82.00	96.00	58.00	64.00	52.00	49.91	56.82	43.00	36.90	58.17	54.36	-0.22	2.41	22.93	0.46

Table H.14. MLP 10-20-1, 10 input layers (categories), Ndeps = 5, Set 2

Training set size		Training: 10 patterns (5 deposits, 5 barren), training-stop: = 10 (5 deposits, 5 barren), test = 220 (110 deposits, 110 barren)																					
Training set type		Randomly selected cells, approximately equal numbers of patterns from each rock type																					
Geol. input format		Fuzzy membership values																					
Learn.	l.r.	Cyc	MSE			Train % correct			Stop % correct			Test % correct			Map % correct			Map statistics			D%/A%	D%*D%/A%	ROC
			Initial	Final		All	Depos	Non	All	Depos	Non	All	Depos	Non	All	Depos	Non	Chi	rho				
trainlm	0.0	7	0.1898	0.1414	80.00	100.00	60.00	40.00	80.00	0.00	55.91	90.00	21.82	15.78	90.00	73.30	0.17	2.45	118.53	0.70			
trainlm	0.0	7	0.2453	0.0798	80.00	80.00	80.00	50.00	40.00	60.00	48.64	28.18	69.09	87.97	30.83	86.03	0.67	4.94	78.21	0.72			
trainlm	0.0	6	0.2032	0.2032	50.00	20.00	80.00	70.00	40.00	100.00	50.45	29.09	71.82	80.14	29.17	125.60	0.85	17.77	103.64	0.62			
trainlm	0.0	9	0.3603	0.0109	100.00	100.00	100.00	80.00	100.00	60.00	56.82	78.18	35.45	46.62	80.00	135.29	0.83	4.66	147.66	0.71			
trainlm	0.0	8	0.3783	0.1428	70.00	80.00	60.00	60.00	80.00	40.00	59.55	73.64	45.45	67.32	74.17	203.10	0.85	4.68	187.25	0.76			
trainlm	0.0	9	0.3189	0.0973	80.00	100.00	60.00	80.00	100.00	60.00	58.18	68.18	48.18	57.04	70.83	161.04	0.55	3.81	209.32	0.72			
trainlm	0.0	9	0.3363	0.1458	60.00	20.00	100.00	50.00	20.00	80.00	54.55	23.64	85.45	76.58	23.33	9.91	-0.17	1.13	6.62	0.55			
trainlm	0.0	7	0.1658	0.0336	100.00	100.00	100.00	50.00	60.00	40.00	51.36	35.45	67.27	74.07	39.17	37.21	0.77	3.55	32.53	0.60			
trainlm	0.0	7	0.1330	0.0045	100.00	100.00	100.00	80.00	60.00	100.00	51.82	36.36	67.27	81.89	40.00	98.11	0.33	0.44	0.74	0.66			
trainlm	0.0	7	0.2219	0.0000	100.00	100.00	100.00	70.00	40.00	100.00	50.91	29.09	72.73	78.38	32.50	21.26	0.55	1.47	18.42	0.60			
Average		8	0.2553	0.0859	82.00	80.00	84.00	63.00	62.00	64.00	53.82	49.18	58.45	66.58	51.00	95.08	0.54	4.49	90.29	0.66			

Table H.15. MLP 10-20-1, 10 input layers (categories), Ndeps = 5, Set 3

Training set size		Training: 10 patterns (5 deposits, 5 barren), training-stop: = 10 (5 deposits, 5 barren), test = 220 (110 deposits, 110 barren)																					
Training set type		Randomly selected cells, approximately equal numbers of patterns from each rock type																					
Geol. input format		Fuzzy membership values																					
Learn. Algorith.	l.r.	Cyc	MSE			Train % correct			Stop % correct			Test % correct			Map % correct			Map statistics			D%/A%	D%*D%/A%	ROC
			Initial	Final	All	Deps	Non	All	Deps	Non	All	Deps	Non	All	Deps	Chi	rho						
trainlm	0.0	6	0.1203	0.1203	80.00	60.00	100.00	60.00	60.00	60.00	55.91	24.55	87.27	93.28	27.50	196.75	0.90	17.22	100.43	0.71			
trainlm	0.0	6	0.2265	0.0233	100.00	100.00	100.00	70.00	60.00	80.00	53.18	35.45	70.91	67.53	39.17	23.18	0.48	1.49	7.44	0.54			
trainlm	0.0	8	0.1451	0.0014	100.00	100.00	100.00	70.00	80.00	60.00	59.55	39.09	80.00	87.88	43.33	345.52	1.00	16.55	262.04	0.74			
trainlm	0.0	7	0.3732	0.0012	100.00	100.00	100.00	60.00	60.00	60.00	53.18	25.45	80.91	90.15	30.00	342.34	0.88	27.93	232.79	0.67			
trainlm	0.0	11	0.3782	0.0130	100.00	100.00	100.00	60.00	60.00	60.00	60.45	48.18	72.73	83.69	50.83	462.05	0.93	23.15	347.27	0.75			
trainlm	0.0	7	0.1338	0.0000	100.00	100.00	100.00	70.00	60.00	80.00	56.36	32.73	80.00	84.19	36.67	451.54	0.43	19.02	332.78	0.60			
trainlm	0.0	8	0.2480	0.0000	100.00	100.00	100.00	80.00	80.00	80.00	59.55	40.00	79.09	77.13	44.17	91.76	0.93	7.24	78.43	0.63			
trainlm	0.0	6	0.2876	0.0140	100.00	100.00	100.00	70.00	60.00	80.00	59.09	22.73	95.45	97.43	27.50	568.08	1.00	25.52	212.63	0.76			
trainlm	0.0	7	0.1972	0.0864	90.00	80.00	100.00	60.00	40.00	80.00	58.64	29.09	88.18	92.88	31.67	225.30	0.73	16.61	83.07	0.58			
trainlm	0.0	7	0.2376	0.1242	70.00	40.00	100.00	80.00	60.00	100.00	57.27	18.18	96.36	99.07	20.83	854.39	0.98	27.82	208.62	0.76			
Average		7	0.2348	0.0384	94.00	88.00	100.00	68.00	62.00	74.00	57.32	31.55	83.09	87.32	35.17	356.09	0.83	18.25	186.55	0.67			

Table H.16. MLP 10-20-1, 10 input layers (categories), Ndeps = 5, Set 4

Training set size		Training: 10 patterns (5 deposits, 5 barren), training-stop: = 10 (5 deposits, 5 barren), test = 220 (110 deposits, 110 barren)																			
Training set type		Randomly selected cells, approximately equal numbers of patterns from each rock type																			
Geol. input format		Fuzzy membership values																			
Learn. Algorith.	l.r.	Cyc	MSE		Train % correct			Stop % correct			Test % correct			Map % correct			Map statistics				
			Initial	Final	All	Deps	Non	All	Deps	Non	All	Deps	Non	All	Deps	Chi	rho	D%/A%	D%-D%/A%	ROC	
trainlm	0.0	6	0.2167	0.2167	60.00	20.00	100.00	60.00	40.00	80.00	55.00	25.45	84.55	89.39	25.83	135.64	0.83	13.37	100.24	0.64	
trainlm	0.0	8	0.3169	0.0072	100.00	100.00	100.00	50.00	60.00	40.00	50.00	51.82	48.18	40.81	54.17	4.94	-0.02	0.90	26.12	0.48	
trainlm	0.0	6	0.1417	0.0092	100.00	100.00	100.00	50.00	60.00	40.00	62.73	61.82	63.64	77.93	63.33	192.29	0.88	6.01	140.20	0.74	
trainlm	0.0	9	0.3777	0.0069	100.00	100.00	100.00	80.00	80.00	80.00	57.73	58.18	57.27	73.34	60.83	286.33	0.73	6.89	298.70	0.75	
trainlm	0.0	9	0.3200	0.0000	100.00	100.00	100.00	70.00	60.00	80.00	63.18	57.27	69.09	82.60	59.17	336.18	0.93	10.44	286.98	0.77	
trainlm	0.0	7	0.3058	0.0577	90.00	100.00	80.00	60.00	80.00	40.00	56.36	57.27	55.45	57.98	60.00	259.85	0.32	7.52	269.47	0.67	
trainlm	0.0	6	0.3014	0.3014	50.00	60.00	40.00	80.00	100.00	60.00	60.91	60.00	61.82	45.85	61.67	26.49	0.08	2.21	27.62	0.58	
trainlm	0.0	6	0.1779	0.0050	100.00	100.00	100.00	60.00	40.00	80.00	59.55	58.18	60.91	65.94	59.17	114.19	0.87	6.22	83.00	0.70	
trainlm	0.0	7	0.2209	0.0006	100.00	100.00	100.00	80.00	80.00	80.00	65.00	54.55	75.45	83.08	57.50	193.84	0.97	4.32	93.57	0.76	
trainlm	0.0	6	0.1640	0.0008	100.00	100.00	100.00	80.00	80.00	80.00	63.64	51.82	75.45	76.32	55.00	105.26	0.97	4.86	68.86	0.70	
Average		7	0.2543	0.0606	90.00	88.00	92.00	67.00	68.00	66.00	59.41	53.64	65.18	69.32	55.67	165.50	0.66	6.27	139.48	0.68	

Table H.17. MLP 10-20-1, 10 input layers (categories), Ndeps = 5, Set 5

Training set size		Training: 10 patterns (5 deposits, 5 barren), training-stop: = 10 (5 deposits, 5 barren), test = 220 (110 deposits, 110 barren)																		
Training set type		Randomly selected cells, approximately equal numbers of patterns from each rock type																		
Geol. input format		Fuzzy membership values																		
Learn.	l.r.	Cyc	MSE		Train % correct			Stop % correct			Test % correct			Map % correct		Map statistics				
			Initial	Final	All	Deps	Non	All	Deps	Non	All	Deps	Non	All	Deps	Chi	rho	D%/A%	D%*D%/A%	ROC
trainlm	0.0	6	0.2748	0.2748	50.00	20.00	80.00	70.00	40.00	100.00	54.09	10.00	98.18	98.24	11.67	176.57	0.98	63.99	53.32	0.68
trainlm	0.0	7	0.3103	0.0886	80.00	80.00	80.00	40.00	20.00	60.00	58.64	44.55	72.73	80.36	45.00	519.50	0.88	27.17	430.23	0.71
trainlm	0.0	6	0.1369	0.1369	60.00	20.00	100.00	60.00	40.00	80.00	53.64	28.18	79.09	91.67	28.33	145.99	0.98	15.37	51.25	0.71
trainlm	0.0	11	0.3815	0.0008	100.00	100.00	100.00	50.00	40.00	60.00	50.45	58.18	42.73	61.79	59.17	35.16	0.70	1.16	19.40	0.61
trainlm	0.0	6	0.2279	0.2279	60.00	80.00	40.00	40.00	40.00	40.00	56.36	64.55	48.18	50.37	64.17	108.62	0.03	3.30	85.20	0.61
trainlm	0.0	6	0.3091	0.3091	50.00	40.00	60.00	70.00	40.00	100.00	60.91	29.09	92.73	96.15	30.00	325.83	0.93	15.15	126.23	0.65
trainlm	0.0	6	0.1223	0.1223	70.00	100.00	40.00	50.00	40.00	60.00	53.18	62.73	43.64	29.79	63.33	59.16	-0.40	2.64	50.67	0.50
trainlm	0.0	6	0.2901	0.2901	50.00	40.00	60.00	60.00	80.00	40.00	42.73	60.00	25.45	22.26	60.00	27.65	-0.72	0.60	11.07	0.40
trainlm	0.0	6	0.1734	0.1734	60.00	80.00	40.00	80.00	80.00	80.00	59.55	58.18	60.91	76.12	60.00	152.45	0.95	5.56	78.78	0.72
trainlm	0.0	9	0.3092	0.0017	100.00	100.00	100.00	40.00	20.00	60.00	58.64	61.82	55.45	71.41	61.67	86.07	0.83	3.17	68.70	0.71
Average		7	0.2535	0.1626	68.00	66.00	70.00	56.00	44.00	68.00	54.82	47.73	61.91	67.82	48.33	163.70	0.52	13.81	97.48	0.63

Table H.18. MLP 10-20-1, 10 input layers (categories), Ndeps = 5, Set 6

Training set size		Training: 10 patterns (5 deposits, 5 barren), training-stop: = 10 (5 deposits, 5 barren), test = 220 (110 deposits, 110 barren)																			
Training set type		Randomly selected cells, approximately equal numbers of patterns from each rock type																			
Geol. input format		Fuzzy membership values																			
Learn.	l.r.	Cyc	MSE		Train % correct			Stop % correct			Test % correct			Map % correct		Map statistics			D%/A %	D%*D%/A %	ROC
			Initial	Final	All	Deps	Non	All	Deps	Non	All	Deps	Non	All	Deps	Chi	rho				
trainlm	0.0	6	0.2339	0.0005	100.00	100.00	100.00	60.00	80.00	40.00	50.00	47.27	52.73	47.35	50.83	7.88	-0.05	0.71	12.98	0.48	
trainlm	0.0	8	0.2361	0.1299	80.00	60.00	100.00	40.00	20.00	60.00	42.27	29.09	55.45	52.29	30.00	60.90	-0.60	0.86	6.42	0.35	
trainlm	0.0	6	0.2134	0.2134	50.00	20.00	80.00	50.00	40.00	60.00	58.64	45.45	71.82	83.82	44.17	150.58	0.97	8.62	64.68	0.71	
trainlm	0.0	12	0.3889	0.0121	100.00	100.00	100.00	30.00	20.00	40.00	56.82	60.91	52.73	30.45	60.83	55.02	0.10	0.45	8.59	0.42	
trainlm	0.0	6	0.1059	0.0002	100.00	100.00	100.00	60.00	40.00	80.00	56.82	56.36	57.27	45.02	57.50	60.79	0.33	2.80	53.58	0.53	
trainlm	0.0	7	0.1700	0.0447	90.00	80.00	100.00	60.00	80.00	40.00	55.00	60.00	50.00	35.70	61.67	30.34	0.23	1.61	38.91	0.53	
trainlm	0.0	6	0.0388	0.0160	100.00	100.00	100.00	80.00	60.00	100.00	51.82	55.45	48.18	35.31	57.50	19.08	-0.50	0.63	11.52	0.43	
trainlm	0.0	9	0.2239	0.0000	100.00	100.00	100.00	60.00	60.00	60.00	51.36	45.45	57.27	33.47	48.33	22.97	-0.90	0.68	17.49	0.38	
trainlm	0.0	6	0.3593	0.3593	40.00	40.00	40.00	60.00	80.00	40.00	58.64	74.55	42.73	55.49	73.33	106.42	0.88	3.94	118.22	0.69	
trainlm	0.0	6	0.2398	0.2398	60.00	100.00	20.00	60.00	40.00	80.00	50.45	66.36	34.55	14.78	66.67	77.75	-0.90	0.46	10.01	0.32	
Average		7	0.2210	0.1016	82.00	80.00	84.00	56.00	52.00	60.00	53.18	54.09	52.27	43.37	55.08	59.17	-0.04	2.07	34.24	0.49	

Table H.19. MLP 10-20-1, 10 input layers (categories), Ndeps = 5, Set 7

Training set size		Training: 10 patterns (5 deposits, 5 barren), training-stop: = 10 (5 deposits, 5 barren), test = 220 (110 deposits, 110 barren)																		
Training set type		Randomly selected cells, approximately equal numbers of patterns from each rock type																		
Geol. input format		Fuzzy membership values																		
Learn.	l.r.	Cyc	MSE		Train % correct			Stop % correct			Test % correct			Map % correct		Map statistics				
			Initial	Final	All	Deps	Non	All	Deps	Non	All	Deps	Non	All	Deps	Chi	rho	D%/A%	D%*D%/A%	ROC
trainlm	0.0	6	0.1964	0.0012	100.00	100.00	100.00	60.00	60.00	60.00	54.09	50.00	58.18	72.93	52.50	81.53	0.85	2.08	19.07	0.71
trainlm	0.0	6	0.3010	0.3010	20.00	20.00	20.00	30.00	20.00	40.00	47.73	49.09	46.36	38.31	46.67	46.51	-0.88	0.07	0.12	0.35
trainlm	0.0	7	0.2183	0.1006	70.00	40.00	100.00	60.00	20.00	100.00	51.36	15.45	87.27	92.08	16.67	23.14	0.37	0.00	0.00	0.58
trainlm	0.0	9	0.3911	0.1174	80.00	100.00	60.00	70.00	100.00	40.00	51.36	64.55	38.18	41.11	67.50	43.39	0.65	1.11	10.16	0.60
trainlm	0.0	6	0.2650	0.2650	60.00	100.00	20.00	30.00	40.00	20.00	41.36	63.64	19.09	12.34	64.17	113.65	-0.80	1.15	40.36	0.43
trainlm	0.0	7	0.1198	0.0002	100.00	100.00	100.00	60.00	60.00	60.00	44.55	37.27	51.82	69.56	40.83	20.13	0.53	1.46	15.79	0.58
trainlm	0.0	8	0.2206	0.0746	80.00	60.00	100.00	80.00	60.00	100.00	53.18	36.36	70.00	84.88	38.33	176.17	0.68	4.21	28.10	0.60
trainlm	0.0	7	0.2696	0.1874	70.00	60.00	80.00	60.00	20.00	100.00	40.45	19.09	61.82	73.36	20.83	14.44	-0.45	0.43	2.13	0.44
trainlm	0.0	5	0.0712	0.0712	90.00	100.00	80.00	60.00	80.00	40.00	55.00	60.91	49.09	53.91	63.33	57.53	0.62	1.00	6.69	0.63
trainlm	0.0	6	0.2567	0.2567	40.00	60.00	20.00	70.00	60.00	80.00	47.73	53.64	41.82	22.31	54.17	153.53	-0.73	0.39	4.49	0.31
Average		7	0.2310	0.1375	71.00	74.00	68.00	58.00	52.00	64.00	48.68	45.00	52.36	56.08	46.50	73.00	0.08	1.19	12.69	0.52

Table H.20. MLP 10-20-1, 10 input layers (categories), Ndeps = 5, Set 8

Training set size		Training: 10 patterns (5 deposits, 5 barren), training-stop: = 10 (5 deposits, 5 barren), test = 220 (110 deposits, 110 barren)																					
Training set type		Randomly selected cells, approximately equal numbers of patterns from each rock type																					
Geol. input format		Fuzzy membership values																					
Learn.	l.r.	Cyc	MSE			Train % correct			Stop % correct			Test % correct			Map % correct			Map statistics			D%/A %	D%*D%/A %	ROC
			Initial	Final	All	Deps	Non	All	Deps	Non	All	Deps	Non	All	Deps	Non	Chi	rho					
trainlm	0.0	10	0.3045	0.0004	100.00	100.00	100.00	80.00	100.00	60.00	47.27	53.64	40.91	35.09	57.50	11.48	-0.30	0.93	21.75		0.45		
trainlm	0.0	6	0.1601	0.0182	100.00	100.00	100.00	30.00	60.00	0.00	43.18	23.64	62.73	41.38	28.33	114.21	-0.63	0.13	0.54		0.26		
trainlm	0.0	6	0.3050	0.3050	50.00	40.00	60.00	50.00	20.00	80.00	58.64	29.09	88.18	90.15	29.17	254.72	0.92	23.16	192.97		0.67		
trainlm	0.0	10	0.3632	0.0475	90.00	80.00	100.00	50.00	60.00	40.00	48.64	38.18	59.09	67.03	40.83	17.02	0.27	1.01	10.91		0.57		
trainlm	0.0	8	0.2788	0.0254	100.00	100.00	100.00	70.00	60.00	80.00	53.64	59.09	48.18	22.95	60.83	66.04	-0.43	0.44	7.98		0.35		
trainlm	0.0	7	0.4044	0.0442	100.00	100.00	100.00	60.00	80.00	40.00	52.73	74.55	30.91	25.44	75.83	16.35	0.20	1.13	46.05		0.53		
trainlm	0.0	6	0.2472	0.2472	60.00	80.00	40.00	90.00	100.00	80.00	58.18	65.45	50.91	41.01	67.50	60.58	0.30	3.11	75.21		0.61		
trainlm	0.0	6	0.3053	0.3053	40.00	20.00	60.00	60.00	60.00	60.00	45.91	45.45	46.36	43.32	45.00	26.20	-0.65	0.79	21.06		0.45		
trainlm	0.0	6	0.1760	0.1760	50.00	80.00	20.00	50.00	100.00	0.00	50.91	79.09	22.73	27.71	80.00	29.44	0.57	1.75	71.59		0.62		
trainlm	0.0	6	0.2068	0.2068	40.00	60.00	20.00	40.00	40.00	40.00	50.45	65.45	35.45	20.41	64.17	23.46	-0.88	0.80	15.25		0.41		
Average		7	0.2751	0.1376	73.00	76.00	70.00	58.00	68.00	48.00	50.95	53.36	48.55	41.45	54.92	61.95	-0.06	3.32	46.33		0.49		

Table H.21. MLP 10-20-1, 10 input layers (categories), Ndeps = 5, Set 9

Training set size		Training: 10 patterns (5 deposits, 5 barren), training-stop: = 10 (5 deposits, 5 barren), test = 220 (110 deposits, 110 barren)															
Training set type		Randomly selected cells, approximately equal numbers of patterns from each rock type															
Geol. input format		Fuzzy membership values															
Learn.	l.r.	Cyc	MSE		Train % correct		Stop % correct		Test % correct		Map % correct		Map statistics		D%/A%		ROC
Algoth.			Initial	Final	All	Deps	Non	All	Deps	Non	All	Deps	Chi	rho	D%/A%	D*D%/A%	ROC
trainlm	0.0	6	0.1840	0.1840	60.00	20.00	100.00	50.00	0.00	100.00	53.18	14.55	91.82	14.17	8.05	6.70	0.66
trainlm	0.0	6	0.1913	0.1913	60.00	60.00	60.00	50.00	60.00	40.00	40.45	34.55	46.36	36.67	0.17	0.73	0.30
trainlm	0.0	6	0.3156	0.3156	30.00	20.00	40.00	60.00	40.00	80.00	56.82	41.82	71.82	40.83	9.93	33.09	0.69
trainlm	0.0	7	0.3723	0.3583	50.00	0.00	100.00	50.00	0.00	100.00	49.09	0.00	98.18	95.83	0.00	0.00	0.39
trainlm	0.0	6	0.2674	0.2674	40.00	80.00	0.00	60.00	100.00	20.00	50.91	78.18	23.64	14.98	-0.42	64.15	0.56
trainlm	0.0	6	0.3441	0.3441	40.00	20.00	60.00	60.00	40.00	80.00	60.00	36.36	83.64	35.83	8.35	90.50	0.57
trainlm	0.0	6	0.1659	0.1659	70.00	60.00	80.00	50.00	80.00	20.00	52.27	81.82	22.73	12.31	0.72	57.17	0.52
trainlm	0.0	6	0.1713	0.1713	70.00	80.00	60.00	40.00	60.00	20.00	45.00	55.45	34.55	56.67	-0.50	22.66	0.43
trainlm	0.0	6	0.1737	0.1737	50.00	40.00	60.00	40.00	40.00	40.00	56.36	47.27	65.45	46.67	4.59	72.60	0.65
trainlm	0.0	7	0.2425	0.2222	60.00	80.00	40.00	60.00	60.00	60.00	62.27	66.36	58.18	43.35	0.82	16.41	0.52
Average		6	0.2428	0.2394	53.00	46.00	60.00	52.00	48.00	56.00	52.64	45.64	59.64	45.75	3.57	36.40	0.53

Table H.22. MLP 10-20-1, 10 input layers (categories), Ndeps = 5, Set 10

Training set size		Training: 10 patterns (5 deposits, 5 barren), training-stop: = 10 (5 deposits, 5 barren), test = 220 (110 deposits, 110 barren)															
Training set type		Randomly selected cells, approximately equal numbers of patterns from each rock type															
Geol. input format		Fuzzy membership values															
Learn.	l.r.	Cyc	MSE		Train % correct		Stop % correct		Test % correct		Map % correct		Map statistics		D%/A%		ROC
Algoth.			Initial	Final	All	Deps	Non	All	Deps	Non	All	Deps	Chi	rho	D%/A%	D*D%/A%	ROC
trainlm	0.0	7	0.1801	0.0330	100.00	100.00	100.00	60.00	80.00	40.00	60.00	66.36	53.64	229.26	1.00	169.47	0.76
trainlm	0.0	7	0.3218	0.0540	90.00	100.00	80.00	70.00	80.00	60.00	55.45	65.45	45.45	67.50	0.85	33.40	0.66
trainlm	0.0	6	0.2473	0.2473	40.00	20.00	60.00	70.00	60.00	80.00	54.55	34.55	74.55	35.00	0.88	6.61	0.67
trainlm	0.0	8	0.3961	0.0662	80.00	100.00	60.00	60.00	60.00	60.00	63.64	68.18	59.09	62.34	0.77	211.20	0.71
trainlm	0.0	7	0.2813	0.0000	100.00	100.00	100.00	50.00	20.00	80.00	65.91	46.36	85.45	47.50	0.93	148.49	0.73
trainlm	0.0	8	0.2748	0.0070	100.00	100.00	100.00	70.00	60.00	80.00	60.91	59.09	62.73	60.83	0.93	128.99	0.74
trainlm	0.0	6	0.2860	0.0013	100.00	100.00	100.00	60.00	40.00	80.00	65.00	41.82	88.18	383.77	0.98	211.37	0.77
trainlm	0.0	7	0.3566	0.0364	100.00	100.00	100.00	50.00	20.00	80.00	59.55	42.73	76.36	44.17	0.72	15.99	0.64
trainlm	0.0	5	0.0969	0.0969	70.00	60.00	80.00	50.00	40.00	60.00	53.18	51.82	54.55	51.67	0.83	33.53	0.64
trainlm	0.0	7	0.2253	0.0402	100.00	100.00	100.00	40.00	20.00	60.00	60.45	50.91	70.00	51.67	0.93	48.09	0.69
Average		7	0.2666	0.0582	88.00	88.00	88.00	58.00	48.00	68.00	59.86	52.73	67.00	54.00	0.88	100.72	0.70

Table H.23. MLP 10-20-1, 10 input layers (categories), Ndeps = 10, Set 1

Training set size		Training: 20 patterns (10 deposits, 10 barren), training-stop: = 20 (10 deposits, 10 barren), test = 200 (100 deposits, 100 barren)																		
Training set type		Randomly selected cells, approximately equal numbers of patterns from each rock type																		
Geol. input format		Fuzzy membership values																		
Learn.	l.r.	Cyc	MSE		Train % correct			Stop % correct			Test % correct			Map % correct		Map statistics			D%*D%/A %	ROC
			Initial	Final	All	Deps	Non	All	Deps	Non	All	Deps	Non	All	Deps	Chi	rho	D%/A %		
trainlm	0.0	10	0.1996	0.0066	100.00	100.00	100.00	60.00	50.00	70.00	51.50	43.00	60.00	75.00	48.33	93.44	0.67	3.08	35.95	0.58
trainlm	0.0	8	0.2476	0.1190	75.00	70.00	80.00	55.00	60.00	50.00	55.00	60.00	50.00	54.19	60.83	38.39	0.82	2.02	59.03	0.63
trainlm	0.0	8	0.1885	0.0587	85.00	80.00	90.00	60.00	40.00	80.00	55.50	31.00	80.00	85.52	35.83	85.96	0.88	2.76	13.81	0.63
trainlm	0.0	10	0.3439	0.0270	95.00	90.00	100.00	75.00	50.00	100.00	65.00	61.00	69.00	85.82	62.50	299.48	0.95	7.95	33.15	0.81
trainlm	0.0	8	0.2410	0.0873	80.00	80.00	80.00	65.00	50.00	80.00	52.50	51.00	54.00	73.64	53.33	89.89	0.93	3.97	96.01	0.66
trainlm	0.0	9	0.2511	0.0131	100.00	100.00	100.00	55.00	40.00	70.00	60.00	69.00	51.00	72.35	69.17	171.94	0.98	4.49	142.20	0.75
trainlm	0.0	7	0.2552	0.0621	80.00	90.00	70.00	65.00	60.00	70.00	51.50	46.00	57.00	75.83	50.83	180.97	0.42	0.00	0.00	0.75
trainlm	0.0	7	0.2778	0.0991	75.00	60.00	90.00	65.00	30.00	100.00	71.00	56.00	86.00	92.88	54.17	565.03	0.98	13.13	240.72	0.80
trainlm	0.0	7	0.1182	0.0738	90.00	100.00	80.00	65.00	70.00	60.00	47.00	43.00	51.00	56.93	50.00	20.68	0.32	1.10	15.58	0.56
trainlm	0.0	9	0.2891	0.0489	90.00	80.00	100.00	75.00	70.00	80.00	55.00	45.00	65.00	72.92	50.00	44.75	0.98	4.08	13.59	0.65
Average		8	0.2412	0.0596	87.00	85.00	89.00	64.00	52.00	76.00	56.40	50.50	62.30	74.51	53.50	159.06	0.79	4.26	65.00	0.68

Table H.24. MLP 10-20-1, 10 input layers (categories), Ndeps = 10, Set 2

Training set size		Training: 20 patterns (10 deposits, 10 barren), training-stop: = 20 (10 deposits, 10 barren), test = 200 (100 deposits, 100 barren)																		
Training set type		Randomly selected cells, approximately equal numbers of patterns from each rock type																		
Geol. input format		Fuzzy membership values																		
Learn.	l.r.	Cyc	MSE			Train % correct			Stop % correct			Test % correct			Map % correct			Map statistics		
			Initial	Final	All	Deps	Non	All	Deps	Non	All	Deps	Non	All	Deps	Chi	rho	D%/A %	D%+D%/A %	ROC
trainlm	0.0	9	0.1975	0.0214	100.00	100.00	100.00	45.00	50.00	40.00	62.00	50.00	74.00	65.36	54.17	33.86	0.87	1.51	16.37	0.64
trainlm	0.0	10	0.2005	0.0001	100.00	100.00	100.00	55.00	50.00	60.00	57.00	41.00	73.00	75.11	46.67	65.30	0.95	3.53	73.62	0.62
trainlm	0.0	10	0.2187	0.0275	95.00	90.00	100.00	65.00	60.00	70.00	55.00	40.00	70.00	77.82	45.83	130.42	0.72	5.23	122.06	0.69
trainlm	0.0	10	0.3956	0.0277	95.00	90.00	100.00	60.00	60.00	60.00	62.50	53.00	72.00	74.67	56.67	190.07	0.82	9.15	144.83	0.68
trainlm	0.0	10	0.2293	0.0291	100.00	100.00	100.00	65.00	70.00	60.00	57.00	45.00	69.00	77.97	51.67	129.75	0.97	4.47	29.78	0.69
trainlm	0.0	6	0.2084	0.2084	70.00	50.00	90.00	65.00	50.00	80.00	61.00	32.00	90.00	92.80	35.00	249.50	0.97	10.28	111.32	0.67
trainlm	0.0	8	0.1555	0.0219	100.00	100.00	100.00	55.00	60.00	50.00	58.50	60.00	57.00	49.41	63.33	28.42	0.57	1.78	37.09	0.60
trainlm	0.0	7	0.2485	0.0980	85.00	70.00	100.00	60.00	40.00	80.00	60.00	30.00	90.00	76.00	34.17	39.35	-0.15	0.00	0.00	0.57
trainlm	0.0	8	0.2046	0.0840	90.00	90.00	90.00	70.00	90.00	50.00	63.50	72.00	55.00	59.35	75.00	290.91	0.92	7.43	278.78	0.78
trainlm	0.0	6	0.2151	0.2151	55.00	70.00	40.00	55.00	80.00	30.00	47.50	69.00	26.00	12.92	70.00	49.05	-0.92	0.54	12.17	0.35
Average		8	0.2274	0.0733	89.00	86.00	92.00	59.50	61.00	58.00	58.40	49.20	67.60	66.14	53.25	120.66	0.57	4.39	82.60	0.63

Table H.25. MLP 10-20-1, 10 input layers (categories), Ndeps = 10, Set 3

Training set size		Training: 20 patterns (10 deposits, 10 barren), training-stop: = 20 (10 deposits, 10 barren), test = 200 (100 deposits, 100 barren)																		
Training set type		Randomly selected cells, approximately equal numbers of patterns from each rock type																		
Geol. input format		Fuzzy membership values																		
Learn.	l.r.	Cyc	MSE		Train % correct			Stop % correct			Test % correct			Map % correct		Map statistics			D%*D%/A%	ROC
			Initial	Final	All	Deps	Non	All	Deps	Non	All	Deps	Non	All	Deps	Chi	rho	D%/A%		
trainlm	0.0	6	0.2373	0.2373	45.00	0.00	90.00	70.00	40.00	100.00	57.00	24.00	90.00	96.29	23.33	179.92	0.98	50.56	42.13	0.71
trainlm	0.0	6	0.2273	0.2273	45.00	20.00	70.00	30.00	0.00	60.00	48.50	25.00	72.00	64.50	22.50	32.71	-0.90	0.00	0.00	0.36
trainlm	0.0	6	0.2187	0.2187	50.00	30.00	70.00	65.00	50.00	80.00	54.50	36.00	73.00	79.70	36.67	58.93	0.97	8.07	26.91	0.65
trainlm	0.0	10	0.3837	0.0821	85.00	80.00	90.00	45.00	20.00	70.00	58.00	50.00	66.00	56.67	50.00	34.27	-0.33	0.67	7.29	0.49
trainlm	0.0	7	0.2649	0.1806	55.00	90.00	20.00	50.00	90.00	10.00	55.00	95.00	15.00	30.94	94.17	73.88	0.85	2.04	139.28	0.75
trainlm	0.0	6	0.2767	0.2767	55.00	20.00	90.00	70.00	40.00	100.00	61.00	35.00	87.00	93.92	34.17	288.23	0.92	13.67	182.31	0.67
trainlm	0.0	7	0.1863	0.0914	75.00	100.00	50.00	50.00	80.00	20.00	59.50	91.00	28.00	38.09	90.83	123.32	0.95	3.41	139.28	0.75
trainlm	0.0	10	0.3027	0.0021	100.00	100.00	100.00	60.00	70.00	50.00	60.00	67.00	53.00	55.03	70.00	60.39	0.68	2.25	107.01	0.69
trainlm	0.0	6	0.1973	0.1973	60.00	60.00	60.00	55.00	50.00	60.00	59.00	63.00	55.00	67.17	61.67	111.47	0.95	5.41	76.61	0.69
trainlm	0.0	6	0.2287	0.2287	50.00	70.00	30.00	45.00	50.00	40.00	47.50	72.00	23.00	11.40	70.00	99.39	-0.75	0.54	13.04	0.33
Average		7	0.2524	0.1742	62.00	57.00	67.00	54.00	49.00	59.00	56.00	55.80	56.20	59.37	55.33	106.25	0.43	8.66	73.39	0.61

Table H.26. MLP 10-20-1, 10 input layers (categories), Ndeps = 10, Set 4

Training set size		Training: 20 patterns (10 deposits, 10 barren), training-stop: = 20 (10 deposits, 10 barren), test = 200 (100 deposits, 100 barren)																		
Training set type		Randomly selected cells, approximately equal numbers of patterns from each rock type																		
Geol. input format		Fuzzy membership values																		
Learn.	l.r.	Cyc	MSE		Train % correct			Stop % correct			Test % correct			Map % correct		Map statistics			D%*D%/A%	ROC
			Initial	Final	All	Deps	Non	All	Deps	Non	All	Deps	Non	All	Deps	Chi	rho	D%/A%		
trainlm	0.0	7	0.2443	0.1235	75.00	100.00	50.00	75.00	100.00	50.00	61.50	84.00	39.00	38.54	86.67	182.95	0.62	4.06	165.60	0.78
trainlm	0.0	7	0.2450	0.0968	80.00	100.00	60.00	50.00	80.00	20.00	51.50	72.00	31.00	38.23	75.00	25.09	0.58	0.82	11.55	0.55
trainlm	0.0	6	0.1811	0.1811	60.00	40.00	80.00	50.00	10.00	90.00	66.50	31.00	82.00	91.22	30.00	215.86	0.95	21.43	107.16	0.68
trainlm	0.0	13	0.3842	0.0094	100.00	100.00	100.00	85.00	90.00	80.00	65.50	54.00	77.00	73.99	60.83	313.99	0.92	9.57	255.17	0.73
trainlm	0.0	6	0.1899	0.1899	60.00	90.00	30.00	65.00	100.00	30.00	47.50	66.00	29.00	29.37	70.83	48.04	0.08	1.55	33.51	0.55
trainlm	0.0	12	0.2566	0.0008	100.00	100.00	100.00	55.00	60.00	50.00	56.50	61.00	52.00	54.17	64.17	36.59	0.78	1.71	45.59	0.63
trainlm	0.0	6	0.1785	0.1785	60.00	60.00	60.00	75.00	100.00	50.00	56.50	60.00	53.00	39.79	63.33	14.29	0.28	1.84	21.45	0.55
trainlm	0.0	7	0.2141	0.1362	75.00	100.00	50.00	85.00	100.00	70.00	53.00	79.00	27.00	38.99	82.50	192.68	0.55	4.72	208.46	0.75
trainlm	0.0	8	0.2616	0.0649	90.00	100.00	80.00	70.00	90.00	50.00	59.00	72.00	46.00	57.17	75.83	310.76	0.27	5.94	217.83	0.76
trainlm	0.0	9	0.2865	0.0002	100.00	100.00	100.00	75.00	80.00	70.00	58.50	59.00	58.00	57.96	64.17	91.93	0.53	1.63	33.99	0.65
Average		8	0.2442	0.0981	80.00	89.00	71.00	68.50	81.00	56.00	56.60	63.80	49.40	51.94	67.33	143.22	0.56	5.33	110.03	0.66

Table H.27. MLP 10-20-1, 10 input layers (categories), Ndeps = 10, Set 5

Training set size		Training: 20 patterns (10 deposits, 10 barren), training-stop: = 20 (10 deposits, 10 barren), test = 200 (100 deposits, 100 barren)																			
Training set type		Randomly selected cells, approximately equal numbers of patterns from each rock type																			
Geol. input format		Fuzzy membership values																			
Learn.	l.r.	Cyc	MSE		Train % correct			Stop % correct			Test % correct			Map % correct			Map statistics			D%*D%/A%	ROC
			Initial	Final	All	Depos	Non	All	Depos	Non	All	Depos	Non	All	Depos	Chi	rho	D%/A%			
trainlm	0.0	8	0.1653	0.0258	95.00	100.00	90.00	65.00	60.00	70.00	57.00	59.00	55.00	65.32	62.50	69.81	0.92	2.05	53.01	0.70	
trainlm	0.0	11	0.1893	0.0399	95.00	100.00	90.00	65.00	70.00	60.00	56.00	59.00	53.00	73.61	63.33	102.33	0.97	3.41	90.85	0.71	
trainlm	0.0	8	0.1849	0.0556	90.00	100.00	80.00	60.00	70.00	50.00	55.00	70.00	40.00	51.26	72.50	57.16	0.82	2.35	94.01	0.68	
trainlm	0.0	10	0.3833	0.0617	85.00	80.00	90.00	65.00	60.00	70.00	59.50	49.00	70.00	81.66	52.50	164.19	0.98	4.27	78.24	0.77	
trainlm	0.0	7	0.2346	0.1485	60.00	50.00	70.00	50.00	30.00	70.00	46.00	34.00	58.00	59.98	35.00	59.86	-0.05	0.37	2.17	0.49	
trainlm	0.0	9	0.1875	0.0203	100.00	100.00	100.00	60.00	50.00	70.00	60.00	44.00	76.00	75.46	49.17	155.64	0.68	6.33	131.96	0.72	
trainlm	0.0	11	0.2638	0.0282	95.00	100.00	90.00	50.00	60.00	40.00	61.50	67.00	56.00	63.39	69.17	65.09	0.97	2.81	53.87	0.69	
trainlm	0.0	10	0.3017	0.1195	70.00	60.00	80.00	65.00	50.00	80.00	56.00	46.00	66.00	63.47	47.50	69.12	0.37	0.60	6.49	0.57	
trainlm	0.0	8	0.1167	0.0185	100.00	100.00	100.00	55.00	50.00	60.00	56.00	62.00	50.00	52.97	64.17	21.81	0.72	1.30	27.15	0.60	
trainlm	0.0	10	0.2753	0.0497	90.00	90.00	90.00	65.00	80.00	50.00	55.50	64.00	47.00	59.01	67.50	124.03	0.33	0.30	1.24	0.64	
Average		9	0.2303	0.0568	88.00	88.00	88.00	60.00	58.00	62.00	56.25	55.40	57.10	64.61	58.33	88.90	0.67	2.38	53.90	0.66	

Table H.28. MLP 10-20-1, 10 input layers (categories), Ndeps = 10, Set 6

Training set size		Training: 20 patterns (10 deposits, 10 barren), training-stop: = 20 (10 deposits, 10 barren), test = 200 (100 deposits, 100 barren)																				
Training set type		Randomly selected cells, approximately equal numbers of patterns from each rock type																				
Geol. input format		Fuzzy membership values																				
Learn.	l.r.	Cyc	MSE			Train % correct			Stop % correct			Test % correct			Map % correct			Map statistics			D%*D%/A%	ROC
			Initial	Final	All	Depos	Non	All	Depos	Non	All	Depos	Non	All	Depos	Chi	rho	D%/A%				
trainlm	0.0	8	0.2495	0.1051	75.00	90.00	60.00	65.00	90.00	40.00	47.00	62.00	32.00	30.60	66.67	35.59	0.00	0.61	11.14	0.43		
trainlm	0.0	7	0.2006	0.1027	70.00	100.00	40.00	45.00	70.00	20.00	55.00	86.00	24.00	30.60	85.83	43.78	0.32	1.09	9.98	0.62		
trainlm	0.0	6	0.2371	0.2371	55.00	20.00	90.00	55.00	30.00	80.00	55.00	33.00	77.00	87.83	31.67	186.25	0.93	16.03	40.07	0.68		
trainlm	0.0	13	0.3859	0.0512	90.00	90.00	90.00	50.00	40.00	60.00	55.00	47.00	63.00	58.38	50.00	30.28	0.47	0.61	6.05	0.53		
trainlm	0.0	10	0.2050	0.0110	100.00	100.00	100.00	70.00	70.00	70.00	57.50	59.00	56.00	45.79	63.33	31.59	0.15	0.70	15.75	0.50		
trainlm	0.0	7	0.2701	0.1314	65.00	100.00	30.00	45.00	70.00	20.00	53.50	87.00	20.00	12.78	86.67	13.52	0.07	1.40	43.06	0.58		
trainlm	0.0	8	0.1990	0.0607	90.00	90.00	90.00	65.00	60.00	70.00	51.50	51.00	52.00	37.98	55.00	14.50	-0.52	0.53	7.11	0.43		
trainlm	0.0	10	0.3561	0.0461	95.00	90.00	100.00	60.00	30.00	90.00	55.00	49.00	61.00	50.71	50.83	22.76	0.25	0.82	24.50	0.50		
trainlm	0.0	6	0.2245	0.2245	55.00	50.00	60.00	65.00	70.00	60.00	54.00	59.00	49.00	55.37	59.17	67.91	0.68	3.52	73.42	0.64		
trainlm	0.0	6	0.2623	0.2623	45.00	70.00	20.00	50.00	60.00	40.00	44.50	65.00	24.00	10.04	65.00	82.85	-0.83	0.54	11.61	0.33		
Average		8	0.2590	0.1232	74.00	80.00	68.00	57.00	59.00	55.00	52.80	59.80	45.80	42.01	61.42	52.90	0.15	2.58	24.27	0.52		

Table H.29. MLP 10-20-1, 10 input layers (categories), Ndeps = 10, Set 7

Training set size		Training: 20 patterns (10 deposits, 10 barren), training-stop: = 20 (10 deposits, 10 barren), test = 200 (100 deposits, 100 barren)																		
Training set type		Randomly selected cells, approximately equal numbers of patterns from each rock type																		
Geol. input format		Fuzzy membership values																		
Learn.	l.r.	Cyc	MSE		Train % correct			Stop % correct			Test % correct			Map % correct		Map statistics			D%*D%/A %	ROC
			Initial	Final	All	Depos	Non	All	Depos	Non	All	Depos	Non	All	Depos	Chi	rho	D%/A %		
trainlm	0.0	7	0.2691	0.1210	70.00	50.00	90.00	70.00	50.00	90.00	58.50	42.00	75.00	67.52	43.33	31.20	0.63	1.26	8.42	0.59
trainlm	0.0	7	0.2284	0.1777	55.00	10.00	100.00	55.00	10.00	100.00	53.50	14.00	93.00	94.89	13.33	44.61	0.85	4.16	6.94	0.64
trainlm	0.0	19	0.1794	0.0000	100.00	100.00	100.00	75.00	80.00	70.00	65.00	71.00	59.00	58.91	74.17	69.28	0.85	2.31	99.90	0.68
trainlm	0.0	9	0.3849	0.0931	80.00	100.00	60.00	45.00	80.00	10.00	61.50	83.00	40.00	37.60	84.17	104.52	0.73	2.63	4.38	0.68
trainlm	0.0	6	0.2349	0.2349	50.00	70.00	30.00	55.00	90.00	20.00	51.00	76.00	26.00	19.08	76.67	57.15	-0.05	1.81	74.00	0.57
trainlm	0.0	7	0.2519	0.2511	65.00	50.00	80.00	80.00	70.00	90.00	63.50	46.00	81.00	90.49	48.33	281.05	0.95	7.56	220.44	0.72
trainlm	0.0	6	0.2009	0.2009	55.00	70.00	40.00	60.00	100.00	20.00	52.00	77.00	27.00	16.50	78.33	51.21	-0.28	2.02	60.63	0.52
trainlm	0.0	10	0.2180	0.0403	90.00	90.00	90.00	45.00	70.00	20.00	63.00	73.00	53.00	43.01	74.17	31.18	0.72	1.56	46.70	0.63
trainlm	0.0	7	0.2083	0.1031	70.00	60.00	80.00	70.00	50.00	90.00	66.00	42.00	90.00	81.55	44.17	159.94	0.18	0.00	0.00	0.65
trainlm	0.0	13	0.1752	0.0135	95.00	90.00	100.00	90.00	90.00	90.00	63.00	68.00	58.00	52.82	71.67	59.27	0.75	2.23	74.30	0.67
Average		9	0.2351	0.1236	73.00	69.00	77.00	64.50	69.00	60.00	59.70	59.20	60.20	56.24	60.83	88.94	0.53	2.55	59.57	0.64

Table H.30. MLP 10-20-1, 10 input layers (categories), Ndeps = 10, Set 8

Training set size		Training: 20 patterns (10 deposits, 10 barren), training-stop: = 20 (10 deposits, 10 barren), test = 200 (100 deposits, 100 barren)																			
Training set type		Randomly selected cells, approximately equal numbers of patterns from each rock type																			
Geol. input format		Fuzzy membership values																			
Learn.	l.r.	Cyc	MSE		Train % correct			Stop % correct			Test % correct			Map % correct			Map statistics			D%*D%/A %	ROC
			Initial	Final	All	Deps	Non	All	Deps	Non	All	Deps	Non	All	Deps	Chi	rho				
trainlm	0.0	7	0.2303	0.2186	60.00	90.00	30.00	55.00	70.00	40.00	62.50	77.00	48.00	30.94	77.50	20.47	0.20	1.42	86.51	0.62	
trainlm	0.0	7	0.2153	0.1557	60.00	90.00	30.00	50.00	70.00	30.00	57.50	80.00	35.00	25.50	80.00	31.15	0.20	0.78	24.71	0.49	
trainlm	0.0	10	0.2504	0.0226	100.00	100.00	100.00	55.00	30.00	80.00	63.00	55.00	71.00	58.64	56.67	37.61	0.70	2.45	48.97	0.61	
trainlm	0.0	10	0.3885	0.0661	85.00	90.00	80.00	45.00	40.00	50.00	62.00	59.00	65.00	50.00	60.00	36.49	0.58	2.80	39.62	0.59	
trainlm	0.0	9	0.2515	0.0784	80.00	80.00	80.00	75.00	80.00	70.00	59.50	61.00	58.00	30.54	64.17	12.82	-0.47	0.74	20.88	0.43	
trainlm	0.0	8	0.2675	0.0752	85.00	70.00	100.00	70.00	60.00	80.00	61.50	55.00	68.00	48.68	56.67	11.03	-0.05	1.05	29.66	0.53	
trainlm	0.0	7	0.2320	0.1248	70.00	70.00	70.00	65.00	30.00	100.00	65.50	46.00	85.00	76.18	46.67	256.95	0.87	20.55	137.02	0.66	
trainlm	0.0	8	0.2667	0.1112	75.00	100.00	50.00	50.00	50.00	50.00	60.00	73.00	47.00	37.26	73.33	18.37	0.48	1.32	42.95	0.58	
trainlm	0.0	6	0.2077	0.2077	60.00	70.00	50.00	50.00	50.00	50.00	52.50	51.00	54.00	59.24	52.50	52.55	0.83	2.82	39.94	0.64	
trainlm	0.0	9	0.2185	0.0549	80.00	80.00	80.00	70.00	60.00	80.00	64.50	59.00	70.00	60.10	60.83	77.10	0.78	3.38	84.52	0.65	
Average		8	0.2528	0.1115	75.50	84.00	67.00	58.50	54.00	63.00	60.85	61.60	60.10	47.71	62.83	55.45	0.41	3.73	55.48	0.58	

Table H.31. MLP 10-20-1, 10 input layers (categories), Ndeps = 10, Set 9

Training set size	Training: 20 patterns (10 deposits, 10 barren), training-stop: = 20 (10 deposits, 10 barren), test = 200 (100 deposits, 100 barren)																					
Training set type	Randomly selected cells, approximately equal numbers of patterns from each rock type																					
Geol. input format	Fuzzy membership values																					
Learn. Algorith.	l.r.	Cyc	MSE			Train % correct			Stop % correct			Test % correct			Map % correct			Map statistics				
			Initial	Final		All	Depos	Non	All	Depos	Non	All	Depos	Non	All	Depos	Non	All	Chi	rho	D%/A %	D%*D%/A %
trainlm	0.0	11	0.2530	0.0123	100.00	100.00	100.00	60.00	50.00	70.00	58.00	38.00	78.00	66.95	44.17	41.43	-0.10	0.67	5.61	0.53		
trainlm	0.0	7	0.2282	0.1099	70.00	60.00	80.00	55.00	40.00	70.00	53.50	29.00	78.00	72.20	32.50	24.85	-0.38	0.64	0.54	0.50		
trainlm	0.0	6	0.1909	0.1909	60.00	40.00	80.00	75.00	50.00	100.00	56.00	36.00	76.00	84.99	37.50	108.36	0.97	15.58	64.93	0.67		
trainlm	0.0	10	0.3940	0.1511	65.00	30.00	100.00	65.00	40.00	90.00	54.50	16.00	93.00	76.34	19.17	4.28	0.07	1.43	3.58	0.48		
trainlm	0.0	9	0.2248	0.0035	100.00	100.00	100.00	70.00	90.00	50.00	59.00	58.00	60.00	55.34	64.17	43.73	0.58	1.73	53.41	0.61		
trainlm	0.0	8	0.2253	0.0480	90.00	80.00	100.00	60.00	60.00	60.00	64.00	46.00	82.00	88.88	50.00	438.50	0.97	26.20	261.95	0.75		
trainlm	0.0	8	0.1721	0.0000	100.00	100.00	100.00	65.00	60.00	70.00	60.50	41.00	80.00	81.00	47.50	311.12	0.50	8.66	310.22	0.62		
trainlm	0.0	9	0.2627	0.0377	95.00	90.00	100.00	70.00	80.00	60.00	55.50	42.00	69.00	76.31	49.17	53.24	0.73	1.88	12.56	0.62		
trainlm	0.0	6	0.2383	0.2383	35.00	30.00	40.00	70.00	80.00	60.00	56.00	60.00	52.00	56.09	59.17	76.36	0.60	3.82	76.31	0.64		
trainlm	0.0	9	0.2426	0.0045	100.00	100.00	100.00	60.00	40.00	80.00	62.00	43.00	81.00	81.32	47.50	133.71	0.95	2.76	23.02	0.72		
Average		8	0.2432	0.0796	81.50	73.00	90.00	65.00	59.00	71.00	57.90	40.90	74.90	73.94	45.08	123.56	0.491	6.34	81.21	0.61		

Table H.32. MLP 10-20-1, 10 input layers (categories), Ndeps = 10, Set 10

Training set size		Training: 20 patterns (10 deposits, 10 barren), training-stop: = 20 (10 deposits, 10 barren), test = 200 (100 deposits, 100 barren)																				
Training set type		Randomly selected cells, approximately equal numbers of patterns from each rock type																				
Geol. input format		Fuzzy membership values																				
Learn.	l.r.	Cyc	MSE			Train % correct			Stop % correct			Test % correct			Map % correct			Map statistics			D%*D%/A %	ROC
			Initial	Final	All	Depos	Non	All	Depos	Non	All	Depos	Non	All	Depos	Chi	rho	D%/A %				
trainlm	0.0	8	0.1816	0.0314	95.00	90.00	100.00	75.00	50.00	100.00	54.50	53.00	56.00	70.93	55.83	89.05	0.88	6.46	43.09		0.67	
trainlm	0.0	8	0.1749	0.0773	85.00	70.00	100.00	60.00	30.00	90.00	50.00	20.00	80.00	84.18	25.00	23.20	0.82	3.87	9.68	0.60		
trainlm	0.0	11	0.1767	0.0000	100.00	100.00	100.00	65.00	60.00	70.00	55.50	44.00	67.00	63.89	50.00	7.61	0.75	1.32	26.49		0.55	
trainlm	0.0	8	0.3887	0.0668	85.00	100.00	70.00	80.00	80.00	80.00	54.50	61.00	48.00	74.09	65.83	253.33	0.92	3.50	52.53		0.74	
trainlm	0.0	8	0.1837	0.0390	90.00	80.00	100.00	70.00	50.00	90.00	50.50	34.00	67.00	64.76	39.17	40.14	0.35	4.53	30.20		0.52	
trainlm	0.0	9	0.2379	0.0469	95.00	100.00	90.00	70.00	60.00	80.00	61.00	70.00	52.00	66.44	71.67	119.65	0.98	4.06	74.39		0.73	
trainlm	0.0	10	0.1849	0.0278	90.00	80.00	100.00	70.00	40.00	100.00	58.00	42.00	74.00	80.53	45.00	82.60	0.77	3.71	95.83		0.65	
trainlm	0.0	7	0.2174	0.1379	70.00	70.00	70.00	75.00	80.00	70.00	58.50	64.00	53.00	80.71	65.83	334.58	0.93	7.55	213.90		0.81	
trainlm	0.0	8	0.2569	0.0245	95.00	90.00	100.00	70.00	40.00	100.00	54.50	40.00	69.00	86.47	44.17	272.64	0.88	2.60	8.68		0.72	
trainlm	0.0	10	0.3259	0.0239	95.00	90.00	100.00	65.00	40.00	90.00	60.50	48.00	73.00	62.53	50.83	51.68	0.25	2.73	81.96		0.57	
Average		9	0.2329	0.0476	90.00	87.00	93.00	70.00	53.00	87.00	55.75	47.60	63.90	73.45	51.33	127.45	0.75	4.03	63.68		0.66	

Table H.33. MLP 10-20-1, 10 input layers (categories), Ndeps = 20, Set 1

Training set size		Training: 40 patterns (20 deposits, 20 barren), training-stop: = 40 (20 deposits, 20 barren), test = 160 (80 deposits, 80 barren)																				
Training set type		Randomly selected cells, approximately equal numbers of patterns from each rock type																				
Geology input format		Fuzzy membership values																				
Learn.	I.r.	Cycles	MSE			Train % correct			Stop % correct			Test % correct			Map % correct			Map statistics				
Algorith.			Initial	Final	All	Deps	Non	Deps	All	Deps	Non	All	Deps	Non	All	Deps	Non	Chi	rho	D%/A%	D%*D%/A%	ROC
trainlm	0.0	7	0.2368	0.1632	67.50	50.00	85.00	40.00	67.50	40.00	95.00	62.50	40.00	85.00	78.39	41.67	85.00	71.64	0.63	3.11	67.39	0.67
trainlm	0.0	7	0.2547	0.1383	70.00	45.00	95.00	25.00	45.00	25.00	65.00	53.13	21.25	85.00	76.03	25.83	85.00	16.85	0.43	1.57	3.92	0.56
trainlm	0.0	11	0.2494	0.0305	92.50	95.00	90.00	60.00	67.50	60.00	75.00	60.00	62.50	57.50	61.49	67.50	61.35	0.92	2.33	58.25	0.69	
trainlm	0.0	8	0.3933	0.1530	57.50	35.00	80.00	47.50	30.00	30.00	65.00	48.75	30.00	67.50	66.78	30.83	38.44	0.08	5.60	27.99	0.52	
trainlm	0.0	6	0.2461	0.2461	50.00	70.00	30.00	80.00	60.00	80.00	40.00	50.00	75.00	25.00	22.31	75.00	58.52	-0.07	2.11	72.14	0.57	
trainlm	0.0	10	0.2484	0.0359	97.50	95.00	100.00	62.50	50.00	50.00	75.00	68.13	66.25	70.00	67.75	68.33	196.20	0.92	6.47	107.85	0.72	
trainlm	0.0	8	0.2313	0.0591	92.50	90.00	95.00	75.00	75.00	75.00	63.75	61.25	63.75	58.75	65.58	70.00	186.13	0.88	6.80	34.01	0.75	
trainlm	0.0	8	0.2081	0.0974	77.50	70.00	85.00	55.00	60.00	60.00	50.00	57.50	61.25	53.75	54.03	62.50	33.00	0.98	2.88	31.17	0.63	
trainlm	0.0	10	0.1673	0.0547	92.50	85.00	100.00	62.50	40.00	85.00	85.00	60.00	35.00	85.00	82.06	44.17	63.19	0.73	1.20	4.00	0.64	
trainlm	0.0	8	0.2778	0.2130	62.50	85.00	40.00	62.50	70.00	62.50	55.00	56.88	73.75	40.00	56.60	75.00	98.57	0.77	2.90	87.11	0.74	
Average		8	0.2513	0.1191	76.00	72.00	80.00	60.50	53.00	68.00	57.81	52.88	62.75	63.10	56.08	82.39	0.63	3.50	49.38	0.65		

Table H.34. MLP 10-20-1, 10 input layers (categories), Ndeps = 20, Set 2

Training set size	Training: 40 patterns (20 deposits, 20 barren), training-stop: = 40 (20 deposits, 20 barren), test = 160 (80 deposits, 80 barren)																						
Training set type	Randomly selected cells, approximately equal numbers of patterns from each rock type																						
Geology input format	Fuzzy membership values																						
Learn. Algorith.	I.r.	Cycles	MSE			Train % correct			Stop % correct			Test % correct			Map % correct			Map statistics					
			Initial	Final		All	Deps	Non	All	Deps	Non	All	Deps	Non	All	Deps	Non	Chi	rho	D%/A%	D%-D%/A%	ROC	
trainlm	0.0	9	0.2661	0.0950	75.00	60.00	90.00	62.50	50.00	75.00	58.13	55.00	61.25	70.60	55.00	61.25	55.57	0.97	2.35	33.29	0.68		
trainlm	0.0	10	0.2254	0.0681	85.00	90.00	80.00	57.50	70.00	45.00	56.25	58.75	53.75	62.72	65.83	62.72	68.02	0.98	3.24	40.46	0.70		
trainlm	0.0	7	0.2115	0.1648	55.00	75.00	35.00	57.50	85.00	30.00	54.37	91.25	17.50	37.46	87.50	153.28	0.98	5.70	94.93	0.76			
trainlm	0.0	9	0.3915	0.1403	70.00	55.00	85.00	55.00	35.00	75.00	59.38	52.50	66.25	70.92	50.00	71.81	0.72	1.13	1.88	0.68			
trainlm	0.0	9	0.2508	0.0940	80.00	75.00	85.00	72.50	75.00	70.00	63.75	66.25	61.25	62.81	69.17	86.75	1.00	4.52	15.06	0.72			
trainlm	0.0	12	0.2697	0.0308	95.00	95.00	95.00	65.00	75.00	55.00	54.37	43.75	65.00	66.35	57.50	46.14	0.77	1.76	33.65	0.64			
trainlm	0.0	7	0.2283	0.1573	57.50	20.00	95.00	62.50	25.00	100.00	63.13	36.25	90.00	94.60	31.67	267.64	0.38	0.00	0.00	0.69			
trainlm	0.0	10	0.3046	0.1207	75.00	75.00	75.00	65.00	70.00	60.00	60.00	65.00	55.00	68.81	67.50	222.83	0.98	7.54	144.58	0.77			
trainlm	0.0	6	0.2157	0.2157	57.50	50.00	65.00	55.00	55.00	55.00	55.63	56.25	55.00	68.02	55.00	118.74	0.93	5.61	79.45	0.68			
trainlm	0.0	8	0.2701	0.1230	72.50	70.00	75.00	62.50	45.00	80.00	68.75	61.25	76.25	73.01	60.00	113.24	0.75	13.78	22.96	0.70			
Average		9	0.2634	0.1210	72.25	66.50	78.00	61.50	58.50	64.50	59.38	58.63	60.13	67.53	59.92	120.40	0.85	4.56	46.63	0.70			

Table H.35. MLP 10-20-1, 10 input layers (categories), Ndeps = 20, Set 3

Training set size	Training: 40 patterns (20 deposits, 20 barren), training-stop: = 40 (20 deposits, 20 barren), test = 160 (80 deposits, 80 barren)																			
Training set type	Randomly selected cells, approximately equal numbers of patterns from each rock type																			
Geology input format	Fuzzy membership values																			
Learn.	l.r.	Cycles	MSE			Train % correct			Stop % correct			Test % correct			Map % correct			Map statistics		
Algorith.			Initial	Final	All	Deps	Non	Deps	All	Deps	Non	All	Deps	Non	All	Deps	Non	Chi	rho	D%/A%
trainlm	0.0	10	0.2016	0.0212	97.50	100.00	95.00	67.50	70.00	65.00	55.00	47.11	70.00	27.78	0.72	1.47	41.68	0.62		
trainlm	0.0	8	0.2430	0.1506	65.00	30.00	100.00	57.50	25.00	90.00	95.00	94.64	25.00	499.59	0.92	39.26	163.60	0.69		
trainlm	0.0	6	0.1913	0.1913	67.50	50.00	85.00	60.00	55.00	65.00	77.50	80.86	41.67	136.55	0.97	15.38	89.71	0.67		
trainlm	0.0	9	0.3694	0.1081	75.00	55.00	95.00	62.50	50.00	75.00	86.25	86.97	37.50	77.43	0.78	2.00	8.32	0.68		
trainlm	0.0	12	0.3167	0.0388	95.00	95.00	95.00	72.50	85.00	60.00	61.88	63.75	60.00	68.88	0.97	2.60	62.81	0.69		
trainlm	0.0	8	0.2454	0.1108	75.00	60.00	90.00	55.00	30.00	80.00	88.75	88.61	39.17	288.80	0.98	21.68	126.44	0.73		
trainlm	0.0	10	0.2994	0.0765	87.50	90.00	85.00	75.00	90.00	60.00	63.75	63.75	71.42	72.50	0.87	5.75	215.64	0.74		
trainlm	0.0	9	0.2522	0.0851	80.00	90.00	70.00	75.00	75.00	65.00	71.25	58.75	75.00	257.34	0.88	9.78	236.35	0.69		
trainlm	0.0	7	0.1545	0.0971	82.50	100.00	65.00	70.00	40.00	70.00	47.50	59.87	73.33	68.91	0.97	3.30	21.99	0.70		
trainlm	0.0	8	0.2728	0.0921	77.50	75.00	80.00	67.50	65.00	60.00	61.88	60.00	63.33	483.60	0.72	16.75	97.73	0.69		
Average		9	0.2546	0.0972	80.25	74.50	86.00	64.25	61.50	67.00	60.56	51.50	69.63	70.52	57.00	212.74	111.80	106.43	0.69	

Table H.36. MLP 10-20-1, 10 input layers (categories), Ndeps = 20, Set 4

Training set size		Training: 40 patterns (20 deposits, 20 barren), training-stop: = 40 (20 deposits, 20 barren), test = 160 (80 deposits, 80 barren)																				
Training set type		Randomly selected cells, approximately equal numbers of patterns from each rock type																				
Geology input format		Fuzzy membership values																				
Learn. Algorith.	l.r.	Cycles	MSE			Train % correct			Stop % correct			Test % correct			Map % correct			Map statistics				
			Initial	Final	All	Deps	Non	All	Deps	Non	All	Deps	Non	All	Deps	Non	Chi	rho	D%/A%	D*P%/A%	ROC	
trainlm	0.0	6	0.2045	0.2045	60.00	20.00	100.00	62.50	35.00	90.00	51.88	11.25	92.50	97.75	16.67	206.72	0.52	31.87	26.56	0.73		
trainlm	0.0	8	0.2212	0.0930	80.00	70.00	90.00	65.00	55.00	75.00	53.75	37.50	70.00	70.40	45.83	79.41	0.02	0.46	0.77	0.62		
trainlm	0.0	8	0.2144	0.1666	65.00	95.00	35.00	70.00	90.00	50.00	55.00	75.00	35.00	57.66	80.83	414.88	0.92	7.66	401.93	0.82		
trainlm	0.0	11	0.3847	0.0475	90.00	95.00	85.00	70.00	80.00	60.00	58.13	70.00	46.25	55.59	75.83	88.86	0.93	2.55	99.98	0.71		
trainlm	0.0	9	0.2108	0.0567	92.50	100.00	85.00	62.50	80.00	45.00	58.13	65.00	51.25	55.60	73.33	72.03	0.82	2.52	83.93	0.68		
trainlm	0.0	6	0.2051	0.2051	67.50	40.00	95.00	67.50	55.00	80.00	53.13	30.00	76.25	81.81	35.83	138.14	0.48	8.99	112.32	0.59		
trainlm	0.0	7	0.2216	0.1268	75.00	60.00	90.00	85.00	85.00	85.00	66.88	60.00	73.75	78.86	64.17	287.52	0.98	11.10	138.69	0.74		
trainlm	0.0	9	0.3042	0.0770	80.00	90.00	70.00	72.50	85.00	60.00	59.38	71.25	47.50	62.55	76.67	408.21	0.98	12.45	290.47	0.79		
trainlm	0.0	7	0.1824	0.1121	77.50	80.00	75.00	82.50	95.00	70.00	63.13	65.00	61.25	66.45	72.50	135.14	0.95	5.44	45.32	0.75		
trainlm	0.0	8	0.2879	0.1098	75.00	65.00	85.00	72.50	70.00	75.00	68.75	53.75	83.75	90.05	58.33	563.22	0.98	24.28	60.70	0.80		
Average		8	0.2437	0.1199	76.25	71.50	81.00	71.00	73.00	69.00	58.81	53.88	63.75	71.67	60.00	239.41	0.76	10.73	126.07	0.72		

Table H.39. MLP 10-20-1, 10 input layers (categories), Ndeps = 20, Set 7

Training set size		Training: 40 patterns (20 deposits, 20 barren), training-stop: = 40 (20 deposits, 20 barren), test = 160 (80 deposits, 80 barren)																			
Training set type		Randomly selected cells, approximately equal numbers of patterns from each rock type																			
Geology input format		Fuzzy membership values																			
Learn.	l.r.	Cycles	MSE			Train % correct			Stop % correct			Test % correct			Map % correct		Map statistics				
Algoth.			Initial	Final	All	Depos	Non	Depos	All	Depos	Non	All	Depos	Non	All	Depos	Chi	rho	D%/A%	D%*D%/A%	ROC
trainlm	0.0	12	0.2423	0.0057	100.00	100.00	100.00	75.00	80.00	80.00	70.00	62.50	68.75	56.25	62.15	75.83	161.17	0.92	3.94	118.13	0.76
trainlm	0.0	12	0.2487	0.0085	100.00	100.00	100.00	70.00	75.00	75.00	65.00	66.88	82.50	51.25	57.15	84.17	121.63	0.83	2.83	125.17	0.75
trainlm	0.0	9	0.2025	0.0542	85.00	85.00	85.00	82.50	85.00	85.00	80.00	62.50	75.00	50.00	57.17	78.33	158.40	0.85	4.25	173.57	0.75
trainlm	0.0	11	0.3923	0.0288	97.50	100.00	95.00	77.50	95.00	95.00	60.00	76.88	83.75	70.00	80.71	88.33	674.21	0.93	13.66	512.30	0.88
trainlm	0.0	8	0.1800	0.0602	90.00	80.00	100.00	70.00	65.00	75.00	61.88	51.25	72.50	68.56	58.33	58.33	127.77	0.82	2.90	24.20	0.66
trainlm	0.0	8	0.2181	0.0636	87.50	85.00	90.00	67.50	80.00	55.00	55.00	60.62	65.00	56.25	54.85	70.83	145.45	0.90	4.78	147.41	0.73
trainlm	0.0	9	0.1982	0.0533	87.50	80.00	95.00	72.50	65.00	80.00	65.63	65.63	65.00	66.25	62.83	67.50	58.75	0.92	2.38	43.67	0.69
trainlm	0.0	9	0.3052	0.0825	85.00	70.00	100.00	75.00	85.00	65.00	65.00	67.50	65.00	70.00	65.81	69.17	145.18	0.87	4.59	149.07	0.73
trainlm	0.0	10	0.1715	0.0113	97.50	100.00	95.00	67.50	75.00	60.00	60.00	63.13	76.25	50.00	52.38	80.00	88.70	0.88	2.57	115.73	0.71
trainlm	0.0	9	0.2808	0.0337	90.00	80.00	100.00	65.00	55.00	75.00	75.00	56.88	43.75	70.00	71.92	51.67	59.92	0.98	2.66	24.43	0.69
Average		10	0.2440	0.0402	92.00	88.00	96.00	72.25	76.00	68.50	61.25	64.44	67.63	61.25	63.35	72.42	174.12	0.89	4.46	143.37	0.73

Table H.40. MLP 10-20-1, 10 input layers (categories), Ndeps = 20, Set 8

Training set size			Training: 40 patterns (20 deposits, 20 barren), training-stop: = 40 (20 deposits, 20 barren), test = 160 (80 deposits, 80 barren)																			
Training set type			Randomly selected cells, approximately equal numbers of patterns from each rock type																			
Geology input format			Fuzzy membership values																			
Learn.	l.r.	Cycles	MSE			Train % correct			Stop % correct			Test % correct			Map % correct			Map statistics			D%*D%/A%	ROC
			Initial	Final	All	Depos	Non	All	Depos	Non	All	Depos	Non	All	Depos	Non	Chi	rho				
trainlm	0.0	10	0.2317	0.0456	92.50	100.00	85.00	80.00	95.00	95.00	65.00	72.50	76.25	68.75	57.38	83.33	137.32	0.88	3.66	125.11	0.76	
trainlm	0.0	8	0.2322	0.0783	85.00	80.00	90.00	72.50	75.00	70.00	63.13	68.75	57.50	69.19	71.67	479.88	1.00	22.23	370.54	0.77		
trainlm	0.0	11	0.1925	0.0473	90.00	100.00	80.00	70.00	65.00	75.00	68.75	61.25	76.25	72.00	68.33	170.10	0.92	4.55	90.95	0.76		
trainlm	0.0	13	0.3960	0.0258	95.00	100.00	90.00	72.50	70.00	75.00	68.75	61.25	76.25	83.38	69.17	455.99	1.00	11.60	328.57	0.84		
trainlm	0.0	10	0.1925	0.0474	90.00	85.00	95.00	67.50	60.00	75.00	63.13	62.50	63.75	65.09	65.83	398.76	0.92	14.69	342.69	0.74		
trainlm	0.0	9	0.2113	0.0848	77.50	70.00	85.00	80.00	70.00	90.00	68.75	58.75	78.75	82.19	62.50	234.17	0.97	7.29	97.23	0.80		
trainlm	0.0	8	0.1929	0.0606	85.00	85.00	85.00	82.50	95.00	70.00	68.75	62.50	75.00	74.88	71.67	419.10	0.97	11.76	333.08	0.81		
trainlm	0.0	9	0.2926	0.1194	77.50	80.00	75.00	80.00	80.00	80.00	58.75	56.25	56.25	53.59	65.83	49.87	0.60	1.68	44.74	0.63		
trainlm	0.0	9	0.1833	0.0439	92.50	85.00	100.00	67.50	70.00	65.00	65.63	61.25	70.00	59.03	66.67	59.95	0.75	1.09	12.73	0.65		
trainlm	0.0	11	0.2349	0.0307	97.50	100.00	95.00	80.00	75.00	85.00	70.00	73.75	66.25	64.23	78.33	183.90	0.68	4.59	133.99	0.76		
Average		10	0.2360	0.0584	88.25	88.50	88.00	75.25	75.50	75.00	66.69	64.50	68.88	68.10	70.33	258.90	0.87	8.31	187.96	0.75		

Table H.41. MLP 10-20-1, 10 input layers (categories), Ndeps = 20, Set 9

Training set size		Training: 40 patterns (20 deposits, 20 barren), training-stop: = 40 (20 deposits, 20 barren), test = 160 (80 deposits, 80 barren)																								
Training set type		Randomly selected cells, approximately equal numbers of patterns from each rock type																								
Geology input format		Fuzzy membership values																								
Learn.	l.r.	Cycles	MSE		Train % correct				Stop % correct				Test % correct				Map % correct				Map statistics				D%*D%/A%	ROC
			Initial	Final	All	Deps	Non	All	Deps	Non	All	Deps	Non	All	Deps	Non	All	Deps	Non	Chi	rho	D%/A%				
trainlm	0.0	7	0.2373	0.0962	80.00	95.00	65.00	62.50	80.00	45.00	60.62	73.75	47.50	60.71	78.33	329.70	0.83	10.76	242.10	0.77						
trainlm	0.0	9	0.2121	0.0407	90.00	90.00	90.00	65.00	65.00	65.00	59.38	63.75	55.00	70.90	68.33	192.29	0.90	6.16	174.47	0.73						
trainlm	0.0	7	0.1625	0.1081	72.50	60.00	85.00	57.50	45.00	70.00	62.50	47.50	77.50	89.57	49.17	374.05	0.35	0.00	0.00	0.81						
trainlm	0.0	12	0.3866	0.0993	75.00	50.00	100.00	57.50	45.00	70.00	61.25	36.25	86.25	89.89	40.00	233.73	0.97	8.14	108.49	0.71						
trainlm	0.0	10	0.2482	0.1050	80.00	65.00	95.00	65.00	60.00	70.00	61.25	60.00	62.50	59.23	60.83	35.76	0.72	2.12	61.84	0.62						
trainlm	0.0	9	0.2681	0.0526	87.50	80.00	95.00	57.50	55.00	60.00	66.88	51.25	82.50	83.66	56.67	375.47	1.00	15.60	220.94	0.76						
trainlm	0.0	9	0.2273	0.0536	90.00	85.00	95.00	55.00	45.00	65.00	60.62	58.75	62.50	74.81	60.83	236.64	0.93	10.62	150.39	0.72						
trainlm	0.0	7	0.2078	0.1097	75.00	65.00	85.00	60.00	75.00	45.00	59.38	65.00	53.75	68.80	66.67	207.51	0.92	5.00	8.33	0.75						
trainlm	0.0	7	0.2033	0.0993	77.50	95.00	60.00	55.00	70.00	40.00	50.63	67.50	33.75	63.84	72.50	197.85	0.98	7.87	98.36	0.76						
trainlm	0.0	8	0.2756	0.1200	62.50	95.00	30.00	60.00	100.00	20.00	55.63	83.75	27.50	22.62	88.33	171.42	0.95	7.53	169.34	0.69						
Average		9	0.2429	0.0885	79.00	78.00	80.00	59.50	64.00	55.00	59.81	60.75	58.88	68.40	64.17	235.44	0.85	7.38	123.43	0.73						

Table H.42. MLP 10-20-1, 10 input layers (categories), Ndeps = 20, Set 10

Training set size			Training: 40 patterns (20 deposits, 20 barren), training-stop: = 40 (20 deposits, 20 barren), test = 160 (80 deposits, 80 barren)																							
Training set type			Randomly selected cells, approximately equal numbers of patterns from each rock type																							
Geology input format			Fuzzy membership values																							
Learn.	l.r.	Cycles	MSE			Train % correct			Stop % correct			Test % correct			Map % correct			Map statistics								
			Initial	Final	All	Deps	Non	All	Deps	Non	All	Deps	Non	All	Deps	Non	All	Deps	Non	Chi	rho	D%/A%	D%*D%/A%	ROC		
trainlm	0.0	10	0.2043	0.0422	95.00	100.00	90.00	90.00	72.50	80.00	65.00	65.00	62.50	67.50	63.30	71.67	108.88	0.93	3.45	106.39	0.73					
trainlm	0.0	10	0.2411	0.0302	97.50	95.00	100.00	62.50	60.00	65.00	65.00	52.50	52.50	59.51	60.83	39.61	0.93	1.98	42.81	0.66						
trainlm	0.0	12	0.2273	0.0066	100.00	100.00	100.00	70.00	80.00	60.00	62.50	77.50	47.50	39.45	81.67	52.76	0.75	1.05	43.71	0.55						
trainlm	0.0	10	0.3908	0.0295	95.00	100.00	90.00	72.50	65.00	80.00	61.25	60.00	62.50	59.37	67.50	78.40	0.68	1.12	17.76	0.63						
trainlm	0.0	9	0.2174	0.0660	90.00	100.00	80.00	75.00	90.00	60.00	65.00	73.75	56.25	50.54	80.83	131.18	0.73	3.03	158.92	0.75						
trainlm	0.0	9	0.1759	0.0210	97.50	95.00	100.00	77.50	75.00	80.00	60.62	63.75	57.50	56.52	70.83	62.55	0.73	0.94	18.04	0.61						
trainlm	0.0	11	0.1839	0.0268	95.00	100.00	90.00	70.00	65.00	75.00	57.50	60.00	55.00	59.32	67.50	47.37	0.78	2.02	72.45	0.64						
trainlm	0.0	8	0.3167	0.0913	80.00	95.00	65.00	70.00	85.00	55.00	60.00	81.25	38.75	34.83	84.17	40.83	0.67	1.99	77.75	0.64						
trainlm	0.0	8	0.1559	0.0684	80.00	80.00	80.00	75.00	75.00	75.00	60.00	66.25	53.75	51.65	70.00	68.46	0.62	0.65	9.25	0.58						
trainlm	0.0	8	0.2388	0.0845	85.00	100.00	70.00	67.50	85.00	50.00	58.13	76.25	40.00	33.68	81.67	23.83	0.80	0.85	14.90	0.57						
Average		10	0.2352	0.0466	91.50	96.50	86.50	71.25	76.00	66.50	60.25	67.38	53.13	50.82	73.67	65.38	0.76	1.71	56.20	0.64						

Table H.43. MLP 10-20-1, 10 input layers (categories), Ndeps = 40, Set 1

Training set size			Training: 80 patterns (40 deposits, 40 barren), training-stop: = 80 (40 deposits, 40 barren), test = 80 (40 deposits, 40 barren)																										
Training set type			Randomly selected cells, approximately equal numbers of patterns from each rock type																										
Geology input format			Fuzzy membership values																										
Learn.	l.r.	Cycles	MSE			Train % correct				Stop % correct				Test % correct				Map % correct				Map statistics							
			Initial	Final	All	Deps	Non	All	Deps	Non	All	Deps	Non	All	Deps	Non	All	Deps	Non	Chi	rho	D%/A%	D%*D%/A%	ROC					
trainlm	0.0	11	0.2371	0.0393	92.50	100.00	85.00	77.50	72.50	75.00	72.50	70.00	57.50	59.47	80.83	125.00	0.97	2.09	67.88	0.75									
trainlm	0.0	11	0.2450	0.0335	93.75	90.00	97.50	82.50	62.50	72.50	62.50	55.00	80.00	70.14	69.17	182.25	0.98	5.13	98.38	0.78									
trainlm	0.0	8	0.2005	0.0991	80.00	77.50	82.50	77.50	65.00	72.50	66.25	57.50	75.00	82.12	66.67	651.43	1.00	43.97	403.06	0.81									
trainlm	0.0	12	0.3851	0.0491	91.25	95.00	87.50	72.50	72.50	70.00	62.50	62.50	77.50	73.73	76.67	254.51	1.00	6.11	66.20	0.81									
trainlm	0.0	10	0.2211	0.0523	91.25	87.50	95.00	82.50	60.00	71.25	61.25	62.50	60.00	67.74	70.00	166.94	0.97	5.94	34.62	0.75									
trainlm	0.0	10	0.2690	0.0793	85.00	82.50	87.50	87.50	55.00	71.25	61.25	57.50	65.00	71.07	65.00	99.52	0.90	2.03	16.93	0.72									
trainlm	0.0	8	0.2071	0.0966	71.25	70.00	72.50	75.00	65.00	70.00	62.50	57.50	67.50	68.44	64.17	104.44	0.83	1.33	5.54	0.71									
trainlm	0.0	10	0.2573	0.0608	87.50	95.00	80.00	77.50	70.00	73.75	65.00	70.00	60.00	56.42	78.33	74.63	0.93	1.40	21.06	0.69									
trainlm	0.0	8	0.1959	0.0892	77.50	92.50	62.50	77.50	72.50	75.00	68.75	72.50	65.00	71.43	79.17	432.69	0.95	12.43	134.63	0.82									
trainlm	0.0	7	0.2315	0.1229	71.25	55.00	87.50	85.00	70.00	55.00	61.25	37.50	85.00	91.42	49.17	621.55	0.95	117.56	293.91	0.79									
Average		10	0.2449	0.0722	84.13	84.50	83.75	72.75	65.00	80.50	64.75	60.25	69.25	71.20	69.92	271.30	0.95	19.80	114.22	0.76									

Table H.44. MLP 10-20-1, 10 input layers (categories), Ndeps = 40, Set 2

Training set size			Training: 80 patterns (40 deposits, 40 barren), training-stop: = 80 (40 deposits, 40 barren), test = 80 (40 deposits, 40 barren)																							
Training set type			Randomly selected cells, approximately equal numbers of patterns from each rock type																							
Geology input format			Fuzzy membership values																							
Learn.	l.r.	Cycles	MSE			Train % correct			Stop % correct			Test % correct			Map % correct			Map statistics			D%*D%/A%			ROC		
			Initial	Final	All	Deps	Non	All	Deps	Non	All	Deps	Non	All	Deps	Non	All	Deps	Chi	rho	D%/A%	D%*D%/A%	ROC			
trainlm	0.0	10	0.2169	0.0240	97.50	95.00	100.00	63.75	60.00	67.50	70.00	67.50	72.50	70.83	74.17	168.07	0.95	3.43	71.50		0.79					
trainlm	0.0	12	0.2012	0.0243	96.25	95.00	97.50	70.00	72.50	67.50	72.50	72.50	72.50	64.71	80.00	188.22	0.92	4.21	161.35		0.80					
trainlm	0.0	8	0.1939	0.1118	75.00	57.50	92.50	56.25	47.50	65.00	52.50	35.00	70.00	87.84	46.67	245.01	0.98	14.77	24.62		0.79					
trainlm	0.0	8	0.3927	0.1067	75.00	57.50	92.50	63.75	52.50	75.00	61.25	37.50	85.00	91.01	49.17	759.32	0.93	26.01	130.07		0.78					
trainlm	0.0	9	0.2462	0.0959	81.25	75.00	87.50	65.00	70.00	60.00	63.75	55.00	72.50	85.74	66.67	541.23	1.00	24.77	185.77		0.86					
trainlm	0.0	10	0.1953	0.0401	95.00	92.50	97.50	70.00	67.50	72.50	76.25	75.00	77.50	77.42	78.33	281.51	0.98	5.86	107.36		0.84					
trainlm	0.0	7	0.2456	0.1131	73.75	57.50	90.00	63.75	60.00	67.50	50.00	63.75	50.00	89.74	55.83	708.26	1.00	31.98	453.03		0.81					
trainlm	0.0	10	0.2625	0.0494	93.75	90.00	97.50	67.50	57.50	77.50	70.00	60.00	80.00	83.94	69.17	433.24	0.90	11.27	112.70		0.80					
trainlm	0.0	9	0.1888	0.0500	86.25	75.00	97.50	70.00	62.50	77.50	75.00	72.50	77.50	80.77	70.00	280.94	0.95	6.80	130.25		0.80					
trainlm	0.0	9	0.3068	0.0828	82.50	80.00	85.00	70.00	70.00	70.00	60.00	62.50	57.50	77.43	70.83	389.83	0.82	8.67	332.49		0.83					
Average		9	0.2450	0.0698	85.63	77.50	93.75	66.00	62.00	70.00	66.50	58.75	74.25	80.94	66.08	399.56	0.94	13.78	170.91		0.81					

Table H.45. MLP 10-20-1, 10 input layers (categories), Ndeps = 40, Set 3

Training set size		Training: 80 patterns (40 deposits, 40 barren), training-stop: = 80 (40 deposits, 40 barren), test = 80 (40 deposits, 40 barren)																					
Training set type		Randomly selected cells, approximately equal numbers of patterns from each rock type																					
Geology input format		Fuzzy membership values																					
Learn.	l.r.	Cycles	MSE			Train % correct			Stop % correct			Test % correct			Map % correct			Map statistics					
Algorith.			Initial	Final	All	Deps	Non	All	Deps	Non	All	Deps	Non	All	Deps	Non	All	Deps	Chi	rho	D%/A%	D%*D%/A%	ROC
trainlm	0.0	10	0.2323	0.0522	92.50	85.00	100.00	72.50	67.50	77.50	73.75	77.50	70.00	75.14	76.67	281.62	0.97	8.80	124.65				
trainlm	0.0	9	0.2472	0.0811	80.00	72.50	87.50	57.50	57.50	55.00	57.50	55.00	60.00	72.34	61.67	147.97	0.95	5.07	88.66				
trainlm	0.0	10	0.1998	0.0503	91.25	97.50	85.00	66.25	80.00	52.50	68.75	80.00	57.50	70.43	85.83	493.37	0.92	9.97	365.65				
trainlm	0.0	10	0.3904	0.0699	82.50	65.00	100.00	66.25	55.00	77.50	65.00	62.50	67.50	85.44	60.83	569.10	0.98	17.89	313.05				
trainlm	0.0	9	0.2160	0.0658	87.50	85.00	90.00	71.25	67.50	75.00	66.25	65.00	67.50	84.28	72.50	461.62	0.97	11.99	259.81				
trainlm	0.0	11	0.2315	0.0344	95.00	95.00	95.00	72.50	77.50	67.50	70.00	72.50	67.50	75.19	81.67	550.56	0.95	10.09	386.69				
trainlm	0.0	13	0.2214	0.0255	95.00	90.00	100.00	76.25	72.50	80.00	73.75	65.00	82.50	82.32	75.83	379.85	1.00	6.54	201.74				
trainlm	0.0	9	0.2759	0.0557	92.50	87.50	97.50	67.50	67.50	67.50	65.00	67.50	62.50	79.46	74.17	482.16	1.00	14.00	280.07				
trainlm	0.0	7	0.1652	0.0847	85.00	90.00	80.00	67.50	75.00	60.00	65.00	77.50	52.50	70.03	80.83	259.07	0.92	6.72	78.40				
trainlm	0.0	8	0.2405	0.0811	80.00	62.50	97.50	61.25	45.00	77.50	65.00	45.00	85.00	84.88	50.83	181.64	0.90	3.17	7.92				
Average		10	0.2420	0.0601	88.13	83.00	93.25	67.88	66.50	69.25	67.00	66.75	67.25	77.95	72.08	380.70	0.96	9.42	210.66				

Table H.46. MLP 10-20-1, 10 input layers (categories), Ndeps = 40, Set 4

Training set size			Training: 80 patterns (40 deposits, 40 barren), training-stop: = 80 (40 deposits, 40 barren), test = 80 (40 deposits, 40 barren)																								
Training set type			Randomly selected cells, approximately equal numbers of patterns from each rock type																								
Geology input format			Fuzzy membership values																								
Learn.	l.r.	Cycles	MSE			Train % correct				Stop % correct				Test % correct				Map % correct				Map statistics				D%*D%/A%	ROC
			Initial	Final	All	Deps	Non	All	Deps	Non	All	Deps	Non	All	Deps	Non	All	Deps	Chi	rho	D%/A%						
trainlm	0.0	12	0.2267	0.0308	96.25	95.00	97.50	72.50	80.00	72.50	70.00	72.50	67.50	67.06	82.50	176.31	0.95	3.89	103.77	0.80							
trainlm	0.0	13	0.2303	0.0225	98.75	97.50	100.00	68.75	75.00	62.50	65.00	70.00	60.00	67.41	80.83	256.76	0.93	5.78	183.19	0.80							
trainlm	0.0	13	0.2059	0.0239	97.50	97.50	97.50	75.00	77.50	72.50	65.00	70.00	60.00	72.67	81.67	249.80	1.00	4.96	123.96	0.83							
trainlm	0.0	9	0.3805	0.1086	70.00	47.50	92.50	68.75	55.00	82.50	66.25	45.00	87.50	90.02	49.17	507.25	0.92	22.26	185.47	0.75							
trainlm	0.0	13	0.2094	0.0239	97.50	97.50	97.50	75.00	67.50	82.50	62.50	57.50	67.50	80.13	74.17	450.23	0.95	6.31	84.19	0.82							
trainlm	0.0	11	0.2562	0.0245	97.50	95.00	100.00	75.00	70.00	80.00	70.00	60.00	80.00	73.83	75.00	236.94	0.97	3.00	42.56	0.80							
trainlm	0.0	7	0.2027	0.1066	76.25	72.50	80.00	71.25	70.00	72.50	65.00	52.50	77.50	75.56	65.00	674.36	0.97	34.49	373.66	0.78							
trainlm	0.0	9	0.2375	0.0686	85.00	87.50	82.50	73.75	70.00	77.50	72.50	57.50	87.50	66.85	71.67	584.31	0.93	21.57	485.38	0.76							
trainlm	0.0	8	0.2377	0.0918	80.00	75.00	85.00	76.25	77.50	75.00	61.25	52.50	70.00	72.64	68.33	388.62	0.93	22.29	130.03	0.75							
trainlm	0.0	9	0.2330	0.0637	92.50	97.50	87.50	61.25	75.00	47.50	70.00	80.00	60.00	62.91	84.17	151.96	1.00	3.45	57.45	0.80							
Average		10	0.2420	0.0565	89.13	86.25	92.00	72.13	71.75	72.50	66.75	61.75	71.75	72.91	73.25	367.66	0.96	12.80	176.97	0.79							

Table H.47. MLP 10-20-1, 10 input layers (categories), Ndeps = 40, Set 5

Training set size		Training: 80 patterns (40 deposits, 40 barren), training-stop: = 80 (40 deposits, 40 barren), test = 80 (40 deposits, 40 barren)																				
Training set type		Randomly selected cells, approximately equal numbers of patterns from each rock type																				
Geology input format		Fuzzy membership values																				
Learn.	l.r.	Cycles	MSE			Train % correct			Stop % correct			Test % correct			Map % correct			Map statistics				
Algorith.			Initial	Final	All	Deps	Non	Deps	Non	All	Deps	Non	All	Deps	Non	All	Deps	Chi	rho	D%/A%	D%*D%/A%	ROC
trainlm	0.0	8	0.2299	0.0861	80.00	65.00	95.00	70.00	65.00	75.00	67.50	85.00	78.39	65.83	325.97	0.98	12.16	202.64			0.81	
trainlm	0.0	10	0.2354	0.0814	82.50	75.00	90.00	70.00	65.00	65.00	62.50	62.50	70.60	70.83	204.52	1.00	6.57	115.05			0.79	
trainlm	0.0	8	0.1961	0.1112	72.50	55.00	90.00	65.00	55.00	75.00	62.50	80.00	88.96	54.17	543.40	0.97	25.98	303.14			0.80	
trainlm	0.0	11	0.3890	0.0862	80.00	65.00	95.00	71.25	70.00	72.50	65.00	72.50	78.40	66.67	282.91	0.92	9.48	173.86			0.79	
trainlm	0.0	8	0.2456	0.0810	82.50	77.50	87.50	68.75	72.50	65.00	67.50	60.00	61.84	75.00	163.20	0.98	4.66	62.08			0.77	
trainlm	0.0	10	0.2261	0.0612	87.50	80.00	95.00	73.75	77.50	70.00	67.50	72.50	80.09	75.00	651.02	0.97	20.96	419.26			0.85	
trainlm	0.0	7	0.2384	0.1209	73.75	55.00	92.50	68.75	52.50	85.00	47.50	82.50	88.23	51.67	906.14	0.97	65.26	435.08			0.76	
trainlm	0.0	9	0.2919	0.0789	82.50	72.50	92.50	68.75	80.00	57.50	66.25	65.00	73.23	72.50	371.47	0.98	13.17	285.28			0.80	
trainlm	0.0	8	0.1639	0.0927	82.50	80.00	85.00	65.00	60.00	50.00	70.00	55.00	70.58	76.67	506.90	0.98	19.70	311.93			0.80	
trainlm	0.0	9	0.2207	0.0871	81.25	70.00	92.50	68.75	67.50	70.00	62.50	82.50	87.66	64.17	365.59	1.00	12.15	91.14			0.85	
Average		9	0.2437	0.0887	80.50	69.50	91.50	69.00	68.50	67.38	62.75	72.00	77.80	67.25	432.11	0.97	19.01	239.95			0.80	

Table H.48. MLP 10-20-1, 10 input layers (categories), Ndeps = 40, Set 6

Training set size	Training: 80 patterns (40 deposits, 40 barren), training-stop: = 80 (40 deposits, 40 barren), test = 80 (40 deposits, 40 barren)																							
Training set type	Randomly selected cells, approximately equal numbers of patterns from each rock type																							
Geology input format	Fuzzy membership values																							
Learn.	l.r.	Cycles	MSE			Train % correct			Stop % correct			Test % correct			Map % correct			Map statistics						
Algorith.			Initial	Final	All	Deps	Non	All	Deps	Non	All	Deps	Non	All	Deps	Non	All	Deps	Non	Chi	rho	D%/A%	D%*D%/A%	ROC
trainlm	0.0	8	0.2201	0.0904	82.50	92.50	72.50	72.50	71.25	82.50	60.00	71.25	95.00	47.50	47.17	90.00	130.85	0.96	3.71	92.76	0.96	3.71	92.76	0.76
trainlm	0.0	11	0.2052	0.0329	98.75	100.00	97.50	66.25	70.00	62.50	77.50	62.50	47.50	65.22	82.50	82.50	316.43	0.95	7.14	237.89	0.95	7.14	237.89	0.83
trainlm	0.0	8	0.2039	0.1124	73.75	92.50	55.00	67.50	62.50	82.50	50.00	66.25	82.50	50.00	54.49	85.83	298.78	1.00	8.86	125.53	1.00	8.86	125.53	0.80
trainlm	0.0	10	0.3918	0.0947	83.75	82.50	85.00	62.50	62.50	62.50	73.75	72.50	75.00	82.85	72.50	986.80	0.98	31.27	729.62	0.98	31.27	729.62	0.84	
trainlm	0.0	11	0.2208	0.0542	90.00	90.00	90.00	65.00	47.50	82.50	70.00	70.00	70.00	76.93	69.17	337.27	0.97	11.20	149.28	0.97	11.20	149.28	0.79	
trainlm	0.0	9	0.2170	0.0822	77.50	65.00	90.00	70.00	52.50	87.50	55.00	72.50	55.00	90.00	85.23	57.50	830.98	1.00	32.86	438.13	1.00	32.86	438.13	0.82
trainlm	0.0	8	0.2221	0.0983	77.50	72.50	82.50	67.50	60.00	75.00	71.25	70.00	72.50	78.94	67.50	67.50	801.07	1.00	43.69	327.71	1.00	43.69	327.71	0.80
trainlm	0.0	11	0.2799	0.0513	93.75	92.50	95.00	63.75	52.50	75.00	66.25	70.00	62.50	70.57	71.67	123.49	0.95	1.98	13.21	0.95	1.98	13.21	0.77	
trainlm	0.0	7	0.1756	0.1184	71.25	97.50	45.00	60.00	80.00	40.00	51.25	82.50	20.00	45.59	86.67	238.92	0.98	8.78	124.43	0.98	8.78	124.43	0.76	
trainlm	0.0	12	0.2434	0.0436	93.75	95.00	92.50	63.75	60.00	67.50	50.00	50.00	57.50	62.95	70.83	110.80	0.85	1.45	25.33	0.85	1.45	25.33	0.71	
Average		10	0.2380	0.0778	84.25	88.00	80.50	65.75	65.00	66.50	73.25	65.50	73.25	57.75	67.00	75.42	417.54	0.96	15.09	226.39	0.96	15.09	226.39	0.79

Table H.49. MLP 10-20-1, 10 input layers (categories), Ndeps = 40, Set 7

Training set size		Training: 80 patterns (40 deposits, 40 barren), training-stop: = 80 (40 deposits, 40 barren), test = 80 (40 deposits, 40 barren)															
Training set type		Randomly selected cells, approximately equal numbers of patterns from each rock type															
Geology input format		Fuzzy membership values															
Learn. Algorith.	l.r. Cycles	MSE		Train % correct			Stop % correct			Test % correct			Map % correct		Map statistics		
		Initial	Final	All	Deps	Non	All	Deps	Non	All	Deps	Non	All	Deps	Chi	rho	D%/A% D%*D%/A%
trainlm	0.0 11	0.2405	0.0132	98.75	97.50	100.00	78.75	80.00	77.50	75.00	75.00	75.00	64.38	84.17	180.54	0.87	2.73 86.30
trainlm	0.0 9	0.2172	0.0593	91.25	95.00	87.50	67.50	75.00	60.00	56.25	67.50	45.00	69.87	79.17	421.02	0.98	15.87 304.23
trainlm	0.0 10	0.2104	0.0700	87.50	87.50	87.50	78.75	72.50	85.00	66.25	60.00	72.50	80.05	73.33	341.74	1.00	10.55 158.27
trainlm	0.0 10	0.3897	0.0856	86.25	85.00	87.50	72.50	75.00	70.00	55.00	55.00	55.00	79.62	71.67	1111.67	1.00	37.58 876.93
trainlm	0.0 12	0.2420	0.0230	96.25	92.50	100.00	77.50	75.00	80.00	58.75	62.50	55.00	68.92	76.67	243.31	0.93	3.45 60.44
trainlm	0.0 10	0.2167	0.0238	97.50	97.50	97.50	82.50	80.00	85.00	66.25	70.00	62.50	77.12	82.50	356.24	0.97	8.23 164.64
trainlm	0.0 11	0.2410	0.0378	95.00	97.50	92.50	82.50	90.00	75.00	67.50	77.50	57.50	55.37	88.33	191.04	0.92	4.27 184.94
trainlm	0.0 10	0.2813	0.0711	87.50	80.00	95.00	72.50	62.50	82.50	60.00	45.00	75.00	82.00	62.50	414.86	0.98	13.45 313.79
trainlm	0.0 8	0.1851	0.0754	85.00	75.00	95.00	78.75	77.50	80.00	62.50	47.50	77.50	86.52	66.67	757.32	0.95	34.75 434.42
trainlm	0.0 7	0.2573	0.1316	71.25	50.00	92.50	70.00	50.00	90.00	65.00	35.00	95.00	95.72	45.00	774.13	1.00	82.45 206.13
Average	10	0.2481	0.0591	89.63	85.75	93.50	76.13	73.75	78.50	63.25	59.50	67.00	75.96	73.00	479.19	0.96	21.33 279.01

Table H.50. MLP 10-20-1, 10 input layers (categories), Ndeps = 40, Set 8

Training set size		Training: 80 patterns (40 deposits, 40 barren), training-stop: = 80 (40 deposits, 40 barren), test = 80 (40 deposits, 40 barren)															
Training set type		Randomly selected cells, approximately equal numbers of patterns from each rock type															
Geology input format		Fuzzy membership values															
Learn. Algorith.	l.r. Cycles	MSE		Train % correct			Stop % correct			Test % correct			Map % correct		Map statistics		
		Initial	Final	All	Deps	Non	All	Deps	Non	All	Deps	Non	All	Deps	Chi	rho	D%/A% D%*D%/A%
trainlm	0.0 7	0.2120	0.1042	73.75	95.00	52.50	51.25	77.50	25.00	56.25	85.00	27.50	48.28	85.83	278.70	0.98	11.34 188.99
trainlm	0.0 10	0.2533	0.0301	92.50	85.00	100.00	70.00	62.50	77.50	61.25	55.00	67.50	76.93	67.50	297.78	0.97	5.23 117.71
trainlm	0.0 7	0.1890	0.1343	65.00	82.50	47.50	52.50	70.00	35.00	56.25	82.50	30.00	47.78	78.33	63.40	0.98	2.28 22.81
trainlm	0.0 9	0.3893	0.0976	77.50	67.50	87.50	61.25	45.00	77.50	71.25	60.00	82.50	87.44	57.50	792.61	1.00	28.23 447.01
trainlm	0.0 9	0.2282	0.0565	88.75	82.50	95.00	65.00	52.50	77.50	62.50	52.50	72.50	80.15	62.50	226.48	0.97	4.22 35.19
trainlm	0.0 9	0.1703	0.0533	90.00	82.50	97.50	65.00	50.00	80.00	62.50	57.50	67.50	82.05	63.33	326.23	0.93	8.24 199.25
trainlm	0.0 9	0.2366	0.0707	82.50	100.00	65.00	65.00	77.50	52.50	57.50	70.00	45.00	41.92	82.50	148.49	0.62	4.12 130.43
trainlm	0.0 9	0.2901	0.0505	93.75	90.00	97.50	63.75	50.00	77.50	65.00	57.50	72.50	78.07	65.83	224.52	0.85	7.31 97.49
trainlm	0.0 8	0.1430	0.0565	90.00	85.00	95.00	56.25	50.00	62.50	65.00	62.50	67.50	81.96	65.83	515.28	0.98	16.55 330.98
trainlm	0.0 9	0.2718	0.0701	88.75	82.50	95.00	58.75	52.50	65.00	56.25	37.50	75.00	80.00	57.50	133.91	0.95	3.54 20.64
Average	9	0.2384	0.0724	84.25	85.25	83.25	60.88	58.75	63.00	61.38	62.00	60.75	70.46	68.67	300.74	0.92	9.11 159.05

Table H.51. MLP 10-20-1, 10 input layers (categories), Ndeps = 40, Set 9

Training set size			Training: 80 patterns (40 deposits, 40 barren), training-stop: = 80 (40 deposits, 40 barren), test = 80 (40 deposits, 40 barren)																							
Training set type			Randomly selected cells, approximately equal numbers of patterns from each rock type																							
Geology input format			Fuzzy membership values																							
Learn.	l.r.	Cycles	MSE			Train % correct			Stop % correct			Test % correct			Map % correct			Map statistics								
Algoth.			Initial	Final	All	Deps	Non	All	Deps	Non	All	Deps	Non	All	Deps	Non	All	Deps	Non	Chi	rho	D%/A%	D%*D%/A%	ROC		
trainlm	0.0	8	0.2450	0.1206	72.50	47.50	97.50	73.75	57.50	90.00	66.25	42.50	90.00	82.11	49.17	49.17	82.11	49.17	49.17	242.16	0.98	29.16	145.82	0.73		
trainlm	0.0	8	0.2302	0.1042	78.75	77.50	80.00	66.25	52.50	80.00	70.00	65.00	75.00	68.90	65.00	75.00	68.90	65.00	75.00	129.30	0.87	8.79	21.99	0.70		
trainlm	0.0	10	0.2097	0.0758	83.75	85.00	82.50	67.50	75.00	60.00	62.50	67.50	57.50	68.18	75.83	199.17	68.18	75.83	199.17	0.98	0.98	6.90	69.03	0.78		
trainlm	0.0	9	0.3883	0.1159	73.75	70.00	77.50	67.50	67.50	72.50	68.75	72.50	65.00	58.00	70.00	258.60	58.00	70.00	258.60	1.00	1.00	16.45	178.23	0.71		
trainlm	0.0	9	0.2182	0.1016	77.50	70.00	85.00	61.25	62.50	60.00	63.75	72.50	55.00	54.57	68.33	123.01	54.57	68.33	123.01	0.95	0.95	4.65	11.63	0.69		
trainlm	0.0	9	0.2399	0.0899	78.75	70.00	87.50	72.50	65.00	80.00	73.75	75.00	72.50	69.36	70.00	128.56	69.36	70.00	128.56	0.95	0.95	4.85	60.66	0.75		
trainlm	0.0	10	0.2103	0.0639	87.50	85.00	90.00	72.50	72.50	72.50	72.50	80.00	65.00	64.41	79.17	115.41	64.41	79.17	115.41	0.95	0.95	2.99	32.38	0.76		
trainlm	0.0	9	0.2582	0.0987	80.00	65.00	95.00	62.50	52.50	72.50	66.25	55.00	77.50	69.07	57.50	73.48	69.07	57.50	73.48	0.93	0.93	4.81	36.04	0.69		
trainlm	0.0	10	0.2045	0.0741	90.00	85.00	95.00	73.75	67.50	80.00	75.00	77.50	72.50	72.45	76.67	414.64	72.45	76.67	414.64	1.00	1.00	15.29	191.10	0.82		
trainlm	0.0	11	0.2567	0.0811	86.25	87.50	85.00	72.50	85.00	60.00	73.75	87.50	60.00	57.56	86.67	362.80	57.56	86.67	362.80	1.00	1.00	17.25	273.10	0.79		
Average		9	0.2461	0.0926	80.88	74.25	87.50	68.50	65.75	71.25	69.25	69.50	69.00	66.46	69.83	204.71	66.46	69.83	204.71	0.96	0.96	11.11	102.00	0.74		

Table H.52. MLP 10-20-1, 10 input layers (categories), Ndeps = 40, Set 10

Training set size	Training: 80 patterns (40 deposits, 40 barren), training-stop: = 80 (40 deposits, 40 barren), test = 80 (40 deposits, 40 barren)																										
Training set type	Randomly selected cells, approximately equal numbers of patterns from each rock type																										
Geology input format	Fuzzy membership values																										
Learn. Algoth.	l.r.	Cycles	MSE			Train % correct			Stop % correct			Test % correct			Map % correct			Map statistics			ROC						
			Initial	Final		All	Deps	Non	All	Deps	Non	All	Deps	Non	All	Deps	Non	Chi	rho	D%/A%	D%*D%/A%						
trainlm	0.0	12	0.2307	0.0243	97.50	97.50	97.50	73.75	77.50	70.00	62.50	60.00	65.00	72.10	78.33	255.76	72.10	78.33	255.76	0.92	3.26	43.51		0.81			
trainlm	0.0	10	0.2236	0.0728	86.25	82.50	90.00	71.25	80.00	62.50	63.75	60.00	67.50	68.73	74.17	139.16	68.73	74.17	139.16	0.90	2.39	11.94		0.77			
trainlm	0.0	12	0.2202	0.0370	91.25	82.50	100.00	71.25	70.00	72.50	66.25	57.50	75.00	81.12	70.00	346.12	81.12	70.00	346.12	0.90	6.20	129.20		0.81			
trainlm	0.0	9	0.3921	0.1028	80.00	77.50	82.50	57.50	67.50	47.50	58.75	65.00	52.50	71.06	70.00	1498.58	71.06	70.00	1498.58	0.98	172.17	1004.32		0.79			
trainlm	0.0	9	0.2592	0.0893	85.00	75.00	95.00	67.50	65.00	70.00	68.75	62.50	75.00	73.38	67.50	249.94	73.38	67.50	249.94	0.98	6.41	53.43		0.77			
trainlm	0.0	8	0.2281	0.0965	78.75	70.00	87.50	68.75	70.00	67.50	67.50	70.00	65.00	73.58	70.00	398.26	73.58	70.00	398.26	1.00	18.47	123.12		0.80			
trainlm	0.0	11	0.2207	0.0335	96.25	92.50	100.00	73.75	80.00	67.50	68.75	70.00	67.50	67.99	80.83	273.26	67.99	80.83	273.26	0.98	6.47	183.21		0.81			
trainlm	0.0	8	0.2570	0.1131	70.00	62.50	77.50	65.00	65.00	65.00	68.75	72.50	65.00	80.80	66.67	446.84	80.80	66.67	446.84	0.97	11.05	36.83		0.82			
trainlm	0.0	8	0.1703	0.1040	75.00	75.00	75.00	65.00	80.00	50.00	65.00	70.00	60.00	76.25	75.00	261.91	76.25	75.00	261.91	0.98	10.75	62.73		0.83			
trainlm	0.0	11	0.2580	0.0897	78.75	60.00	97.50	68.75	60.00	77.50	68.75	57.50	80.00	89.76	59.17	408.79	89.76	59.17	408.79	0.98	10.98	173.87		0.84			
Average		10	0.2460	0.0763	83.88	77.50	90.25	68.25	71.50	65.00	65.88	64.50	67.25	75.48	71.17	427.86	75.48	71.17	427.86	0.96	24.82	182.22		0.81			

Table H.53. MLP 10-20-1, 10 input layers (categories), Ndeps = 80, Set 1

Training set size		Training: 160 patterns (80 deposits, 80 barren), training-stop: = 40 (20 deposits, 20 barren), test = 40 (20 deposits, 20 barren)																				
Training set type		Randomly selected cells, approximately equal numbers of patterns from each rock type																				
Geology input format		Fuzzy membership values																				
Learn.	l.r.	Cycles	MSE			Train % correct			Stop % correct			Test % correct			Map % correct			Map statistics				
Algoth.			Initial	Final	All	Deps	Non	All	Deps	Non	All	Deps	Non	All	Deps	Chi	rho	D%/A%	D%*D%/A%	ROC		
trainlm	0.0	10	0.2302	0.0710	86.25	87.50	85.00	75.00	65.00	85.00	65.00	60.00	70.00	63.65	79.17	141.90	0.98	3.90	84.41	0.78		
trainlm	0.0	13	0.2211	0.0419	93.13	96.25	90.00	75.00	80.00	70.00	67.50	80.00	55.00	67.79	90.83	308.96	0.88	3.36	92.32	0.84		
trainlm	0.0	11	0.2020	0.0745	83.75	92.50	75.00	70.00	75.00	65.00	75.00	90.00	60.00	62.85	89.17	247.06	0.98	4.19	132.61	0.84		
trainlm	0.0	8	0.3885	0.1254	68.13	46.25	90.00	60.00	45.00	75.00	65.00	40.00	90.00	92.28	45.00	852.34	0.98	89.03	370.94	0.81		
trainlm	0.0	8	0.2148	0.1073	79.38	86.25	72.50	52.50	70.00	35.00	72.50	80.00	65.00	53.03	82.50	272.79	0.98	7.75	32.30	0.78		
trainlm	0.0	10	0.2311	0.0768	82.50	85.00	80.00	65.00	70.00	60.00	75.00	75.00	75.00	68.95	80.83	456.55	1.00	18.91	173.32	0.85		
trainlm	0.0	10	0.2235	0.0773	83.75	72.50	95.00	77.50	70.00	85.00	72.50	70.00	75.00	78.04	71.67	238.59	0.98	7.96	86.19	0.81		
trainlm	0.0	9	0.2723	0.0853	81.88	78.75	85.00	70.00	70.00	70.00	72.50	70.00	75.00	67.36	75.83	259.30	0.97	14.93	149.25	0.78		
trainlm	0.0	9	0.1869	0.0792	83.75	81.25	86.25	65.00	60.00	70.00	67.50	65.00	70.00	75.19	75.00	435.86	0.93	18.19	197.11	0.81		
trainlm	0.0	10	0.2496	0.0851	83.75	78.75	88.75	75.00	70.00	80.00	67.50	65.00	70.00	73.17	75.00	228.66	0.97	5.69	23.70	0.81		
Average		10	0.2420	0.0824	82.63	80.50	84.75	68.50	67.50	69.50	70.00	69.50	70.50	70.23	76.50	344.20	0.97	17.39	134.22	0.81		

Table H.54. MLP 10-20-1, 10 input layers (categories), Ndeps = 80, Set 2

Training set size		Training: 160 patterns (80 deposits, 80 barren), training-stop: = 40 (20 deposits, 20 barren), test = 40 (20 deposits, 20 barren)															
Training set type		Randomly selected cells, approximately equal numbers of patterns from each rock type															
Geology input format		Fuzzy membership values															
Learn.	l.r.	Cycles	MSE		Train % correct		Stop % correct		Test % correct		Map % correct		Map statistics		D%D%/A%		ROC
Algoth.			Initial	Final	All	Deps	Non	All	Deps	Non	All	Deps	Chi	rho	D%/A%	D%D%/A%	ROC
trainlm	0.0	10	0.2291	0.0758	81.88	85.00	78.75	82.50	77.50	70.00	72.08	83.33	491.25	1.00	11.22	187.03	0.86
trainlm	0.0	10	0.2191	0.0838	80.00	77.50	82.50	75.00	62.50	60.00	75.19	74.17	411.54	0.98	10.62	309.82	0.84
trainlm	0.0	12	0.2020	0.0638	86.88	83.75	90.00	80.00	67.50	70.00	79.52	82.50	635.80	0.98	13.77	424.58	0.88
trainlm	0.0	11	0.3887	0.0910	78.13	68.75	87.50	75.00	67.50	50.00	86.73	66.67	931.35	0.98	29.30	586.07	0.87
trainlm	0.0	10	0.2318	0.0724	86.25	85.00	87.50	90.00	77.50	80.00	73.26	84.17	297.75	0.98	5.51	55.10	0.85
trainlm	0.0	8	0.2149	0.0911	79.38	73.75	85.00	75.00	72.50	65.00	81.01	72.50	779.96	0.98	26.77	401.49	0.84
trainlm	0.0	7	0.2225	0.1279	67.50	41.25	93.75	80.00	60.00	30.00	93.84	43.33	999.37	0.98	38.86	129.54	0.78
trainlm	0.0	11	0.2682	0.0742	84.38	75.00	93.75	87.50	77.50	60.00	82.23	73.33	474.68	0.98	9.41	47.03	0.85
trainlm	0.0	11	0.1930	0.0505	93.13	96.25	90.00	95.00	72.50	75.00	67.63	92.50	321.03	0.98	5.61	102.90	0.86
trainlm	0.0	9	0.2674	0.0866	83.13	85.00	81.25	75.00	75.00	60.00	76.48	84.17	743.53	1.00	32.15	348.27	0.87
Average		10	0.2437	0.0817	82.06	77.13	87.00	82.00	71.00	63.00	78.80	75.67	608.63	0.99	18.32	259.18	0.85

Table H.55. MLP 10-20-1, 10 input layers (categories), Ndeps = 80, Set 3

Training set size		Training: 160 patterns (80 deposits, 80 barren), training-stop: = 40 (20 deposits, 20 barren), test = 40 (20 deposits, 20 barren)															
Training set type		Randomly selected cells, approximately equal numbers of patterns from each rock type															
Geology input format		Fuzzy membership values															
Learn.	l.r.	Cycles	MSE		Train % correct		Stop % correct		Test % correct		Map % correct		Map statistics		D%*D%/A%		ROC
Algoth.			Initial	Final	All	Deps	Non	All	Deps	Non	All	Deps	Chi	rho	D%/A%	D%*D%/A%	ROC
trainlm	0.0	18	0.2179	0.0167	96.88	98.75	95.00	80.00	80.00	75.00	67.50	75.00	60.00	294.05	0.98	2.75	114.48
trainlm	0.0	11	0.2189	0.0778	85.00	83.75	86.25	62.50	50.00	75.00	60.00	50.00	70.00	560.97	1.00	13.58	101.85
trainlm	0.0	9	0.1896	0.0852	81.25	68.75	93.75	57.50	40.00	75.00	67.50	50.00	85.00	477.97	0.98	21.27	124.10
trainlm	0.0	11	0.3883	0.0615	87.50	88.75	86.25	65.00	65.00	75.00	70.00	75.00	65.00	420.53	0.97	9.19	206.78
trainlm	0.0	9	0.2305	0.1318	71.25	51.25	91.25	57.50	35.00	80.00	67.50	35.00	100.00	553.46	0.92	11.14	120.69
trainlm	0.0	14	0.2241	0.0397	92.50	95.00	90.00	67.50	60.00	75.00	65.00	70.00	60.00	316.92	0.97	4.82	124.48
trainlm	0.0	9	0.2338	0.0905	80.63	86.25	75.00	65.00	60.00	75.00	72.50	75.00	70.00	359.07	1.00	11.63	87.24
trainlm	0.0	8	0.2546	0.1135	72.50	66.25	78.75	57.50	50.00	65.00	73.47	65.00	70.00	213.92	0.98	16.58	27.63
trainlm	0.0	9	0.1677	0.0688	86.88	93.75	80.00	67.50	75.00	60.00	63.84	75.00	65.00	443.15	0.90	12.24	142.79
trainlm	0.0	8	0.2664	0.1065	78.75	78.75	78.75	57.50	60.00	55.00	74.58	55.00	80.00	418.97	1.00	33.25	83.12
Average		11	0.2392	0.0792	83.31	81.13	85.50	63.75	57.50	70.00	77.53	62.50	72.50	405.90	0.97	13.65	113.32

Table H.56. MLP 10-20-1, 10 input layers (categories), Ndeps = 80, Set 4

Training set size		Training: 160 patterns (80 deposits, 80 barren), training-stop: = 40 (20 deposits, 20 barren), test = 40 (20 deposits, 20 barren)															
Training set type		Randomly selected cells, approximately equal numbers of patterns from each rock type															
Geology input format		Fuzzy membership values															
Learn.	l.r.	Cycles	MSE		Train % correct		Stop % correct		Test % correct		Map % correct		Map statistics		D%*D%/A%		ROC
Algoth.			Initial	Final	All	Deps	Non	All	Deps	Non	All	Deps	Chi	rho	D%/A%	D%*D%/A%	ROC
trainlm	0.0	9	0.2304	0.0691	88.75	87.50	90.00	70.00	65.00	75.00	71.16	78.33	200.34	0.87	2.53	39.99	0.79
trainlm	0.0	11	0.2240	0.0459	93.13	93.75	92.50	75.00	65.00	65.00	72.84	87.50	491.58	1.00	10.98	329.38	0.87
trainlm	0.0	10	0.1900	0.0751	82.50	78.75	86.25	77.50	70.00	85.00	83.39	75.00	438.62	0.98	13.14	153.29	0.87
trainlm	0.0	12	0.3891	0.0595	90.63	90.00	91.25	72.50	75.00	75.00	75.80	85.83	360.29	0.97	8.59	107.41	0.85
trainlm	0.0	10	0.2346	0.0590	91.25	90.00	92.50	75.00	85.00	65.00	78.42	84.17	704.31	0.98	23.10	423.46	0.87
trainlm	0.0	14	0.2424	0.0283	95.00	92.50	97.50	85.00	95.00	75.00	67.85	88.33	235.69	0.88	2.36	84.67	0.80
trainlm	0.0	10	0.2201	0.0596	92.50	92.50	92.50	75.00	70.00	80.00	76.42	85.00	438.01	0.93	11.12	176.12	0.85
trainlm	0.0	11	0.2556	0.0605	88.13	85.00	91.25	80.00	75.00	85.00	81.82	80.00	556.38	1.00	12.96	291.67	0.87
trainlm	0.0	8	0.1787	0.1189	68.75	67.50	70.00	72.50	75.00	70.00	76.41	65.83	339.58	0.97	11.21	130.77	0.80
trainlm	0.0	10	0.2395	0.0578	88.13	90.00	86.25	80.00	70.00	75.00	76.73	85.83	322.42	0.97	4.70	70.51	0.86
Average		11	0.2405	0.0634	87.88	86.75	89.00	76.25	78.00	74.50	76.08	81.58	408.72	0.96	10.07	180.73	0.84

Table H.57. MLP 10-20-1, 10 input layers (categories), Ndeps = 80, Set 5

Training set size		Training: 160 patterns (80 deposits, 80 barren), training-stop: = 40 (20 deposits, 20 barren), test = 40 (20 deposits, 20 barren)																	
Training set type		Randomly selected cells, approximately equal numbers of patterns from each rock type																	
Geology input format		Fuzzy membership values																	
Learn. Algorith.	l.r. Cycles	MSE	Train % correct			Stop % correct			Test % correct			Map % correct		Map statistics			D%*D%/A%	ROC	
		Initial	Final	All	Deps	Non	All	Deps	Non	All	Deps	Non	All	Deps	Chi	rho			D%/A%
trainlm	0.0 12	0.2107	0.0385	91.88	91.25	92.50	70.00	90.00	50.00	65.00	75.00	55.00	66.36	88.33	243.97	0.87	3.22	102.00	0.82
trainlm	0.0 8	0.2301	0.1275	72.50	51.25	93.75	62.50	50.00	75.00	52.50	25.00	80.00	93.24	46.67	625.97	0.98	63.10	262.92	0.81
trainlm	0.0 11	0.2072	0.0549	88.75	90.00	87.50	65.00	70.00	60.00	65.00	60.00	70.00	74.12	81.67	463.01	0.90	5.89	152.17	0.86
trainlm	0.0 8	0.3932	0.1393	62.50	28.75	96.25	67.50	45.00	90.00	62.50	35.00	90.00	97.08	32.50	605.12	1.00	34.75	86.88	0.81
trainlm	0.0 9	0.2220	0.0886	85.00	77.50	92.50	65.00	60.00	70.00	57.50	50.00	65.00	75.22	70.00	382.53	1.00	11.37	161.03	0.82
trainlm	0.0 11	0.2091	0.0550	91.88	85.00	98.75	77.50	95.00	60.00	70.00	75.00	65.00	72.33	85.00	323.17	0.98	6.39	95.79	0.84
trainlm	0.0 14	0.2284	0.0354	95.00	93.75	96.25	72.50	85.00	60.00	72.50	70.00	75.00	65.80	88.33	230.80	0.97	3.37	103.78	0.82
trainlm	0.0 13	0.2786	0.0395	95.63	92.50	98.75	75.00	85.00	65.00	67.50	75.00	60.00	73.70	88.33	467.97	0.97	8.88	369.96	0.88
trainlm	0.0 7	0.1733	0.1020	79.38	73.75	85.00	60.00	70.00	50.00	65.00	65.00	65.00	79.55	71.67	675.70	0.98	29.20	316.37	0.82
trainlm	0.0 17	0.2401	0.0068	100.00	100.00	100.00	72.50	85.00	60.00	57.50	65.00	50.00	62.34	91.67	240.80	0.93	2.91	116.23	0.82
Average	11	0.2393	0.0687	86.25	78.38	94.13	68.75	73.50	64.00	63.50	59.50	67.50	75.97	74.42	425.90	0.96	16.91	176.71	0.83

Table H.58. MLP 10-20-1, 10 input layers (categories), Ndeps = 80, Set 6

Training set size		Training: 160 patterns (80 deposits, 80 barren), training-stop: = 40 (20 deposits, 20 barren), test = 40 (20 deposits, 20 barren)																			
Training set type		Randomly selected cells, approximately equal numbers of patterns from each rock type																			
Geology input format		Fuzzy membership values																			
Learn.	l.r.	Cycles	MSE		Train % correct			Stop % correct			Test % correct			Map % correct		Map statistics			D%*D%/A%	ROC	
			Initial	Final	All	Deps	Non	All	Deps	Non	All	Deps	Non	All	Deps	Chi	rho	D%/A%			
trainlm	0.0	9	0.2177	0.0997	76.25	82.50	70.00	75.00	85.00	65.00	65.00	55.00	75.00	55.78	78.33	99.34	0.96	2.68	31.22	0.74	
trainlm	0.0	10	0.2256	0.0607	89.38	90.00	88.75	77.50	75.00	80.00	80.00	75.00	85.00	71.63	85.00	311.67	1.00	7.16	77.59	0.85	
trainlm	0.0	12	0.2040	0.0664	85.63	91.25	80.00	85.00	85.00	85.00	70.00	80.00	60.00	69.73	88.33	274.29	0.98	5.97	109.40	0.84	
trainlm	0.0	13	0.3907	0.0524	92.50	92.50	92.50	85.00	85.00	85.00	60.00	65.00	55.00	74.82	86.67	384.82	0.98	7.80	266.65	0.86	
trainlm	0.0	9	0.2454	0.1002	85.00	83.75	86.25	77.50	70.00	85.00	60.00	55.00	65.00	76.47	76.67	610.60	0.97	28.59	285.88	0.84	
trainlm	0.0	15	0.2365	0.0272	95.63	93.75	97.50	85.00	80.00	90.00	67.50	65.00	70.00	69.50	86.67	245.47	0.98	4.65	162.61	0.84	
trainlm	0.0	12	0.2415	0.0380	95.00	95.00	95.00	82.50	85.00	80.00	75.00	70.00	80.00	52.81	89.17	132.70	0.95	2.61	99.92	0.77	
trainlm	0.0	14	0.2778	0.0331	93.13	92.50	93.75	72.50	70.00	75.00	67.50	70.00	65.00	74.17	85.00	377.63	0.98	6.17	159.27	0.86	
trainlm	0.0	11	0.1775	0.0506	91.88	91.25	92.50	85.00	75.00	95.00	80.00	70.00	90.00	74.59	85.00	305.04	0.90	3.68	18.39	0.84	
trainlm	0.0	11	0.2498	0.0807	82.50	92.50	72.50	82.50	85.00	80.00	62.50	75.00	50.00	68.50	88.33	346.71	1.00	10.51	140.16	0.86	
Average		12	0.2467	0.0609	88.69	90.50	86.88	80.75	79.50	82.00	68.75	68.00	69.50	68.80	84.92	308.83	0.97	7.98	135.11	0.83	

Table H.59. MLP 10-20-1, 10 input layers (categories), Ndeps = 80, Set 7

Training set size		Training: 160 patterns (80 deposits, 80 barren), training-stop: = 40 (20 deposits, 20 barren), test = 40 (20 deposits, 20 barren)																					
Training set type		Randomly selected cells, approximately equal numbers of patterns from each rock type																					
Geology input format		Fuzzy membership values																					
Learn.	l.r.	Cycles	MSE			Train % correct			Stop % correct			Test % correct			Map % correct			Map statistics					
Algoth.			Initial	Final	All	Deps	Non	All	Deps	Non	All	Deps	Non	All	Deps	Non	All	Deps	Chi	rho	D%/A%	D%*D%/A%	ROC
trainlm	0.0	10	0.2352	0.0748	84.38	92.50	76.25	60.00	70.00	50.00	95.00	90.00	100.00	100.00	88.33	277.99	61.29	88.33	0.98	7.32	158.65	0.84	
trainlm	0.0	8	0.2172	0.1186	73.13	66.25	80.00	55.00	40.00	70.00	75.00	65.00	85.00	83.41	61.67	806.58	83.41	61.67	0.98	26.42	132.10	0.83	
trainlm	0.0	7	0.2046	0.1429	60.62	86.25	35.00	52.50	75.00	30.00	65.00	85.00	45.00	61.24	84.17	370.37	61.24	84.17	0.98	5.97	19.89	0.83	
trainlm	0.0	8	0.3866	0.1364	62.50	36.25	88.75	62.50	30.00	95.00	72.50	50.00	95.00	93.95	37.50	537.51	93.95	37.50	1.00	76.07	190.18	0.77	
trainlm	0.0	9	0.2358	0.1013	79.38	82.50	76.25	70.00	75.00	65.00	87.50	90.00	85.00	65.47	82.50	464.41	65.47	82.50	0.98	19.41	210.26	0.82	
trainlm	0.0	8	0.2385	0.0984	79.38	75.00	83.75	55.00	45.00	65.00	90.00	85.00	95.00	80.81	71.67	807.40	80.81	71.67	0.98	36.76	367.56	0.84	
trainlm	0.0	8	0.2327	0.1418	64.38	62.50	66.25	70.00	70.00	70.00	62.50	55.00	70.00	58.73	62.50	139.72	58.73	62.50	0.72	8.38	125.63	0.66	
trainlm	0.0	8	0.2618	0.1212	70.00	82.50	57.50	60.00	55.00	65.00	77.50	80.00	75.00	56.22	77.50	410.75	56.22	77.50	0.93	13.97	34.92	0.76	
trainlm	0.0	10	0.1828	0.0906	80.63	78.75	82.50	70.00	65.00	75.00	92.50	85.00	100.00	82.01	77.50	592.09	82.01	77.50	0.98	24.39	304.82	0.84	
trainlm	0.0	9	0.2561	0.0776	85.63	76.25	95.00	75.00	60.00	90.00	87.50	75.00	100.00	82.37	73.33	468.63	82.37	73.33	0.98	15.25	254.13	0.84	
Average		9	0.2451	0.1104	74.00	73.88	74.13	63.00	58.50	67.50	80.50	76.00	85.00	72.55	71.67	492.55	72.55	71.67	0.95	23.39	179.81	0.80	

Table H.60. MLP 10-20-1, 10 input layers (categories), Ndeps = 80, Set 8

Training set size			Training: 160 patterns (80 deposits, 80 barren), training-stop: = 40 (20 deposits, 20 barren), test = 40 (20 deposits, 20 barren)																			
Training set type			Randomly selected cells, approximately equal numbers of patterns from each rock type																			
Geology input format			Fuzzy membership values																			
Learn.	l.r.	Cycles	MSE		Train % correct			Stop % correct			Test % correct			Map % correct			Map statistics			D%/A%	D%*D%/A%	ROC
			Initial	Final	All	Deps	Non	All	Deps	Non	All	Deps	Non	All	Deps	Non	All	Chi	rho			
trainlm	0.0	9	0.2225	0.0821	85.63	86.25	85.00	65.00	70.00	60.00	80.00	80.00	80.00	68.21	82.50	168.19	0.98	3.48	23.22	0.80		
trainlm	0.0	11	0.2222	0.0719	86.25	86.25	86.25	60.00	50.00	70.00	70.00	70.00	70.00	83.30	77.50	528.34	0.98	7.43	49.53	0.88		
trainlm	0.0	9	0.1939	0.1115	70.63	65.00	76.25	72.50	55.00	90.00	77.50	60.00	95.00	80.54	62.50	348.67	1.00	14.90	74.50	0.81		
trainlm	0.0	14	0.3859	0.0413	93.13	91.25	95.00	77.50	70.00	85.00	60.00	60.00	60.00	74.64	82.50	301.94	0.98	5.27	101.05	0.86		
trainlm	0.0	11	0.2443	0.0692	85.63	85.00	86.25	67.50	55.00	80.00	75.00	75.00	75.00	83.79	78.33	504.99	0.95	6.75	61.90	0.88		
trainlm	0.0	9	0.2360	0.0833	85.63	81.25	90.00	77.50	60.00	95.00	80.00	70.00	90.00	82.27	75.83	741.29	1.00	25.99	238.21	0.88		
trainlm	0.0	9	0.2404	0.0790	80.63	83.75	77.50	72.50	70.00	75.00	67.50	60.00	75.00	66.49	77.50	209.33	0.97	7.56	113.33	0.80		
trainlm	0.0	9	0.2632	0.0937	77.50	80.00	75.00	67.50	60.00	75.00	80.00	90.00	70.00	75.30	78.33	571.80	1.00	21.06	245.73	0.86		
trainlm	0.0	11	0.1760	0.0446	91.88	91.25	92.50	72.50	65.00	80.00	70.00	75.00	65.00	70.99	84.17	258.75	0.98	4.13	72.36	0.83		
trainlm	0.0	12	0.2614	0.0560	89.38	86.25	92.50	85.00	75.00	95.00	70.00	60.00	80.00	78.94	80.00	310.64	0.95	4.27	46.27	0.85		
Average		10	0.2446	0.0733	84.63	83.63	85.63	71.75	63.00	80.50	73.00	70.00	76.00	76.45	77.92	394.39	0.98	10.08	102.61	0.84		

Table H.63. MLP 10-20-1, 10 input layers (categories), Ndeps = 100, Set 1

Training set size		Training: 200 patterns (100 deposits, 100 barren), training-stop: = 20 (10 deposits, 10 barren), test = 20 (10 deposits, 10 barren)															
Training set type		Randomly selected cells, approximately equal numbers of patterns from each rock type															
Geology input format		Fuzzy membership values															
Learn. Algorith.	l.r. Cycles	MSE		Train % correct			Stop % correct			Test % correct			Map % correct		Map statistics		
		Initial	Final	All	Deps	Non	All	Deps	Non	All	Deps	Non	All	Deps	Chi	rho	D%/A% D%*D%/A%
trainlm	0.0 10	0.2251	0.1128	73.50	76.00	71.00	85.00	90.00	80.00	80.00	70.00	50.00	69.21	76.67	251.43	0.95	6.98 197.76 0.81
trainlm	0.0 12	0.2190	0.0548	89.50	88.00	91.00	95.00	90.00	100.00	65.00	60.00	70.00	78.31	85.83	548.57	0.98	13.86 265.74 0.89
trainlm	0.0 10	0.1985	0.0837	83.50	89.00	78.00	90.00	90.00	90.00	65.00	60.00	70.00	71.55	86.67	372.85	0.98	7.91 250.62 0.86
trainlm	0.0 14	0.3927	0.0426	93.50	97.00	90.00	90.00	80.00	100.00	70.00	70.00	60.00	73.50	93.33	436.68	0.97	6.75 264.33 0.89
trainlm	0.0 11	0.2396	0.0724	86.00	77.00	95.00	95.00	90.00	100.00	60.00	40.00	80.00	83.08	75.00	427.05	0.98	7.62 31.77 0.88
trainlm	0.0 10	0.2358	0.0859	82.00	70.00	94.00	95.00	90.00	100.00	50.00	40.00	60.00	84.85	69.17	527.98	0.98	15.68 248.23 0.86
trainlm	0.0 9	0.2255	0.0863	80.50	80.00	81.00	90.00	90.00	90.00	70.00	60.00	60.00	68.51	79.17	324.44	1.00	13.63 193.12 0.82
trainlm	0.0 12	0.2730	0.0891	80.50	70.00	91.00	85.00	70.00	100.00	60.00	60.00	60.00	87.02	69.17	515.62	0.98	13.84 207.58 0.86
trainlm	0.0 8	0.1871	0.1569	61.50	94.00	29.00	75.00	90.00	60.00	65.00	100.00	30.00	36.20	94.17	306.42	0.98	7.16 262.59 0.83
trainlm	0.0 13	0.2389	0.0441	94.00	95.00	93.00	85.00	90.00	80.00	65.00	70.00	60.00	73.29	92.50	485.93	0.97	6.86 160.06 0.89
Average	11	0.2435	0.0829	82.45	83.60	81.30	88.50	87.00	90.00	63.00	63.00	63.00	72.55	82.17	419.70	0.98	10.03 208.18 0.86

Table H.64. MLP 10-20-1, 10 input layers (categories), Ndeps = 100, Set 2

Training set size		Training: 200 patterns (100 deposits, 100 barren), training-stop: = 20 (10 deposits, 10 barren), test = 20 (10 deposits, 10 barren)															
Training set type		Randomly selected cells, approximately equal numbers of patterns from each rock type															
Geology input format		Fuzzy membership values															
Learn. Algorith.	l.r. Cycles	MSE		Train % correct			Stop % correct			Test % correct			Map % correct		Map statistics		
		Initial	Final	All	Deps	Non	All	Deps	Non	All	Deps	Non	All	Deps	Chi	rho	D%/A% D%*D%/A%
trainlm	0.0 14	0.2217	0.0549	89.00	92.00	86.00	85.00	90.00	80.00	70.00	80.00	60.00	65.84	90.83	249.50	0.97	3.35 114.54 0.84
trainlm	0.0 13	0.2166	0.0581	88.00	81.00	95.00	80.00	80.00	80.00	80.00	80.00	80.00	77.25	80.83	394.16	0.98	8.81 132.16 0.87
trainlm	0.0 9	0.2060	0.1048	77.50	88.00	67.00	75.00	90.00	60.00	80.00	100.00	60.00	71.67	89.17	632.94	0.98	19.29 434.10 0.87
trainlm	0.0 11	0.3894	0.0799	83.50	80.00	87.00	80.00	80.00	80.00	75.00	90.00	60.00	76.39	80.83	354.35	1.00	8.86 206.62 0.87
trainlm	0.0 13	0.2230	0.0583	90.00	82.00	98.00	80.00	80.00	80.00	75.00	70.00	60.00	82.23	80.83	408.95	1.00	7.25 66.44 0.89
trainlm	0.0 13	0.2283	0.0387	92.00	90.00	94.00	85.00	100.00	70.00	75.00	90.00	60.00	70.89	90.83	304.94	0.98	4.22 112.45 0.87
trainlm	0.0 9	0.2265	0.1047	73.50	66.00	81.00	80.00	90.00	70.00	65.00	70.00	60.00	67.19	68.33	271.97	0.98	17.09 142.43 0.77
trainlm	0.0 12	0.2635	0.0632	87.50	88.00	87.00	80.00	100.00	60.00	70.00	80.00	60.00	71.16	88.33	498.77	0.98	12.78 308.91 0.88
trainlm	0.0 10	0.1903	0.1159	74.50	58.00	91.00	70.00	60.00	80.00	80.00	80.00	80.00	77.38	60.00	317.38	0.98	15.11 188.92 0.78
trainlm	0.0 12	0.2583	0.0585	87.50	85.00	90.00	85.00	90.00	80.00	80.00	90.00	70.00	73.88	85.83	349.63	0.98	6.32 142.25 0.87
Average	12	0.2423	0.0737	84.30	81.00	87.60	80.00	86.00	74.00	75.00	83.00	67.00	73.39	81.58	378.26	0.98	10.31 184.88 0.85

Table H.65. MLP 10-20-1, 10 input layers (categories), Ndeps = 100, Set 3

Training set size		Training: 200 patterns (100 deposits, 100 barren), training-stop: = 20 (10 deposits, 10 barren), test = 20 (10 deposits, 10 barren)																							
Training set type		Randomly selected cells, approximately equal numbers of patterns from each rock type																							
Geology input format		Fuzzy membership values																							
Learn.	l.r.	Cycles	MSE			Train % correct			Stop % correct			Test % correct			Map % correct			Map statistics							
			Initial	Final	All	Deps	Non	All	Deps	Non	All	Deps	Non	All	Deps	Non	All	Deps	Chi	rho	D%/A%	D%*D%/A%	ROC		
trainlm	0.0	12	0.2236	0.0635	88.50	86.00	91.00	85.00	80.00	90.00	90.00	90.00	90.00	90.00	90.00	77.07	85.83	435.20	1.00	8.57	214.29	0.88			
trainlm	0.0	8	0.2275	0.1185	73.50	69.00	78.00	65.00	40.00	90.00	85.00	70.00	100.00	82.09	66.67	867.56	0.97	12.65	31.61	0.84					
trainlm	0.0	9	0.2067	0.1033	78.00	64.00	92.00	70.00	50.00	90.00	90.00	80.00	100.00	88.53	64.17	856.73	1.00	31.75	502.74	0.87					
trainlm	0.0	11	0.3896	0.0813	82.00	77.00	87.00	75.00	70.00	80.00	90.00	90.00	90.00	78.66	77.50	548.15	1.00	20.98	297.15	0.87					
trainlm	0.0	14	0.2335	0.0391	93.50	95.00	92.00	80.00	80.00	80.00	90.00	90.00	100.00	65.62	93.33	272.00	0.91	3.92	130.53	0.86					
trainlm	0.0	11	0.2297	0.0613	88.00	87.00	89.00	75.00	80.00	70.00	80.00	90.00	70.00	73.09	86.67	372.82	1.00	9.15	160.20	0.87					
trainlm	0.0	8	0.2264	0.1047	79.00	88.00	70.00	85.00	90.00	80.00	80.00	100.00	60.00	65.98	89.17	468.81	0.97	14.42	348.60	0.84					
trainlm	0.0	9	0.2645	0.0991	78.00	68.00	88.00	70.00	80.00	60.00	65.00	50.00	80.00	77.99	67.50	545.74	0.98	14.09	152.60	0.80					
trainlm	0.0	12	0.1933	0.0413	92.00	95.00	89.00	85.00	90.00	80.00	90.00	80.00	100.00	64.41	93.33	349.13	0.97	7.06	241.22	0.87					
trainlm	0.0	12	0.2476	0.0544	91.50	88.00	95.00	80.00	80.00	80.00	95.00	90.00	100.00	74.84	87.50	307.07	0.93	3.98	79.58	0.86					
Average		11	0.2443	0.0767	84.40	81.70	87.10	77.00	74.00	80.00	86.00	83.00	89.00	74.83	81.17	502.32	0.97	12.66	215.85	0.86					

Table H.66. MLP 10-20-1, 10 input layers (categories), Ndeps = 100, Set 4

Training set size			Training: 200 patterns (100 deposits, 100 barren), training-stop: = 20 (10 deposits, 10 barren), test = 20 (10 deposits, 10 barren)																										
Training set type			Randomly selected cells, approximately equal numbers of patterns from each rock type																										
Geology input format			Fuzzy membership values																										
Learn.	l.r.	Cycles	MSE			Train % correct				Stop % correct				Test % correct				Map % correct				Map statistics							
			Initial	Final	All	Deps	Non	All	Deps	Non	All	Deps	Non	All	Deps	Non	All	Deps	Non	Chi	rho	D%/A%	D%*D%/A%	ROC					
trainlm	0.0	9	0.2244	0.1146	75.50	55.00	96.00	65.00	50.00	80.00	75.00	50.00	100.00	88.87	54.17	344.64	1.00	17.54	146.15	0.84									
trainlm	0.0	7	0.2073	0.1797	51.00	39.00	63.00	70.00	70.00	70.00	60.00	60.00	60.00	56.20	43.33	21.63	0.41	1.23	3.09	0.51									
trainlm	0.0	9	0.2061	0.1045	76.00	81.00	71.00	60.00	80.00	40.00	90.00	100.00	80.00	59.00	82.50	215.79	1.00	10.68	115.73	0.79									
trainlm	0.0	8	0.3912	0.1189	72.50	52.00	93.00	55.00	30.00	80.00	65.00	40.00	90.00	92.59	49.17	1084.85	0.95	10.80	18.00	0.82									
trainlm	0.0	9	0.2300	0.1076	75.50	62.00	89.00	70.00	60.00	80.00	80.00	70.00	90.00	87.98	62.50	418.97	0.47	0.00	0.00	0.84									
trainlm	0.0	7	0.2325	0.1231	69.00	82.00	56.00	65.00	90.00	40.00	60.00	80.00	40.00	35.91	82.50	626.08	0.83	29.90	423.65	0.71									
trainlm	0.0	8	0.2246	0.1048	78.00	77.00	79.00	50.00	60.00	40.00	80.00	70.00	90.00	67.51	75.00	759.46	0.98	29.71	148.56	0.81									
trainlm	0.0	10	0.2606	0.0772	86.50	82.00	91.00	50.00	60.00	40.00	80.00	70.00	90.00	73.28	79.17	390.58	0.98	14.77	233.84	0.84									
trainlm	0.0	6	0.1980	0.1980	53.50	45.00	62.00	75.00	70.00	80.00	65.00	50.00	80.00	73.15	47.50	89.72	0.90	3.57	32.70	0.68									
trainlm	0.0	12	0.2399	0.0557	90.00	88.00	92.00	60.00	60.00	60.00	90.00	90.00	90.00	74.18	85.83	362.72	0.95	3.63	51.47	0.86									
Average		9	0.2415	0.1184	72.75	66.30	79.20	62.00	63.00	61.00	74.50	68.00	81.00	70.87	66.17	431.44	0.85	12.18	117.32	0.77									

Table H.67. MLP 10-20-1, 10 input layers (categories), Ndeps = 100, Set 5

Training set size		Training: 200 patterns (100 deposits, 100 barren), training-stop: = 20 (10 deposits, 10 barren), test = 20 (10 deposits, 10 barren)															
Training set type		Randomly selected cells, approximately equal numbers of patterns from each rock type															
Geology input format		Fuzzy membership values															
Learn. Algorith.	l.r. Cycles	MSE		Train % correct			Stop % correct			Test % correct			Map % correct		Map statistics		
		Initial	Final	All	Deps	Non	All	Deps	Non	All	Deps	Non	All	Deps	Chi	rho	D%/A% D%*D%/A%
trainlm	0.0 12	0.2362	0.0533	88.50	87.00	90.00	80.00	90.00	90.00	80.00	90.00	70.00	67.66	87.50	193.70	1.00	3.53 99.90 0.83
trainlm	0.0 17	0.2281	0.0234	97.50	97.00	98.00	85.00	100.00	70.00	55.00	50.00	60.00	69.63	93.33	324.54	1.00	5.01 179.60 0.87
trainlm	0.0 12	0.1975	0.0603	90.50	90.00	91.00	85.00	100.00	70.00	60.00	70.00	50.00	73.16	89.17	318.30	1.00	6.61 104.61 0.87
trainlm	0.0 18	0.3912	0.0207	98.00	96.00	100.00	90.00	100.00	80.00	55.00	60.00	50.00	69.46	93.33	252.64	0.87	3.55 165.83 0.84
trainlm	0.0 22	0.2378	0.0073	99.50	100.00	99.00	85.00	100.00	70.00	70.00	90.00	50.00	61.09	99.17	277.30	0.76	2.65 163.49 0.81
trainlm	0.0 11	0.2451	0.0742	86.50	84.00	89.00	85.00	90.00	80.00	80.00	70.00	90.00	74.15	83.33	298.84	0.98	6.21 46.58 0.85
trainlm	0.0 10	0.2286	0.0646	89.50	91.00	88.00	80.00	90.00	90.00	95.00	100.00	90.00	66.33	91.67	328.57	0.98	5.14 42.82 0.86
trainlm	0.0 13	0.2608	0.0672	86.50	76.00	97.00	85.00	80.00	90.00	65.00	40.00	90.00	83.08	73.33	483.20	0.98	12.31 184.58 0.86
trainlm	0.0 17	0.1895	0.0168	98.50	100.00	97.00	80.00	90.00	70.00	65.00	50.00	80.00	64.03	95.00	257.93	0.93	3.38 168.76 0.84
trainlm	0.0 14	0.2401	0.0546	90.50	90.00	91.00	80.00	90.00	70.00	85.00	80.00	90.00	69.01	89.17	262.72	0.97	3.98 66.28 0.85
Average	15	0.2455	0.0442	92.55	91.10	94.00	83.50	93.00	74.00	71.00	70.00	72.00	69.76	89.50	299.78	0.95	5.24 122.24 0.85

Table H.68. MLP 10-20-1, 10 input layers (categories), Ndeps = 100, Set 6

Training set size		Training: 200 patterns (100 deposits, 100 barren), training-stop: = 20 (10 deposits, 10 barren), test = 20 (10 deposits, 10 barren)															
Training set type		Randomly selected cells, approximately equal numbers of patterns from each rock type															
Geology input format		Fuzzy membership values															
Learn. Algorith.	l.r. Cycles	MSE		Train % correct			Stop % correct			Test % correct			Map % correct		Map statistics		
		Initial	Final	All	Deps	Non	All	Deps	Non	All	Deps	Non	All	Deps	Chi	rho	D%/A% D%*D%/A%
trainlm	0.0 8	0.2200	0.0930	79.00	68.00	90.00	90.00	90.00	90.00	60.00	50.00	70.00	83.53	68.33	591.52	0.97	13.51 112.59 0.86
trainlm	0.0 13	0.2195	0.0406	93.00	89.00	97.00	80.00	80.00	80.00	75.00	80.00	70.00	78.42	87.50	524.45	0.98	9.78 277.20 0.90
trainlm	0.0 11	0.1945	0.0704	88.00	81.00	95.00	70.00	70.00	70.00	65.00	70.00	60.00	85.25	79.17	635.99	0.98	15.93 331.92 0.90
trainlm	0.0 10	0.3894	0.0919	80.50	68.00	93.00	80.00	80.00	80.00	55.00	40.00	70.00	90.40	66.67	728.01	1.00	24.09 281.04 0.88
trainlm	0.0 11	0.2332	0.0625	88.50	84.00	93.00	80.00	90.00	90.00	65.00	70.00	60.00	80.89	83.33	739.30	0.98	17.83 386.26 0.90
trainlm	0.0 9	0.2244	0.0984	79.00	68.00	90.00	95.00	90.00	100.00	70.00	70.00	70.00	78.25	70.00	403.02	1.00	10.99 183.13 0.82
trainlm	0.0 9	0.2349	0.0796	83.50	81.00	86.00	85.00	90.00	80.00	65.00	70.00	60.00	72.10	80.83	361.19	1.00	13.12 164.03 0.84
trainlm	0.0 13	0.2691	0.0398	93.50	94.00	93.00	80.00	80.00	80.00	60.00	70.00	50.00	74.76	90.83	533.64	0.97	7.79 253.06 0.90
trainlm	0.0 8	0.1747	0.1008	78.50	74.00	83.00	80.00	70.00	90.00	65.00	70.00	60.00	82.45	73.33	544.13	1.00	13.36 178.18 0.85
trainlm	0.0 9	0.2486	0.0955	78.50	87.00	70.00	85.00	100.00	70.00	70.00	90.00	50.00	68.12	88.33	733.19	1.00	15.17 531.00 0.88
Average	10	0.2408	0.0773	84.20	79.40	89.00	82.50	84.00	81.00	65.00	68.00	62.00	79.42	78.83	579.45	0.99	14.16 269.84 0.87

Table H.69. MLP 10-20-1, 10 input layers (categories), Ndeps = 100, Set 7

Training set size		Training: 200 patterns (100 deposits, 100 barren), training-stop: = 20 (10 deposits, 10 barren), test = 20 (10 deposits, 10 barren)																				
Training set type		Randomly selected cells, approximately equal numbers of patterns from each rock type																				
Geology input format		Fuzzy membership values																				
Learn.	l.r.	Cycles	MSE			Train % correct			Stop % correct			Test % correct			Map % correct			Map statistics			D%*D%/A%	ROC
			Initial	Final	All	Depos	Non	All	Depos	Non	All	Depos	Non	All	Depos	Chi	rho	D%/A%				
trainlm	0.0	14	0.2179	0.0306	95.00	96.00	94.00	85.00	100.00	100.00	70.00	70.00	90.00	90.00	66.57	95.83	284.41	0.97	3.21	147.29	0.84	
trainlm	0.0	12	0.2230	0.0470	91.00	85.00	97.00	85.00	80.00	90.00	90.00	70.00	90.00	50.00	76.56	85.00	620.38	0.98	13.40	301.48	0.89	
trainlm	0.0	8	0.1958	0.1091	75.50	63.00	88.00	85.00	70.00	100.00	100.00	65.00	50.00	80.00	83.61	62.50	240.58	0.97	4.54	11.35	0.81	
trainlm	0.0	13	0.3892	0.0563	88.00	93.00	83.00	80.00	90.00	70.00	70.00	80.00	90.00	70.00	68.76	92.50	467.65	1.00	8.47	296.32	0.89	
trainlm	0.0	10	0.2356	0.0822	83.50	85.00	82.00	75.00	90.00	60.00	60.00	70.00	90.00	50.00	68.85	85.83	665.07	0.98	19.37	290.48	0.86	
trainlm	0.0	13	0.2292	0.0403	92.50	96.00	89.00	75.00	90.00	60.00	60.00	75.00	90.00	60.00	65.10	95.00	298.24	0.98	5.90	186.76	0.87	
trainlm	0.0	13	0.2302	0.0566	88.50	81.00	96.00	90.00	80.00	100.00	100.00	85.00	70.00	100.00	80.23	80.00	311.62	0.88	4.30	64.49	0.85	
trainlm	0.0	24	0.2552	0.0012	100.00	100.00	100.00	95.00	100.00	100.00	90.00	65.00	70.00	60.00	64.51	97.50	329.37	0.68	3.86	279.60	0.82	
trainlm	0.0	10	0.1809	0.0639	87.00	81.00	93.00	80.00	80.00	80.00	80.00	75.00	80.00	70.00	78.27	80.83	502.62	0.98	16.13	282.23	0.87	
trainlm	0.0	12	0.2502	0.0381	94.50	95.00	94.00	80.00	100.00	100.00	60.00	85.00	90.00	80.00	60.87	95.00	290.39	1.00	4.86	254.93	0.86	
Average		13	0.2407	0.0525	89.55	87.50	91.60	83.00	88.00	78.00	78.00	74.00	81.00	67.00	71.33	87.00	401.03	0.94	8.40	211.49	0.86	

Table H.70. MLP 10-20-1, 10 input layers (categories), Ndeps = 100, Set 8

Training set size			Training: 200 patterns (100 deposits, 100 barren), training-stop: = 20 (10 deposits, 10 barren), test = 20 (10 deposits, 10 barren)																			
Training set type			Randomly selected cells, approximately equal numbers of patterns from each rock type																			
Geology input format			Fuzzy membership values																			
Learn.	l.r.	Cycles	MSE			Train % correct			Stop % correct			Test % correct			Map % correct			Map statistics				
			Initial	Final	All	Depos	Non	All	Depos	Non	All	Depos	Non	All	Depos	Chi	rho	D%/A%	D%*D%/A%	ROC		
trainlm	0.0	9	0.2275	0.0832	83.50	79.00	88.00	90.00	90.00	90.00	90.00	75.00	90.00	60.00	71.41	80.83	327.31	1.00	10.44	104.39	0.85	
trainlm	0.0	9	0.2179	0.0855	83.00	81.00	85.00	90.00	90.00	90.00	90.00	55.00	50.00	60.00	73.61	79.17	337.62	1.00	10.25	102.53	0.83	
trainlm	0.0	12	0.2025	0.0640	89.00	84.00	94.00	85.00	80.00	90.00	60.00	60.00	60.00	60.00	84.47	81.67	712.10	1.00	14.30	250.25	0.90	
trainlm	0.0	16	0.3955	0.0303	94.50	95.00	94.00	90.00	95.00	100.00	100.00	65.00	60.00	70.00	75.35	91.67	401.73	0.97	5.34	240.18	0.88	
trainlm	0.0	16	0.2202	0.0178	98.00	99.00	97.00	97.00	80.00	70.00	40.00	50.00	60.00	40.00	67.47	94.17	345.39	0.95	3.49	110.40	0.85	
trainlm	0.0	18	0.2245	0.0146	98.00	98.00	98.00	95.00	90.00	100.00	100.00	60.00	80.00	40.00	71.22	95.83	416.92	0.91	3.71	151.39	0.87	
trainlm	0.0	9	0.2200	0.0875	82.50	79.00	86.00	80.00	70.00	90.00	50.00	60.00	70.00	50.00	77.06	77.50	752.43	1.00	30.51	432.28	0.84	
trainlm	0.0	21	0.2814	0.0068	99.50	100.00	99.00	95.00	90.00	100.00	100.00	45.00	60.00	30.00	74.16	95.83	529.78	0.73	4.14	189.85	0.88	
trainlm	0.0	8	0.1818	0.0971	78.00	82.00	74.00	85.00	80.00	90.00	60.00	65.00	70.00	60.00	76.78	80.83	722.33	1.00	19.01	427.64	0.87	
trainlm	0.0	9	0.2326	0.0825	85.50	88.00	83.00	80.00	70.00	90.00	55.00	70.00	70.00	40.00	74.69	85.00	353.42	0.88	4.50	11.25	0.86	
Average		13	0.2404	0.0569	89.15	88.50	89.80	87.00	83.00	91.00	59.00	59.00	67.00	51.00	74.62	86.25	489.90	0.94	10.57	202.02	0.86	

Table H.71. MLP 10-20-1, 10 input layers (categories), Ndeps = 100, Set 9

Training set size		Training: 200 patterns (100 deposits, 100 barren), training-stop: = 20 (10 deposits, 10 barren), test = 20 (10 deposits, 10 barren)															
Training set type		Randomly selected cells, approximately equal numbers of patterns from each rock type															
Geology input format		Fuzzy membership values															
Learn. Algorith.	l.r. Cycles	MSE		Train % correct			Stop % correct			Test % correct			Map % correct		Map statistics		
		Initial	Final	All	Deps	Non	All	Deps	Non	All	Deps	Non	All	Deps	Chi	rho	D%/A% D%*D%/A%
trainlm	0.0 10	0.2267	0.0743	85.50	87.00	84.00	95.00	100.00	90.00	65.00	80.00	50.00	71.47	87.50	292.88	0.95	2.46 22.52
trainlm	0.0 14	0.2208	0.0269	95.50	96.00	95.00	95.00	100.00	100.00	45.00	60.00	30.00	65.64	92.50	311.75	0.98	5.34 195.77
trainlm	0.0 12	0.1971	0.0486	89.50	96.00	83.00	95.00	100.00	90.00	65.00	80.00	50.00	63.06	95.00	349.06	0.93	6.39 202.21
trainlm	0.0 16	0.3910	0.0245	97.50	99.00	96.00	100.00	100.00	100.00	60.00	80.00	40.00	75.27	97.50	515.71	0.95	6.72 268.67
trainlm	0.0 17	0.2329	0.0221	97.00	96.00	98.00	100.00	100.00	100.00	65.00	70.00	60.00	78.39	94.17	451.27	0.95	6.21 217.42
trainlm	0.0 13	0.2263	0.0484	92.00	91.00	93.00	90.00	90.00	90.00	60.00	60.00	60.00	72.12	88.33	431.75	0.98	9.32 279.48
trainlm	0.0 9	0.2296	0.0792	84.00	83.00	85.00	90.00	90.00	90.00	65.00	80.00	50.00	69.21	83.33	377.95	1.00	14.66 244.28
trainlm	0.0 10	0.2731	0.0866	81.50	78.00	85.00	80.00	70.00	90.00	70.00	60.00	80.00	74.38	75.83	584.56	1.00	24.45 346.36
trainlm	0.0 9	0.1823	0.0928	78.50	84.00	73.00	85.00	80.00	90.00	55.00	60.00	50.00	73.29	81.67	484.22	1.00	14.42 324.42
trainlm	0.0 21	0.2539	0.0066	98.50	99.00	98.00	95.00	100.00	90.00	60.00	70.00	50.00	65.65	96.67	371.75	0.65	4.07 247.61
Average	13	0.2434	0.0510	89.95	90.90	89.00	92.50	92.00	93.00	61.00	70.00	52.00	70.85	89.25	417.09	0.94	9.40 234.88

Table H.72. MLP 10-20-1, 10 input layers (categories), Ndeps = 100, Set 10

Training set size		Training: 200 patterns (100 deposits, 100 barren), training-stop: = 20 (10 deposits, 10 barren), test = 20 (10 deposits, 10 barren)															
Training set type		Randomly selected cells, approximately equal numbers of patterns from each rock type															
Geology input format		Fuzzy membership values															
Learn. Algorith.	l.r. Cycles	MSE		Train % correct			Stop % correct			Test % correct			Map % correct		Map statistics		
		Initial	Final	All	Deps	Non	All	Deps	Non	All	Deps	Non	All	Deps	Chi	rho	D%/A% D%*D%/A%
trainlm	0.0 9	0.2297	0.1108	76.50	95.00	58.00	70.00	90.00	50.00	55.00	80.00	30.00	48.51	93.33	262.86	0.98	5.17 189.55
trainlm	0.0 10	0.2158	0.0867	81.50	79.00	84.00	65.00	60.00	70.00	60.00	60.00	60.00	79.68	75.83	1271.30	1.00	56.41 705.09
trainlm	0.0 8	0.1973	0.1126	74.00	76.00	72.00	70.00	90.00	50.00	65.00	80.00	50.00	70.29	77.50	319.73	1.00	12.99 108.29
trainlm	0.0 10	0.3893	0.1095	75.00	76.00	74.00	75.00	80.00	70.00	55.00	50.00	60.00	73.41	74.17	635.15	1.00	20.55 445.27
trainlm	0.0 11	0.2197	0.0756	84.00	81.00	87.00	75.00	80.00	70.00	50.00	70.00	30.00	77.14	80.00	421.51	1.00	14.54 133.27
trainlm	0.0 8	0.2333	0.0989	78.50	75.00	82.00	75.00	80.00	70.00	60.00	60.00	60.00	78.33	74.17	922.46	0.98	40.90 443.13
trainlm	0.0 10	0.2108	0.0721	85.00	81.00	89.00	90.00	80.00	100.00	65.00	60.00	70.00	81.86	79.17	683.87	0.98	11.21 130.78
trainlm	0.0 16	0.2601	0.0389	91.00	83.00	99.00	80.00	80.00	80.00	65.00	60.00	70.00	77.48	80.83	376.88	0.93	6.71 206.88
trainlm	0.0 6	0.1909	0.1909	54.00	43.00	65.00	65.00	70.00	60.00	55.00	70.00	40.00	72.22	47.50	86.47	0.85	3.47 31.79
trainlm	0.0 13	0.2393	0.0383	94.50	95.00	94.00	80.00	70.00	90.00	60.00	70.00	50.00	76.88	90.83	483.78	0.91	4.69 117.20
Average	10	0.2386	0.0934	79.40	78.40	80.40	74.50	78.00	71.00	59.00	66.00	52.00	73.58	77.33	546.40	0.96	17.66 251.12

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Table H.73. MLP 10-20-1, 10 input layers (categories), Average results for number of deposits in training set,

Training set size		Training: different for each row see Table 7.24 on page 291																				
Training set type		Randomly selected cells, approximately equal numbers of patterns from each rock type																				
Geology input format		Fuzzy membership values																				
No. of deposits	l.r.	Cycles	MSE		Train % correct			Stop % correct			Test % correct			Map % correct			Map statistics			D%/A%	D%-D%/A%	ROC
			Initial	Final	All	Deps	Non	All	Deps	Non	All	Deps	Non	All	Deps	Non	Chi	rho				
5		7	0.2487	0.1084	79.00	76.80	81.20	59.40	56.80	62.00	54.06	48.97	59.15	60.04	50.46	126.86	0.32	6.17	76.71		0.58	
10		8	0.2418	0.0947	80.00	79.80	80.20	62.10	59.50	64.70	57.06	54.38	59.75	60.99	56.92	106.64	0.54	4.43	66.91		0.62	
20		9	0.2464	0.0863	81.50	77.85	85.15	65.60	65.60	65.60	61.11	60.16	62.05	65.73	64.02	169.71	0.83	6.62	101.97		0.70	
40		9	0.2434	0.0725	85.04	81.15	88.92	68.72	66.95	70.50	65.76	63.90	67.63	73.61	70.67	368.14	0.95	15.63	186.14		0.79	
80		10	0.2435	0.0799	82.96	81.14	84.78	72.20	71.00	73.40	70.80	68.00	73.60	74.34	77.26	415.68	0.97	14.25	155.08		0.83	
100		12	0.2421	0.0727	84.87	82.84	86.90	81.05	82.80	79.30	68.75	71.90	65.60	73.12	81.93	446.54	0.95	11.06	201.78		0.85	

Table H.74. MLP 10-0-1, 10 input layers (categories)

Training set size		Training: 99 patterns (46 deposits, 53 barren), training-stop: = 88 (39 deposits, 49 barren), test = 81 (35 deposits, 46 barren)																			
Training set type		Randomly selected cells, approximately equal numbers of patterns from each rock type																			
Geology input format		Fuzzy membership values																			
Learn. Algorith.	l.r. Cycles	MSE			Train % correct			Stop % correct			Test % correct			Map % correct			Map statistics			D%*D%/A%	ROC
		Initial	Final	All	Depos	Non	All	Depos	Non	All	Depos	Non	All	Depos	Chi	rho	D%/A%				
trainlm	0.0 8	0.1954	0.1147	76.77	71.74	81.13	73.86	69.23	77.55	67.90	71.43	65.22	70.56	70.83	605.19	0.95	27.80	393.87	0.77		
trainlm	0.0 12	0.3006	0.1126	77.78	73.91	81.13	71.59	71.79	71.43	65.43	71.43	60.87	66.83	72.50	512.07	0.95	23.53	313.75	0.77		
trainlm	0.0 10	0.3528	0.1125	77.78	73.91	81.13	71.59	71.79	71.43	64.20	71.43	58.70	65.81	72.50	552.40	0.95	21.93	292.38	0.77		
trainlm	0.0 9	0.2729	0.1131	80.81	82.61	79.25	72.73	71.79	73.47	64.20	71.43	58.70	67.92	75.83	612.51	0.90	16.64	332.89	0.79		
trainlm	0.0 10	0.2489	0.1128	76.77	71.74	81.13	71.59	71.79	71.43	65.43	71.43	60.87	66.52	71.67	548.67	0.95	24.80	330.67	0.77		
trainlm	0.0 8	0.2195	0.1143	74.75	63.04	84.91	73.86	69.23	77.55	69.14	71.43	67.39	69.53	67.50	526.65	0.95	28.11	327.96	0.75		
trainlm	0.0 10	0.2845	0.1129	79.80	78.26	81.13	72.73	71.79	73.47	67.90	74.29	63.04	65.94	75.00	581.31	0.95	16.52	330.45	0.78		
trainlm	0.0 12	0.2616	0.1127	77.78	73.91	81.13	70.45	71.79	69.39	65.43	71.43	60.87	66.86	72.50	522.56	0.95	24.96	332.75	0.76		
trainlm	0.0 12	0.2807	0.1125	76.77	71.74	81.13	71.59	71.79	71.43	65.43	71.43	60.87	66.22	71.67	531.53	0.95	23.05	307.35	0.77		
trainlm	0.0 9	0.3457	0.1136	76.77	69.57	83.02	72.73	69.23	75.51	67.90	74.29	63.04	67.39	70.83	596.16	0.93	26.34	351.21	0.76		
Average	10	0.2763	0.1132	77.58	73.04	81.51	72.27	71.03	73.27	66.30	72.00	61.96	67.36	72.08	558.90	0.94	23.37	331.33	0.77		

Table H.75. MLP 10-5-1, 10 input layers (categories)

Training set size		Training: 99 patterns (46 deposits, 53 barren), training-stop: = 88 (39 deposits, 49 barren), test = 81 (35 deposits, 46 barren)																				
Training set type		Randomly selected cells, approximately equal numbers of patterns from each rock type																				
Geology input format		Fuzzy membership values																				
Learn.	l.r.	Cycles	MSE			Train % correct			Stop % correct			Test % correct			Map % correct			Map statistics			D%*D%/A%	ROC
			Initial	Final	All	Depos	Non	All	Depos	Non	All	Depos	Non	All	Depos	Chi	rho	D%/A%				
trainlm	0.0	10	0.2910	0.1020	75.76	82.61	69.81	67.05	76.92	59.18	65.43	82.86	52.17	59.95	80.83	774.53	0.98	19.77	98.84	0.79		
trainlm	0.0	14	0.3221	0.0567	87.88	84.78	90.57	73.86	74.36	73.47	64.20	62.86	65.22	74.00	75.00	181.68	0.98	3.54	82.58	0.81		
trainlm	0.0	12	0.2995	0.0876	82.83	89.13	77.36	69.32	76.92	63.27	69.14	82.86	58.70	62.11	83.33	343.00	0.97	15.02	162.67	0.82		
trainlm	0.0	13	0.3495	0.0905	81.82	71.74	90.57	72.73	58.97	83.67	69.14	62.86	73.91	69.50	65.00	111.98	0.93	6.33	31.64	0.72		
trainlm	0.0	11	0.2432	0.1035	76.77	82.61	71.70	63.64	71.79	57.14	64.20	74.29	56.52	62.39	76.67	395.77	0.98	31.06	155.32	0.79		
trainlm	0.0	9	0.1637	0.0918	80.81	76.09	84.91	78.41	69.23	85.71	71.60	71.43	71.74	78.38	72.50	616.51	1.00	22.88	209.72	0.84		
trainlm	0.0	12	0.2425	0.0723	84.85	84.78	84.91	77.27	82.05	73.47	72.84	82.86	65.22	70.10	83.33	266.00	1.00	7.75	109.83	0.83		
trainlm	0.0	13	0.2359	0.0626	88.89	82.61	94.34	75.00	66.67	81.63	69.14	65.71	71.74	82.62	72.50	474.51	0.98	14.64	231.79	0.86		
trainlm	0.0	10	0.4019	0.1588	64.65	23.91	100.00	64.77	20.51	100.00	59.26	8.57	97.83	96.29	18.33	330.95	0.53	11.47	85.99	0.52		
trainlm	0.0	10	0.2826	0.0922	78.79	69.57	86.79	71.59	64.10	77.55	66.67	68.57	65.22	76.03	67.50	200.59	1.00	6.55	21.83	0.79		
Average		11	0.2832	0.0918	80.30	74.78	85.09	71.36	66.15	75.51	67.16	66.29	67.83	73.14	69.50	369.55	0.94	13.90	119.02	0.78		

Table H.76. MLP 10-10-1, 10 input layers (categories)

Training set size		Training: 99 patterns (46 deposits, 53 barren), training-stop: = 88 (39 deposits, 49 barren), test = 81 (35 deposits, 46 barren)																						
Training set type		Randomly selected cells, approximately equal numbers of patterns from each rock type																						
Geology input format		Fuzzy membership values																						
Learn.	I.r.	Cycles	MSE			Train % correct			Stop % correct			Test % correct			Map % correct			Map statistics						
Algoth.			Initial	Final	All	Depos	Non	All	Depos	Non	All	Depos	Non	All	Depos	Non	All	Depos	Non	Chi	rho	D%/A%	D%*D%/A%	ROC
trainlm	0.0	9	0.3355	0.1112	71.72	45.65	94.34	68.18	33.33	95.92	62.96	31.43	86.96	94.33	37.50	659.98	1.00	30.15	326.67	0.81				
trainlm	0.0	10	0.3378	0.0903	79.80	67.39	90.57	73.86	58.97	85.71	60.49	57.14	63.04	68.44	61.67	288.94	0.98	17.50	102.09	0.72				
trainlm	0.0	27	0.3952	0.0366	92.93	91.30	94.34	72.73	74.36	71.43	71.60	80.00	65.22	63.80	82.50	177.02	0.92	4.36	137.93	0.79				
trainlm	0.0	9	0.1451	0.0828	81.82	78.26	84.91	71.59	66.67	75.51	64.20	68.57	60.87	63.11	71.67	92.42	0.92	2.11	19.35	0.72				
trainlm	0.0	12	0.3259	0.0710	85.86	84.78	86.79	75.00	71.79	77.55	70.37	71.43	69.57	66.17	76.67	143.04	1.00	4.42	80.96	0.77				
trainlm	0.0	11	0.2232	0.0597	88.89	91.30	86.79	75.00	82.05	69.39	67.90	82.86	56.52	65.79	85.83	258.55	0.95	5.42	67.70	0.82				
trainlm	0.0	10	0.2609	0.0999	81.82	71.74	90.57	69.32	51.28	83.67	71.60	62.86	78.26	87.07	62.50	422.44	0.88	5.21	8.68	0.84				
trainlm	0.0	12	0.1697	0.0676	85.86	80.43	90.57	76.14	74.36	77.55	58.02	74.29	45.65	64.85	76.67	251.60	0.97	3.55	23.68	0.79				
trainlm	0.0	11	0.3552	0.0908	80.81	80.43	81.13	67.05	66.67	67.35	69.14	77.14	63.04	65.29	75.00	195.88	0.98	10.12	84.34	0.79				
trainlm	0.0	9	0.1791	0.0772	83.84	86.96	81.13	71.59	69.23	73.47	66.67	74.29	60.87	60.65	77.50	156.80	0.95	6.54	65.40	0.76				
Average		12	0.2728	0.0787	83.33	77.83	88.11	72.05	64.87	77.76	66.30	68.00	65.00	69.95	70.75	264.67	0.95	8.94	91.68	0.78				

Table H.77. MLP 10-15-1, 10 input layers (categories)

Training set size			Training: 99 patterns (46 deposits, 53 barren), training-stop: = 88 (39 deposits, 49 barren), test = 81 (35 deposits, 46 barren)																								
Training set type			Randomly selected cells, approximately equal numbers of patterns from each rock type																								
Geology input format			Fuzzy membership values																								
Learn.	I.r.	Cycles	MSE			Train % correct				Stop % correct				Test % correct				Map % correct				Map statistics					
Algoth.			Initial	Final	All	Depos	Non	All	Depos	Non	All	Depos	Non	All	Depos	Non	All	Depos	Non	Chi	rho	D%/A%	D%*D%/A%	ROC			
trainlm	0.0	9	0.2118	0.0951	79.80	80.43	79.25	72.73	74.36	71.43	70.37	80.00	63.04	68.34	78.33	463.51	68.34	78.33	463.51	0.98	18.19	181.91	0.83	0.83			
trainlm	0.0	8	0.2447	0.1067	75.76	84.78	67.92	72.73	92.31	57.14	67.90	80.00	58.70	60.79	85.83	739.28	60.79	85.83	739.28	0.98	18.11	60.37	0.84	0.84			
trainlm	0.0	12	0.3717	0.0679	86.87	78.26	94.34	69.32	64.10	73.47	64.20	65.71	63.04	73.41	70.00	171.04	73.41	70.00	171.04	0.98	5.49	91.58	0.78	0.78			
trainlm	0.0	13	0.2386	0.0566	88.89	80.43	96.23	76.14	71.79	79.59	72.84	65.71	78.26	77.17	73.33	266.56	77.17	73.33	266.56	0.95	6.55	141.92	0.82	0.82			
trainlm	0.0	14	0.3778	0.0411	92.93	93.48	92.45	73.86	74.36	73.47	58.02	74.29	45.65	65.08	81.67	146.43	65.08	81.67	146.43	1.00	4.56	75.92	0.78	0.78			
trainlm	0.0	14	0.3092	0.0490	92.93	89.13	96.23	77.27	79.49	75.51	66.67	74.29	60.87	69.96	81.67	179.35	69.96	81.67	179.35	0.97	3.47	86.75	0.79	0.79			
trainlm	0.0	12	0.2359	0.0674	86.87	89.13	84.91	73.86	61.54	83.67	61.73	68.57	56.52	65.60	74.17	237.69	65.60	74.17	237.69	1.00	7.69	160.22	0.78	0.78			
trainlm	0.0	9	0.4090	0.1251	71.72	67.39	75.47	67.05	64.10	69.39	62.96	62.86	63.04	64.67	65.00	190.54	64.67	65.00	190.54	1.00	10.58	61.70	0.74	0.74			
trainlm	0.0	10	0.3000	0.0994	77.78	89.13	67.92	69.32	76.92	63.27	61.73	77.14	50.00	52.49	81.67	230.66	52.49	81.67	230.66	0.97	6.41	16.03	0.77	0.77			
trainlm	0.0	11	0.2413	0.0570	87.88	89.13	86.79	75.00	74.36	75.51	67.90	80.00	58.70	65.84	81.67	173.50	65.84	81.67	173.50	0.95	2.77	43.81	0.79	0.79			
Average		11	0.2940	0.0765	84.14	84.13	84.15	72.73	73.33	72.24	65.43	72.86	59.78	66.34	77.33	279.86	66.34	77.33	279.86	0.98	8.38	92.02	0.79	0.79			

Table H.78. MLP 10-20-1, 10 input layers (categories)

Training set size		Training: 99 patterns (46 deposits, 53 barren), training-stop: = 88 (39 deposits, 49 barren), test = 81 (35 deposits, 46 barren)																				
Training set type		Randomly selected cells, approximately equal numbers of patterns from each rock type																				
Geology input format		Fuzzy membership values																				
Learn. Algorith.	l.r.	Cycles	MSE			Train % correct			Stop % correct			Test % correct			Map % correct			Map statistics			D%*D%/A%	ROC
			Initial	Final	All	Depos	Non	All	Depos	Non	All	Depos	Non	All	Depos	Non	All	Depos	Chi	rho		
trainlm	0.0	10	0.2229	0.0718	88.89	89.13	88.68	72.73	69.23	75.51	76.54	77.14	76.09	70.05	79.17	348.46	0.90	9.63	256.69	0.82		
trainlm	0.0	10	0.2270	0.0670	87.88	91.30	84.91	68.18	74.36	63.27	64.20	77.14	54.35	64.21	81.67	258.31	1.00	9.45	118.18	0.80		
trainlm	0.0	8	0.1794	0.1010	74.75	58.70	88.68	67.05	48.72	81.63	64.20	51.43	73.91	70.44	53.33	137.52	0.98	5.98	34.90	0.69		
trainlm	0.0	18	0.4180	0.0702	82.83	80.43	84.91	76.14	82.05	71.43	66.67	65.71	67.39	67.44	76.67	170.27	0.97	4.28	114.11	0.78		
trainlm	0.0	11	0.2583	0.0569	87.88	73.91	100.00	70.45	61.54	77.55	69.14	57.14	78.26	76.31	65.00	210.66	1.00	7.84	124.15	0.80		
trainlm	0.0	13	0.2471	0.0318	93.94	89.13	98.11	72.73	61.54	81.63	65.43	60.00	69.57	73.20	71.67	201.74	0.97	4.98	124.61	0.81		
trainlm	0.0	9	0.2398	0.0832	80.81	76.09	84.91	71.59	66.67	75.51	66.67	71.43	63.04	66.09	71.67	278.45	0.97	16.21	81.04	0.79		
trainlm	0.0	8	0.2600	0.1018	77.78	76.09	79.25	67.05	69.23	65.31	65.43	68.57	63.04	63.37	71.67	446.45	0.95	5.11	4.26	0.76		
trainlm	0.0	10	0.1949	0.0644	84.85	78.26	90.57	80.68	74.36	85.71	72.84	80.00	67.39	76.94	77.50	333.39	1.00	9.06	120.82	0.83		
trainlm	0.0	11	0.2650	0.0655	84.85	89.13	81.13	80.68	84.62	77.55	67.90	71.43	65.22	69.80	82.50	250.69	0.98	8.91	74.24	0.82		
Average		11	0.2512	0.0714	84.44	80.22	88.11	72.73	69.23	75.51	67.90	68.00	67.83	69.79	73.08	263.59	0.97	8.15	105.30	0.79		

Table H.79. MLP 10-25-1, 10 input layers (categories)

Training set size		Training: 99 patterns (46 deposits, 53 barren), training-stop: = 88 (39 deposits, 49 barren), test = 81 (35 deposits, 46 barren)																					
Training set type		Randomly selected cells, approximately equal numbers of patterns from each rock type																					
Geology input format		Fuzzy membership values																					
Learn. Algorith.	l.r.	Cycles	MSE			Train % correct			Stop % correct			Test % correct			Map % correct			Map statistics			D%/A%	D%-D%/A%	ROC
			Initial	Final	All	Depos	Non	All	Depos	Non	All	Depos	Non	All	Depos	Non	All	Depos	Chi	rho			
trainlm	0.0	10	0.2394	0.0419	93.94	89.13	98.11	71.59	71.79	71.43	66.67	71.43	63.04	73.91	78.33	464.68	1.00	13.51	247.76			0.84	
trainlm	0.0	12	0.4035	0.0915	81.82	69.57	92.45	80.68	66.67	91.84	67.90	60.00	73.91	76.28	65.83	169.71	0.97	3.85	35.27			0.77	
trainlm	0.0	9	0.1864	0.0691	85.86	86.96	84.91	71.59	69.23	73.47	66.67	74.29	60.87	72.48	77.50	286.99	0.98	6.69	178.48			0.82	
trainlm	0.0	10	0.1868	0.0741	85.86	78.26	92.45	75.00	76.92	73.47	61.73	54.29	67.39	73.78	70.83	209.66	0.97	6.25	109.30			0.80	
trainlm	0.0	9	0.1402	0.0601	89.90	93.48	86.79	67.05	76.92	59.18	66.67	74.29	60.87	66.39	82.50	271.37	0.93	7.41	148.24			0.82	
trainlm	0.0	10	0.2468	0.0709	84.85	80.43	88.68	71.59	61.54	79.59	70.37	71.43	69.57	66.11	71.67	127.03	1.00	5.45	81.73			0.75	
trainlm	0.0	13	0.2435	0.0268	96.97	93.48	100.00	75.00	74.36	75.51	66.67	71.43	63.04	70.63	80.83	232.64	0.98	4.44	110.99			0.82	
trainlm	0.0	11	0.2652	0.0418	92.93	93.48	92.45	72.73	82.05	65.31	61.73	77.14	50.00	61.35	85.00	171.22	0.97	2.67	64.44			0.79	
trainlm	0.0	11	0.3198	0.0314	94.95	95.65	94.34	73.86	82.05	67.35	70.37	82.86	60.87	62.41	87.50	240.51	0.97	5.01	208.68			0.82	
Average		11	0.2480	0.0564	89.68	86.72	92.24	73.23	73.50	73.02	66.53	70.80	63.28	69.26	77.78	241.53	0.97	6.14	131.65			0.80	

Table H.80. MLP 10-3-2-1, 10 input layers (categories)

Training set size		Training: 99 patterns (46 deposits, 53 barren), training-stop: = 88 (39 deposits, 49 barren), test = 81 (35 deposits, 46 barren)																			
Training set type		Randomly selected cells, approximately equal numbers of patterns from each rock type																			
Geology input format		Fuzzy membership values																			
Learn.	I.r.	Cycles	MSE		Train % correct			Stop % correct			Test % correct			Map % correct		Map statistics			D%/A%	D%*D%/A%	ROC
			Initial	Final	All	Depos	Non	All	Depos	Non	All	Depos	Non	All	Depos	Chi	rho				
trainlm	0.0	21	0.3781	0.0767	87.88	82.61	92.45	79.55	71.79	85.71	71.60	60.00	80.43	75.77	72.50	165.23	0.83	2.98	181.42	0.79	
trainlm	0.0	14	0.2312	0.0963	78.79	67.39	88.68	71.59	53.85	85.71	69.14	54.29	80.43	76.85	59.17	131.38	0.78	3.13	125.01	0.72	
trainlm	0.0	19	0.3230	0.0901	78.79	82.61	75.47	71.59	82.05	63.27	61.73	71.43	54.35	60.63	79.17	425.39	0.92	18.53	308.80	0.79	
trainlm	0.0	18	0.3849	0.1010	78.79	71.74	84.91	77.27	71.79	81.63	66.67	65.71	67.39	78.13	70.00	248.19	0.92	5.05	260.74	0.80	
trainlm	0.0	18	0.2005	0.1085	78.79	73.91	83.02	75.00	74.36	75.51	70.37	77.14	65.22	84.06	75.00	380.98	0.40	5.55	406.84	0.81	
trainlm	0.0	12	0.2985	0.0905	80.81	82.61	79.25	72.73	71.79	73.47	66.67	68.57	65.22	68.01	75.00	216.29	0.97	7.13	124.75	0.81	
trainlm	0.0	15	0.3181	0.0852	83.84	84.78	83.02	75.00	71.79	77.55	66.67	71.43	63.04	62.65	76.67	185.82	0.88	9.15	129.69	0.75	
trainlm	0.0	15	0.4050	0.1592	53.54	0.00	100.00	55.68	0.00	100.00	56.79	0.00	100.00	99.99	0.00	2.28	0.77	1.03	100.17	0.50	
trainlm	0.0	26	0.2572	0.0780	83.84	89.13	79.25	70.45	89.74	55.10	60.49	74.29	50.00	57.58	85.00	306.75	0.52	8.18	279.46	0.79	
trainlm	0.0	13	0.3070	0.0953	80.81	82.61	79.25	75.00	79.49	71.43	65.43	77.14	56.52	68.49	80.00	615.97	0.93	89.81	374.19	0.79	
Average		17	0.3104	0.0981	78.59	71.74	84.53	72.39	66.67	76.94	65.56	62.00	68.26	73.22	67.25	267.83	0.79	15.05	229.11	0.75	

Table H.81. MLP 10-7-3-1, 10 input layers (categories)

Training set size			Training: 99 patterns (46 deposits, 53 barren), training-stop: = 88 (39 deposits, 49 barren), test = 81 (35 deposits, 46 barren)																			
Training set type			Randomly selected cells, approximately equal numbers of patterns from each rock type																			
Geology input format			Fuzzy membership values																			
Learn.	I.r.	Cycles	MSE		Train % correct			Stop % correct			Test % correct			Map % correct		Map statistics						
Algoth.			Initial	Final	All	Depos	Non	All	Depos	Non	All	Depos	Non	All	Depos	Chi	rho	D%/A%	D%*D%/A%	ROC		
trainlm	0.0	11	0.2176	0.0932	80.81	82.61	79.25	63.64	53.85	71.43	71.60	80.00	65.22	70.65	72.50	223.13	0.98	12.04	70.26	0.81		
trainlm	0.0	12	0.3023	0.1006	81.82	78.26	84.91	75.00	69.23	79.59	71.60	71.43	71.74	80.58	73.33	440.33	0.93	10.77	350.07	0.84		
trainlm	0.0	16	0.3494	0.1011	73.74	56.52	88.68	73.86	61.54	83.67	70.37	57.14	80.43	90.94	58.33	447.10	1.00	9.19	130.24	0.84		
trainlm	0.0	13	0.3938	0.1549	53.54	0.00	100.00	55.68	0.00	100.00	56.79	0.00	100.00	99.99	0.00	18.23	0.65	1.15	115.19	0.57		
trainlm	0.0	11	0.1693	0.0808	80.81	71.74	88.68	64.77	41.03	83.67	60.49	48.57	69.57	77.81	55.00	385.66	0.90	21.78	163.32	0.76		
trainlm	0.0	14	0.2967	0.0971	81.82	71.74	90.57	71.59	53.85	85.71	71.60	65.71	76.09	84.45	64.17	881.69	1.00	29.31	537.32	0.84		
trainlm	0.0	18	0.3279	0.0757	84.85	86.96	83.02	75.00	82.05	69.39	70.37	82.86	60.87	68.25	84.17	546.93	0.97	16.44	219.26	0.85		
trainlm	0.0	13	0.2758	0.0832	81.82	86.96	77.36	69.32	71.79	67.35	64.20	80.00	52.17	62.61	80.00	150.09	1.00	3.69	156.78	0.79		
trainlm	0.0	16	0.2450	0.0166	97.98	97.83	98.11	73.86	64.10	81.63	70.37	71.43	69.57	72.63	79.17	213.96	1.00	3.80	177.43	0.80		
trainlm	0.0	13	0.3471	0.0938	80.81	71.74	88.68	73.86	56.41	87.76	72.84	57.14	84.78	86.88	62.50	318.49	0.98	5.98	29.90	0.84		
Average		15	0.3085	0.0880	80.51	70.43	89.25	71.25	57.18	82.45	68.02	59.43	74.57	79.99	62.92	356.77	0.93	10.51	206.09	0.79		

Table H.82. MLP 10-10-5-1, 10 input layers (categories)

Training set size		Training: 99 patterns (46 deposits, 53 barren), training-stop: = 88 (39 deposits, 49 barren), test = 81 (35 deposits, 46 barren)																				
Training set type		Randomly selected cells, approximately equal numbers of patterns from each rock type																				
Geology input format		Fuzzy membership values																				
Learn.	l.r.	Cycles	MSE			Train % correct			Stop % correct			Test % correct			Map % correct			Map statistics				
Algorith.			Initial	Final	All	Depos	Non	All	Depos	Non	All	Depos	Non	All	Depos	Non	All	Chi	rho	D%/A%	D%*D%/A%	ROC
trainlm	0.0	17	0.3500	0.0469	90.91	84.78	96.23	72.73	64.10	79.59	71.60	65.71	76.09	79.66	72.50	468.22	0.97	10.62	354.09		0.85	
trainlm	0.0	11	0.1817	0.0559	89.90	86.96	92.45	73.86	61.54	83.67	66.67	74.29	60.87	70.13	75.00	172.03	0.98	3.98	86.33		0.79	
trainlm	0.0	14	0.2282	0.0836	82.83	91.30	75.47	72.73	84.62	63.27	66.67	80.00	56.52	50.31	85.83	157.60	0.95	5.31	84.04		0.75	
trainlm	0.0	20	0.4007	0.0915	83.84	84.78	83.02	76.14	71.79	79.59	67.90	77.14	60.87	73.62	78.33	276.46	0.83	1.38	3.46		0.79	
trainlm	0.0	14	0.3988	0.0859	82.83	84.78	81.13	75.00	76.92	73.47	70.37	77.14	65.22	64.88	80.00	211.46	0.40	0.00	0.00		0.80	
trainlm	0.0	13	0.2805	0.0516	90.91	93.48	88.68	65.91	69.23	63.27	69.14	82.86	58.70	72.50	82.50	250.35	1.00	4.87	137.85		0.83	
trainlm	0.0	13	0.2916	0.0980	79.80	71.74	86.79	73.86	53.85	89.80	70.37	60.00	78.26	84.79	62.50	276.05	0.87	3.77	9.43		0.79	
trainlm	0.0	14	0.3025	0.0497	89.90	86.96	92.45	76.14	74.36	77.55	67.90	68.57	67.39	74.37	77.50	245.10	0.93	4.63	189.23		0.83	
trainlm	0.0	11	0.2575	0.1054	74.75	63.04	84.91	71.59	53.85	85.71	75.31	62.86	84.78	80.08	60.00	530.66	0.97	16.01	200.14		0.79	
trainlm	0.0	1	0.3965	0.3817	53.54	0.00	100.00	55.68	0.00	100.00	56.79	0.00	100.00	99.99	0.00	379.34	0.33	72.70	181.74		0.50	
Average		13	0.3116	0.1080	81.62	74.57	87.74	72.05	61.79	80.20	68.27	64.29	71.30	74.64	67.42	266.43	0.81	11.56	107.36		0.77	

Table H.83. MLP 10-20-5-1, 10 input layers (categories)

Training set size	Training: 99 patterns (46 deposits, 53 barren), training-stop: = 88 (39 deposits, 49 barren), test = 81 (35 deposits, 46 barren)																					
Training set type	Randomly selected cells, approximately equal numbers of patterns from each rock type																					
Geology input format	Fuzzy membership values																					
Learn.	l.r.	Cycles	MSE			Train % correct			Stop % correct			Test % correct			Map % correct			Map statistics				
Algoth.			Initial	Final	All	Depos	Non	All	Depos	Non	All	Depos	Non	All	Depos	Chi	rho	D%/A%	D%*D%/A%	ROC		
trainlm	0.0	17	0.3500	0.0469	90.91	84.78	96.23	72.73	64.10	79.59	71.60	65.71	76.09	79.66	72.50	468.22	0.97	10.62	354.09	0.85		
trainlm	0.0	13	0.3045	0.0778	80.81	91.30	71.70	72.73	82.05	65.31	66.67	82.86	54.35	56.47	85.83	404.20	0.98	12.82	256.33	0.81		
trainlm	0.0	11	0.2225	0.0626	87.88	91.30	84.91	71.59	74.36	69.39	60.49	68.57	54.35	66.72	79.17	177.43	0.98	4.05	47.29	0.80		
trainlm	0.0	9	0.3350	0.1439	63.64	71.74	56.60	63.64	69.23	59.18	66.67	68.57	65.22	58.24	70.00	50.21	0.37	2.05	76.82	0.66		
trainlm	0.0	9	0.1763	0.0931	81.82	80.43	83.02	70.45	74.36	67.35	70.37	74.29	67.39	73.15	76.67	896.95	0.95	127.58	531.57	0.79		
trainlm	0.0	11	0.3119	0.0784	81.82	78.26	84.91	65.91	61.54	69.39	56.79	68.57	47.83	71.20	70.00	461.30	0.97	17.77	325.72	0.79		
trainlm	0.0	15	0.2455	0.0695	87.88	95.65	81.13	73.86	76.92	71.43	61.73	68.57	56.52	56.04	81.67	118.70	0.80	0.82	6.18	0.70		
trainlm	0.0	12	0.2484	0.0615	87.88	78.26	96.23	70.45	58.97	79.59	64.20	62.86	65.22	75.17	67.50	197.63	0.97	4.57	41.86	0.79		
trainlm	0.0	19	0.3804	0.1071	71.72	41.30	98.11	61.36	25.64	89.80	62.96	25.71	91.30	90.45	31.67	128.58	0.91	5.05	84.12	0.69		
trainlm	0.0	12	0.2649	0.0758	79.80	91.30	69.81	72.73	84.62	63.27	64.20	82.86	50.00	58.45	86.67	205.92	0.98	6.72	39.21	0.80		
Average		13	0.2868	0.0846	81.11	80.22	81.89	70.23	67.95	72.04	64.57	66.29	63.26	68.17	72.17	280.61	0.87	18.44	159.05	0.76		

Table H.84. MLP 10-20-1, 10 input layers (categories)

Training set size		Training: 99 patterns (46 deposits, 53 barren), training-stop: = 88 (39 deposits, 49 barren), test = 81 (35 deposits, 46 barren)															
Training set type		Randomly selected cells, approximately equal numbers of patterns from each rock type															
Geology input format		Fuzzy membership values															
Learn. Algorith.	l.r. Cycles	MSE		Train % correct			Stop % correct			Test % correct			Map % correct		Map statistics		
		Initial	Final	All	Depos	Non	All	Depos	Non	All	Depos	Non	All	Depos	Chi	rho	D%/A% D%*D%/A%
traingd	0.5 5222	0.2229	0.0643	87.88	84.78	90.57	72.73	64.10	79.59	67.90	77.14	60.87	66.19	75.83	115.24	1.00	3.18 42.44 0.77
traingd	0.5 3146	0.2270	0.0731	85.86	84.78	86.79	73.86	74.36	73.47	62.96	62.86	63.04	70.14	75.00	371.87	0.98	14.08 211.13 0.80
traingd	0.5 5486	0.1794	0.0614	87.88	86.96	88.68	68.18	64.10	71.43	67.90	65.71	69.57	68.44	73.33	173.51	1.00	6.09 71.07 0.77
traingd	0.5 392	0.4180	0.1234	65.66	56.52	73.58	63.64	51.28	73.47	66.67	54.29	76.09	81.56	54.17	663.85	0.95	54.79 273.93 0.77
traingd	0.5 4003	0.2583	0.0728	87.88	89.13	86.79	73.86	71.79	75.51	70.37	77.14	65.22	67.19	80.00	238.96	1.00	9.02 142.87 0.80
traingd	0.5 1355	0.2471	0.0888	79.80	80.43	79.25	71.59	66.67	75.51	69.14	77.14	63.04	65.80	75.00	515.87	0.97	38.80 323.32 0.78
traingd	0.5 6211	0.2398	0.0440	92.93	91.30	94.34	75.00	76.92	73.47	69.14	74.29	65.22	64.47	81.67	250.33	0.98	8.73 130.94 0.80
traingd	0.5 873	0.2600	0.1012	78.79	76.09	81.13	65.91	61.54	69.39	70.37	68.57	71.74	70.70	69.17	710.18	0.93	15.38 76.88 0.77
traingd	0.5 991	0.1949	0.0966	78.79	84.78	73.58	65.91	69.23	63.27	65.43	74.29	58.70	64.92	76.67	337.06	0.97	8.89 37.05 0.76
traingd	0.5 2831	0.2650	0.0873	81.82	78.26	84.91	75.00	66.67	81.63	72.84	71.43	73.91	72.16	72.50	529.32	0.98	42.10 315.73 0.81
Average	3051	0.2512	0.0813	82.73	81.30	83.96	70.57	66.67	73.67	68.27	70.29	66.74	69.16	73.33	390.62	0.98	20.11 162.54 0.78

Table H.85. MLP 10-20-1, 10 input layers (categories), Initial momentum = 0.5

Training set size		Training: 99 patterns (46 deposits, 53 barren), training-stop: = 88 (39 deposits, 49 barren), test = 81 (35 deposits, 46 barren)															
Training set type		Randomly selected cells, approximately equal numbers of patterns from each rock type															
Geology input format		Fuzzy membership values															
Learn. Algorith.	l.r. Cycles	MSE		Train % correct			Stop % correct			Test % correct			Map % correct		Map statistics		
		Initial	Final	All	Depos	Non	All	Depos	Non	All	Depos	Non	All	Depos	Chi	rho	D%/A% D%*D%/A%
traingd	0.5 314	0.2229	0.0901	81.82	76.09	86.79	75.00	69.23	79.59	65.43	71.43	60.87	62.92	72.50	98.50	0.90	1.56 6.51 0.73
traingd	0.5 332	0.2270	0.0828	83.84	80.43	86.79	71.59	66.67	75.51	64.20	62.86	65.22	74.89	70.83	455.76	0.97	20.84 260.46 0.80
traingd	0.5 422	0.1794	0.0801	81.82	80.43	83.02	64.77	56.41	71.43	67.90	68.57	67.39	67.80	69.17	167.53	1.00	6.75 56.25 0.75
traingd	0.5 164	0.4180	0.1237	65.66	56.52	73.58	62.50	51.28	71.43	65.43	54.29	73.91	81.69	54.17	689.77	0.93	55.40 277.01 0.77
traingd	0.5 329	0.2583	0.0886	86.87	84.78	88.68	70.45	64.10	75.51	66.67	65.71	67.39	69.88	72.50	279.77	0.98	7.60 76.00 0.79
traingd	0.5 276	0.2471	0.0888	79.80	80.43	79.25	71.59	66.67	75.51	69.14	77.14	63.04	65.75	75.00	516.36	0.97	39.04 325.32 0.78
traingd	0.5 351	0.2398	0.0708	82.83	76.09	88.68	71.59	66.67	75.51	72.84	77.14	69.57	65.94	73.33	277.94	1.00	19.85 148.90 0.78
traingd	0.5 234	0.2600	0.1014	78.79	76.09	81.13	65.91	61.54	69.39	70.37	68.57	71.74	70.75	69.17	712.45	0.93	15.26 76.31 0.77
traingd	0.5 246	0.1949	0.0967	77.78	82.61	73.58	65.91	69.23	63.27	65.43	74.29	58.70	64.89	75.83	337.10	0.97	8.90 37.10 0.76
traingd	0.5 345	0.2650	0.0882	81.82	78.26	84.91	75.00	66.67	81.63	72.84	71.43	73.91	72.54	72.50	486.54	0.98	39.21 261.41 0.81
Average	301	0.2512	0.0911	80.10	77.17	82.64	69.43	63.85	73.88	68.02	69.14	67.17	69.71	70.50	402.17	0.96	21.44 152.53 0.78

Table H.88. MLP 10-15-1, 10 input layers (categories), Uniform random noise 10%

Training set size		Training: 2111 patterns (1058 deposits, 1053 barren), training-stop: = 88 (39 deposits, 49 barren), test = 81 (35 deposits, 46 barren)															
Training set type		Randomly selected cells, approximately equal numbers of patterns from each rock type															
Geology input format		Fuzzy membership values															
Learn. Algorith.	l.r. Cycles	MSE		Train % correct			Stop % correct			Test % correct			Map % correct		Map statistics		
		Initial	Final	All	Depos	Non	All	Depos	Non	All	Depos	Non	All	Depos	Chi	rho	D%/A% D%*D%/A%
trainlm	0.0 11	0.2300	0.0730	84.18	80.81	87.56	77.27	64.10	87.76	72.84	71.43	73.91	79.96	73.33	525.66	1.00	27.65 253.49 0.84
trainlm	0.0 10	0.2201	0.0807	81.34	89.41	73.22	73.86	79.49	69.39	71.60	80.00	65.22	69.71	83.33	607.82	0.98	20.67 361.73 0.86
trainlm	0.0 11	0.1781	0.0802	82.38	84.88	79.87	73.86	69.23	77.55	69.14	68.57	69.57	76.05	75.83	508.92	0.98	14.84 247.38 0.85
trainlm	0.0 12	0.3511	0.0691	85.50	81.85	89.17	73.86	58.97	85.71	75.31	68.57	80.43	82.63	72.50	509.25	0.95	6.06 20.19 0.86
trainlm	0.0 10	0.3285	0.1012	77.17	70.51	83.86	70.45	56.41	81.63	70.37	62.86	76.09	74.67	63.33	512.24	0.95	4.88 8.14 0.79
trainlm	0.0 10	0.2143	0.0876	81.15	79.11	83.19	70.45	66.67	73.47	67.90	68.57	67.39	78.19	70.83	457.09	0.95	21.00 175.01 0.84
trainlm	0.0 10	0.3858	0.0863	79.11	75.80	82.43	77.27	66.67	85.71	72.84	68.57	76.09	76.41	70.83	392.57	1.00	11.94 39.81 0.84
trainlm	0.0 14	0.2895	0.0677	84.08	89.32	78.82	76.14	74.36	77.55	74.07	71.43	76.09	73.90	80.00	510.45	0.98	15.71 314.26 0.86
trainlm	0.0 11	0.2427	0.0827	82.38	88.19	76.54	72.73	87.18	61.22	71.60	77.14	67.39	68.68	85.00	440.14	0.97	18.94 284.13 0.84
trainlm	0.0 11	0.3632	0.0847	80.91	73.06	88.79	81.82	71.79	89.80	70.37	68.57	71.74	82.54	71.67	378.63	0.98	11.84 49.32 0.85
Average		0.2803	0.0813	81.82	81.29	82.35	74.77	69.49	78.98	71.60	70.57	72.39	76.27	74.67	484.28	0.97	15.35 175.35 0.84

Table H.89. MLP 10-20-1, 10 input layers (categories), Uniform random noise 10%

Training set size		Training: 2111 patterns (1058 deposits, 1053 barren), training-stop: = 88 (39 deposits, 49 barren), test = 81 (35 deposits, 46 barren)															
Training set type		Randomly selected cells, approximately equal numbers of patterns from each rock type															
Geology input format		Fuzzy membership values															
Learn. Algorith.	l.r. Cycles	MSE		Train % correct			Stop % correct			Test % correct			Map % correct		Map statistics		
		Initial	Final	All	Depos	Non	All	Depos	Non	All	Depos	Non	All	Depos	Chi	rho	D%/A% D%*D%/A%
trainlm	0.0 11	0.2300	0.0730	84.18	80.81	87.56	77.27	64.10	87.76	72.84	71.43	73.91	79.96	73.33	525.66	1.00	27.65 253.49 0.84
trainlm	0.0 10	0.2201	0.0807	81.34	89.41	73.22	73.86	79.49	69.39	71.60	80.00	65.22	69.71	83.33	607.82	0.98	20.67 361.73 0.86
trainlm	0.0 11	0.1781	0.0802	82.38	84.88	79.87	73.86	69.23	77.55	69.14	68.57	69.57	76.05	75.83	508.92	0.98	14.84 247.38 0.85
trainlm	0.0 13	0.3920	0.0792	80.72	75.52	85.94	71.59	64.10	77.55	67.90	62.86	71.74	83.84	68.33	338.78	0.97	6.99 29.12 0.84
trainlm	0.0 9	0.2683	0.0975	79.87	69.75	90.03	70.45	53.85	83.67	75.31	65.71	82.61	89.75	63.33	595.06	0.98	20.37 135.83 0.87
trainlm	0.0 9	0.2527	0.0745	83.99	86.96	81.01	75.00	76.92	73.47	76.54	80.00	73.91	75.68	82.50	374.73	0.98	9.66 96.63 0.86
trainlm	0.0 12	0.2789	0.0633	86.36	94.90	77.78	77.27	84.62	71.43	71.60	85.71	60.87	73.32	88.33	459.49	0.92	9.10 189.49 0.87
trainlm	0.0 11	0.2591	0.0635	88.02	93.67	82.34	68.18	66.67	69.39	74.07	74.29	73.91	77.06	79.17	551.46	0.98	20.58 308.77 0.85
trainlm	0.0 9	0.1739	0.0934	79.30	71.17	87.46	73.86	71.79	75.51	71.60	60.00	80.43	84.28	70.00	434.34	0.97	15.05 87.78 0.82
trainlm	0.0 12	0.2580	0.0587	87.97	88.09	87.84	79.55	76.92	81.63	72.84	65.71	78.26	80.91	77.50	413.33	0.97	7.81 78.14 0.87
Average		0.2499	0.0784	83.07	83.70	82.47	72.73	69.74	75.10	72.22	72.29	72.17	78.13	76.08	450.71	0.97	13.71 160.51 0.85

Table H.90. MLP 10-25-1, 10 input layers (categories), Uniform random noise 10%

Training set size		Training: 2111 patterns (1058 deposits, 1053 barren), training-stop: = 88 (39 deposits, 49 barren), test = 81 (35 deposits, 46 barren)															
Training set type		Randomly selected cells, approximately equal numbers of patterns from each rock type															
Geology input format		Fuzzy membership values															
Learn. Algorith.	l.r. Cycles	MSE		Train % correct			Stop % correct			Test % correct			Map % correct		Map statistics		
		Initial	Final	All	Depos	Non	All	Depos	Non	All	Depos	Non	All	Depos	Chi	rho	D%/A% D%*D%/A%
trainlm	0.0 10	0.2211	0.0754	85.50	86.29	84.71	73.86	71.79	73.86	71.60	74.29	69.57	77.54	78.33	597.32	0.98	13.48 112.30 0.86
trainlm	0.0 9	0.3784	0.1137	73.42	70.42	76.45	71.59	69.23	73.47	65.43	65.71	65.22	72.55	67.50	681.32	1.00	47.65 397.05 0.80
trainlm	0.0 8	0.1726	0.1003	76.50	68.81	84.24	73.86	64.10	81.63	71.60	65.71	76.09	79.61	66.67	312.40	0.98	13.39 167.43 0.81
trainlm	0.0 11	0.2283	0.0666	86.55	82.33	90.79	73.86	61.54	83.67	66.67	57.14	73.91	91.06	68.33	992.51	0.95	5.97 19.90 0.90
trainlm	0.0 7	0.1504	0.1037	77.40	66.26	88.60	72.73	51.28	89.80	72.84	62.86	80.43	88.76	60.00	595.05	0.98	18.84 94.18 0.85
trainlm	0.0 11	0.2120	0.0728	85.74	84.31	87.18	73.86	61.54	83.67	69.14	51.43	82.61	74.91	68.33	173.16	0.97	4.95 37.15 0.78
trainlm	0.0 10	0.2143	0.0651	86.07	84.31	87.84	69.32	56.41	79.59	67.90	60.00	73.91	83.74	69.17	485.87	0.98	16.86 112.38 0.85
trainlm	0.0 10	0.2642	0.0754	86.64	88.19	85.09	70.45	64.10	75.51	75.31	74.29	76.09	81.92	75.83	464.03	0.98	20.48 68.25 0.86
trainlm	0.0 12	0.2819	0.0580	90.76	97.26	84.24	77.27	76.92	77.55	71.60	74.29	69.57	80.09	85.00	767.12	0.98	22.65 396.41 0.87
trainlm	0.0 11	0.3144	0.0812	81.90	81.47	82.34	72.73	69.23	75.51	69.14	71.43	67.39	82.85	74.17	546.56	0.98	20.29 118.34 0.87
Average	10	0.2437	0.0812	83.05	80.96	85.15	72.95	64.62	79.59	70.12	65.71	73.48	81.30	71.33	561.53	0.98	18.45 152.34 0.85

Table H.91. MLP 10-50-1, 10 input layers (categories), Uniform random noise 10%

Training set size		Training: 2111 patterns (1058 deposits, 1053 barren), training-stop: = 88 (39 deposits, 49 barren), test = 81 (35 deposits, 46 barren)															
Training set type		Randomly selected cells, approximately equal numbers of patterns from each rock type															
Geology input format		Fuzzy membership values															
Learn. Algorith.	l.r. Cycles	MSE		Train % correct			Stop % correct			Test % correct			Map % correct		Map statistics		
		Initial	Final	All	Depos	Non	All	Depos	Non	All	Depos	Non	All	Depos	Chi	rho	D%/A% D%*D%/A%
trainlm	0.0 9	0.3419	0.0818	84.04	88.09	79.96	73.86	79.49	69.39	69.14	74.29	65.22	74.92	81.67	369.89	0.98	15.47 116.02 0.85
trainlm	0.0 9	0.3042	0.0838	80.20	71.46	88.98	68.18	51.28	81.63	74.07	71.43	76.09	85.92	65.00	363.50	0.98	7.44 24.80 0.86
trainlm	0.0 8	0.2136	0.1051	75.27	89.13	61.35	70.45	82.05	61.22	65.43	82.86	52.17	55.01	85.00	326.67	0.98	13.03 119.45 0.79
trainlm	0.0 8	0.2054	0.0939	77.31	83.27	71.32	69.32	64.10	73.47	71.60	71.43	71.74	72.37	74.17	437.69	0.97	12.45 207.55 0.83
trainlm	0.0 12	0.2531	0.0301	95.97	99.81	92.12	72.73	58.97	83.67	67.90	60.00	73.91	85.68	75.00	999.35	0.95	23.21 599.55 0.89
trainlm	0.0 11	0.2339	0.0510	92.04	95.94	88.13	72.73	66.67	77.55	77.78	74.29	80.43	83.32	81.67	651.16	0.92	7.16 29.83 0.87
trainlm	0.0 11	0.2480	0.0714	84.75	93.57	75.88	69.32	69.23	69.39	74.07	65.71	80.43	69.42	79.17	388.44	0.98	10.83 162.44 0.82
trainlm	0.0 12	0.3070	0.0430	92.33	92.34	92.31	72.73	64.10	79.59	66.67	54.29	76.09	87.35	73.33	723.46	0.98	18.08 241.04 0.86
trainlm	0.0 10	0.3665	0.0589	88.58	87.43	89.74	76.14	64.10	85.71	70.37	60.00	78.26	81.51	70.83	368.67	0.93	12.03 120.31 0.83
trainlm	0.0 9	0.2752	0.1014	74.23	56.14	92.40	68.18	41.03	89.80	69.14	45.71	86.96	93.21	48.33	522.54	0.98	14.32 35.80 0.86
Average	10	0.2749	0.0720	84.47	85.72	83.22	71.36	64.10	77.14	70.62	66.00	74.13	78.87	73.42	515.14	0.97	13.40 165.68 0.84

Table H.92. MLP 10-20-1, 10 input layers (categories), Uniform random noise 5%

Training set size		Training: 2111 patterns (1058 deposits, 1053 barren), training-stop: = 88 (39 deposits, 49 barren), test = 81 (35 deposits, 46 barren)															
Training set type		Randomly selected cells, approximately equal numbers of patterns from each rock type															
Geology input format		Fuzzy membership values															
Learn. Algorith.	l.r. Cycles	MSE		Train % correct			Stop % correct			Test % correct			Map % correct		Map statistics		
		Initial	Final	All	Depos	Non	All	Depos	Non	All	Depos	Non	All	Depos	Chi	rho	D%/A%
trainlm	0.0 15	0.2274	0.0385	94.32	97.35	91.26	67.05	38.46	89.80	71.60	60.00	80.43	83.88	67.50	587.40	0.98	18.15
trainlm	0.0 10	0.2250	0.0783	81.43	78.26	84.62	73.86	58.97	85.71	72.84	74.29	71.74	81.62	71.67	664.36	0.98	28.48
trainlm	0.0 10	0.1785	0.0875	80.15	80.15	80.15	70.45	64.10	75.51	69.14	68.57	69.57	79.49	71.67	471.83	0.98	15.58
trainlm	0.0 16	0.3911	0.0618	86.83	83.18	90.50	72.73	61.54	81.63	76.54	62.86	86.96	86.55	69.17	638.49	1.00	20.45
trainlm	0.0 9	0.2720	0.0975	81.53	74.01	89.08	72.73	58.97	83.67	76.54	71.43	80.43	89.29	68.33	627.96	1.00	21.02
trainlm	0.0 8	0.2488	0.0932	79.77	93.29	66.19	71.59	84.62	61.22	70.37	82.86	60.87	63.07	87.50	360.30	0.98	14.14
trainlm	0.0 10	0.2773	0.0828	81.48	80.91	82.05	82.95	84.62	81.63	74.07	74.29	73.91	77.88	80.83	570.24	0.93	2.83
trainlm	0.0 14	0.2576	0.0426	92.23	92.91	91.55	65.91	46.15	81.63	71.60	48.57	89.13	88.86	65.83	640.17	0.98	16.75
trainlm	0.0 9	0.1736	0.0737	84.04	82.70	85.38	72.73	74.36	71.43	77.78	74.29	80.43	84.75	78.33	642.54	0.92	12.93
trainlm	0.0 11	0.2567	0.0860	81.34	74.20	88.51	80.68	69.23	89.80	79.01	74.29	82.61	89.27	73.33	696.82	0.98	13.18
Average	11	0.2510	0.0777	83.30	82.04	84.56	74.09	66.67	80.00	74.07	70.29	76.96	82.07	74.00	583.84	0.98	17.30

Table H.93. MLP 10-20-1, 10 input layers (categories), Uniform random noise 10%

Training set size		Training: 2111 patterns (1058 deposits, 1053 barren), training-stop: = 88 (39 deposits, 49 barren), test = 81 (35 deposits, 46 barren)															
Training set type		Randomly selected cells, approximately equal numbers of patterns from each rock type															
Geology input format		Fuzzy membership values															
Learn. Algorith.	l.r. Cycles	MSE		Train % correct			Stop % correct			Test % correct			Map % correct		Map statistics		
		Initial	Final	All	Depos	Non	All	Depos	Non	All	Depos	Non	All	Depos	Chi	rho	D%/A%
trainlm	0.0 11	0.2300	0.0730	84.18	80.81	87.56	77.27	64.10	87.76	72.84	71.43	73.91	79.96	73.33	525.66	1.00	27.65
trainlm	0.0 10	0.2201	0.0807	81.34	89.41	73.22	73.86	79.49	69.39	71.60	80.00	65.22	69.71	83.33	607.82	0.98	20.67
trainlm	0.0 11	0.1781	0.0802	82.38	84.88	79.87	73.86	69.23	77.55	69.14	68.57	69.57	76.05	75.83	508.92	0.98	14.84
trainlm	0.0 13	0.3920	0.0792	80.72	75.52	85.94	71.59	64.10	77.55	67.90	62.86	71.74	83.84	68.33	338.78	0.97	6.99
trainlm	0.0 9	0.2683	0.0975	79.87	69.75	90.03	70.45	53.85	83.67	75.31	65.71	82.61	89.75	63.33	595.06	0.98	20.37
trainlm	0.0 9	0.2527	0.0745	83.99	86.96	81.01	75.00	76.92	73.47	76.54	80.00	73.91	75.68	82.50	374.73	0.98	9.66
trainlm	0.0 12	0.2789	0.0633	86.36	94.90	77.78	77.27	84.62	71.43	71.60	85.71	60.87	73.32	88.33	459.49	0.92	9.10
trainlm	0.0 11	0.2591	0.0635	88.02	93.67	82.34	68.18	66.67	69.39	74.07	74.29	73.91	77.06	79.17	551.46	0.98	20.58
trainlm	0.0 9	0.1739	0.0934	79.30	71.17	87.46	73.86	71.79	75.51	71.60	60.00	80.43	84.28	70.00	434.34	0.97	15.05
trainlm	0.0 12	0.2580	0.0587	87.97	88.09	87.84	79.55	76.92	81.63	72.84	65.71	78.26	80.91	77.50	413.33	0.97	7.81
Average	11	0.2511	0.0764	83.41	83.52	83.30	74.09	70.77	76.73	72.35	71.43	73.04	79.06	76.17	480.96	0.97	15.27

Table H.94. MLP 10-20-1, 10 input layers (categories), Uniform random noise 20%

Training set size		Training: 2111 patterns (1058 deposits, 1053 barren), training-stop: = 88 (39 deposits, 49 barren), test = 81 (35 deposits, 46 barren)																				
Training set type		Randomly selected cells, approximately equal numbers of patterns from each rock type																				
Geology input format		Fuzzy membership values																				
Learn.	l.r.	Cycles	MSE			Train % correct			Stop % correct			Test % correct			Map % correct			Map statistics			D%*D%/A%	ROC
			Initial	Final	All	Depos	Non	All	Depos	Non	All	Depos	Non	All	Depos	Non	All	Depos	Chi	rho		
trainlm	0.0	11	0.2356	0.0687	84.94	87.24	82.62	72.73	66.67	77.55	75.31	65.71	82.61	78.47	75.00	425.05	1.00	9.70	80.87	0.85		
trainlm	0.0	12	0.2131	0.0619	87.97	89.70	86.23	78.41	74.36	81.63	70.37	71.43	69.57	79.33	80.83	625.13	0.98	19.68	360.87	0.86		
trainlm	0.0	10	0.1780	0.0890	78.92	76.75	81.10	72.73	64.10	79.59	66.67	62.86	69.57	81.05	70.00	585.03	0.98	22.45	318.10	0.84		
trainlm	0.0	13	0.3933	0.0811	82.66	81.85	83.48	75.00	66.67	81.63	76.54	80.00	73.91	72.55	76.67	392.58	0.95	16.66	152.71	0.82		
trainlm	0.0	14	0.2617	0.0376	93.65	98.77	88.51	76.14	64.10	85.71	72.84	65.71	78.26	84.33	78.33	695.27	0.95	14.64	280.70	0.88		
trainlm	0.0	11	0.2600	0.0757	84.08	76.09	92.12	70.45	51.28	85.71	70.37	60.00	78.26	90.22	65.00	568.33	0.98	16.89	197.08	0.88		
trainlm	0.0	11	0.2824	0.0706	85.79	79.77	91.83	77.27	56.41	93.88	69.14	60.00	76.09	89.46	67.50	499.14	0.97	12.23	71.35	0.86		
trainlm	0.0	9	0.2628	0.0952	77.83	75.05	80.63	63.64	53.85	71.43	72.84	71.43	73.91	76.42	67.50	637.32	1.00	25.30	189.79	0.81		
trainlm	0.0	15	0.1760	0.0341	94.41	97.54	91.26	75.00	66.67	81.63	71.60	54.29	84.78	86.08	75.83	905.33	0.95	19.43	437.27	0.86		
trainlm	0.0	10	0.2618	0.0818	82.05	77.13	86.99	79.55	79.49	79.59	72.84	68.57	76.09	79.41	75.83	408.70	0.95	13.59	113.23	0.84		
Average		12	0.2519	0.0700	85.15	83.35	86.97	74.55	64.10	82.86	71.60	66.57	75.43	81.88	73.08	584.25	0.97	18.85	237.46	0.85		

Table H.95. MLP 10-20-1, 10 input layers (categories), Uniform random noise 40%

Training set size		Training: 2111 patterns (1058 deposits, 1053 barren), training-stop: = 88 (39 deposits, 49 barren), test = 81 (35 deposits, 46 barren)																				
Training set type		Randomly selected cells, approximately equal numbers of patterns from each rock type																				
Geology input format		Fuzzy membership values																				
Learn. Algoth.	l.r.	Cycles	MSE			Train % correct			Stop % correct			Test % correct			Map % correct			Map statistics				
			Initial	Final	All	Depos	Non	All	Depos	Non	All	Depos	Non	All	Depos	Non	All	Chi	rho	D%/A%	D%*D%/A%	ROC
trainlm	0.0	17	0.2358	0.0482	90.57	90.45	90.69	72.73	61.54	81.63	70.37	57.14	80.43	84.64	73.33	735.75	0.98	15.77	486.35	0.88		
trainlm	0.0	11	0.2039	0.0749	84.13	85.54	82.72	72.73	69.23	75.51	71.60	80.00	65.22	75.99	80.00	446.91	0.98	11.07	129.18	0.86		
trainlm	0.0	11	0.1823	0.0693	85.84	88.37	83.29	72.73	74.36	71.43	74.07	80.00	69.57	79.97	84.17	580.78	1.00	12.93	194.02	0.89		
trainlm	0.0	14	0.3954	0.0624	86.83	89.89	83.76	73.86	74.36	73.47	72.84	77.14	69.57	78.34	82.50	686.21	0.98	20.28	354.91	0.87		
trainlm	0.0	11	0.2575	0.0793	82.85	86.29	79.39	75.00	82.05	69.39	76.54	85.71	69.57	77.98	87.50	677.99	1.00	14.40	215.96	0.90		
trainlm	0.0	11	0.2735	0.0774	83.85	89.04	78.63	72.73	82.05	65.31	72.84	82.86	65.22	72.37	85.00	443.50	0.98	8.26	110.15	0.87		
trainlm	0.0	9	0.2905	0.1016	75.51	86.67	64.29	72.73	87.18	61.22	69.14	88.57	54.35	66.59	89.17	454.66	1.00	11.72	214.93	0.86		
trainlm	0.0	9	0.2782	0.1013	77.03	71.46	82.62	63.64	51.28	73.47	70.37	68.57	71.74	82.72	64.17	674.70	1.00	42.07	315.55	0.82		
trainlm	0.0	12	0.1801	0.0751	83.51	84.59	82.43	78.41	74.36	81.63	74.07	71.43	76.09	82.10	80.00	726.87	0.98	19.71	394.28	0.87		
trainlm	0.0	10	0.2709	0.0880	80.96	74.76	87.18	72.73	58.97	83.67	74.07	65.71	80.43	85.79	66.67	452.46	1.00	10.83	81.19	0.87		
Average		11	0.2562	0.0802	82.47	83.74	81.19	73.18	71.79	74.29	72.84	77.14	69.57	78.18	79.25	566.97	0.99	17.89	226.36	0.87		

Table H.96. MLP 10-20-1, 10 input layers (categories), Uniform random noise 80%

Training set size		Training: 2111 patterns (1058 deposits, 1053 barren), training-stop: = 88 (39 deposits, 49 barren), test = 81 (35 deposits, 46 barren)																	
Training set type		Randomly selected cells, approximately equal numbers of patterns from each rock type																	
Geology input format		Fuzzy membership values																	
Learn. Algorith.	l.r. Cycles	MSE		Train % correct			Stop % correct			Test % correct			Map % correct		Map statistics				
		Initial	Final	All	Depos	Non	All	Depos	Non	All	Depos	Non	All	Depos	Chi	rho	D%/A%	D%*D%/A%	ROC
trainlm	0.0 11	0.2196	0.0739	84.23	92.16	76.26	71.59	74.36	69.39	76.54	85.71	69.57	72.40	82.50	468.66	1.00	14.47	253.24	0.86
trainlm	0.0 11	0.1981	0.0723	85.36	84.69	86.04	73.86	64.10	81.63	74.07	74.29	73.91	81.38	72.50	333.60	0.98	11.06	101.36	0.85
trainlm	0.0 10	0.1923	0.0781	83.99	87.43	80.53	71.59	61.54	79.59	64.20	62.86	65.22	77.61	66.67	303.00	0.97	7.69	12.82	0.82
trainlm	0.0 12	0.3985	0.0880	81.15	85.54	76.73	63.64	66.67	61.22	69.14	77.14	63.04	70.64	75.83	492.71	1.00	25.25	294.53	0.82
trainlm	0.0 13	0.2624	0.0680	85.88	87.90	83.86	70.45	58.97	79.59	65.43	60.00	69.57	78.66	67.50	307.63	1.00	12.64	179.12	0.83
trainlm	0.0 12	0.2873	0.0704	86.17	86.67	85.66	80.68	71.79	87.76	72.84	71.43	73.91	79.03	74.17	293.26	1.00	7.96	53.06	0.84
trainlm	0.0 17	0.2992	0.0454	91.90	91.49	92.31	76.14	64.10	85.71	76.54	65.71	84.78	83.16	74.17	551.46	1.00	13.84	380.48	0.86
trainlm	0.0 11	0.3056	0.0712	84.84	87.62	82.05	70.45	64.10	75.51	70.37	65.71	73.91	76.52	70.00	362.70	1.00	17.59	190.59	0.81
trainlm	0.0 16	0.1874	0.0401	92.85	92.44	93.26	79.55	66.67	89.80	80.25	74.29	84.78	83.37	76.67	434.05	0.97	10.99	247.25	0.86
trainlm	0.0 15	0.2817	0.0571	88.77	92.25	85.28	75.00	64.10	83.67	69.14	65.71	71.74	78.12	72.50	323.86	0.93	11.26	168.89	0.83
Average	13	0.2643	0.0664	86.51	87.68	85.33	73.86	64.62	81.22	71.48	68.86	73.48	78.85	72.33	392.79	0.98	14.59	188.16	0.84

Table H.97. MLP 10-20-1, 10 input layers (categories), Normally-distributed random noise 5%

Training set size		Training: 2111 patterns (1058 deposits, 1053 barren), training-stop: = 88 (39 deposits, 49 barren), test = 81 (35 deposits, 46 barren)																	
Training set type		Randomly selected cells, approximately equal numbers of patterns from each rock type																	
Geology input format		Fuzzy membership values																	
Learn. Algorith.	l.r. Cycles	MSE		Train % correct			Stop % correct			Test % correct			Map % correct		Map statistics				
		Initial	Final	All	Depos	Non	All	Depos	Non	All	Depos	Non	All	Depos	Chi	rho	D%/A%	D%*D%/A%	ROC
trainlm	0.0 10	0.2329	0.0779	83.94	88.09	79.77	77.27	82.05	73.47	79.01	85.71	73.91	74.59	85.00	548.42	0.97	18.99	269.03	0.87
trainlm	0.0 10	0.2150	0.0768	83.14	82.70	83.57	73.86	61.54	83.67	75.31	82.86	69.57	80.41	75.83	507.95	0.98	14.06	128.90	0.88
trainlm	0.0 11	0.1749	0.0709	84.46	78.92	90.03	78.41	61.54	91.84	72.84	65.71	78.26	87.41	70.00	561.91	0.92	10.45	34.82	0.87
trainlm	0.0 14	0.3920	0.0781	82.24	81.29	83.19	72.73	71.79	73.47	72.84	74.29	71.74	78.62	76.67	419.50	0.93	11.85	128.34	0.84
trainlm	0.0 10	0.2577	0.0848	82.28	83.46	81.10	72.73	71.79	73.47	70.37	74.29	67.39	76.14	77.50	576.17	1.00	18.35	244.61	0.86
trainlm	0.0 10	0.2523	0.0671	87.92	93.67	82.15	72.73	71.79	73.47	76.54	80.00	73.91	74.48	83.33	464.95	0.92	11.06	129.03	0.87
trainlm	0.0 15	0.2738	0.0323	94.05	99.81	89.46	82.95	74.36	89.80	69.14	62.86	73.91	88.94	80.83	948.84	0.97	14.72	429.25	0.89
trainlm	0.0 8	0.2660	0.1146	74.56	58.03	91.17	60.23	30.77	83.67	71.60	51.43	86.96	92.54	46.67	568.50	0.92	5.87	4.89	0.80
trainlm	0.0 9	0.1794	0.0784	83.33	81.57	85.09	67.05	64.10	69.39	74.07	71.43	76.09	83.69	73.33	520.93	0.98	14.59	72.95	0.87
trainlm	0.0 10	0.2610	0.1119	74.32	79.02	69.61	70.45	76.92	65.31	72.84	80.00	67.39	51.54	78.33	59.94	0.77	0.65	3.24	0.66
Average	11	0.2502	0.0788	83.11	81.93	84.29	72.84	64.87	79.18	72.84	71.43	73.91	79.37	73.58	515.43	0.94	12.92	142.95	0.84

Table H.98. MLP 10-20-1, 10 input layers (categories), Normally distributed random noise 10%

Training set size		Training: 2111 patterns (1058 deposits, 1053 barren), training-stop: = 88 (39 deposits, 49 barren), test = 81 (35 deposits, 46 barren)																			
Training set type		Randomly selected cells, approximately equal numbers of patterns from each rock type																			
Geology input format		Fuzzy membership values																			
Learn. Algorith.	l.r. Cycles	MSE		Train % correct			Stop % correct			Test % correct			Map % correct			Map statistics			ROC		
		Initial	Final	All	Depos	Non	All	Depos	Non	All	Depos	Non	All	Depos	Non	Chi	rho	D%/A%	D%*D%/A%	D%/A%	ROC
trainlm	0.0 10	0.2437	0.1096	73.66	52.65	94.78	70.45	38.46	95.92	74.07	48.57	93.48	90.18	49.17	93.76	333.76	0.43	0.00	0.00	0.81	0.81
trainlm	0.0 11	0.2057	0.0711	86.64	86.29	86.99	75.00	71.79	77.55	74.07	71.43	76.09	81.15	79.17	433.28	0.97	12.44	114.05		0.87	0.87
trainlm	0.0 11	0.1789	0.0711	86.55	83.74	89.36	77.27	69.23	83.67	75.31	71.43	78.26	80.91	76.67	387.17	0.95	9.56	95.55		0.85	0.85
trainlm	0.0 14	0.3937	0.0633	87.49	88.28	86.70	71.59	66.67	75.51	80.25	80.00	80.43	79.50	80.00	436.47	0.98	12.04	130.44		0.85	0.85
trainlm	0.0 12	0.2517	0.0716	83.66	76.75	90.60	72.73	61.54	81.63	66.67	51.43	78.26	89.36	65.00	642.53	0.95	5.37	17.90		0.88	0.88
trainlm	0.0 10	0.2661	0.0931	79.58	66.82	92.40	73.86	48.72	93.88	71.60	54.29	84.78	92.15	58.33	617.57	0.95	18.65	170.95		0.87	0.87
trainlm	0.0 12	0.2738	0.0666	87.07	87.90	86.23	79.55	71.79	85.71	76.54	77.14	76.09	82.79	80.83	644.31	0.98	16.10	187.81		0.89	0.89
trainlm	0.0 9	0.2670	0.0968	78.73	74.95	82.53	62.50	48.72	73.47	72.84	71.43	73.91	81.08	66.67	648.12	0.98	23.81	138.89		0.81	0.81
trainlm	0.0 11	0.1819	0.0627	88.77	92.53	85.00	71.59	69.23	73.47	71.60	68.57	73.91	79.47	78.33	594.87	1.00	17.86	312.46		0.88	0.88
trainlm	0.0 10	0.2635	0.0849	82.24	78.45	86.04	81.82	74.36	87.76	75.31	74.29	76.09	82.83	76.67	629.80	0.98	21.59	143.93		0.86	0.86
Average	11	0.2526	0.0791	83.44	78.84	88.06	73.64	62.05	82.86	73.83	66.86	79.13	83.94	71.08	536.79	0.92	13.74	131.20		0.86	0.86

Table H.99. MLP 10-20-1, 10 input layers (categories), Normally distributed random noise 20%

Training set size		Training: 2111 patterns (1058 deposits, 1053 barren), training-stop: = 88 (39 deposits, 49 barren), test = 81 (35 deposits, 46 barren)																			
Training set type		Randomly selected cells, approximately equal numbers of patterns from each rock type																			
Geology input format		Fuzzy membership values																			
Learn. Algorith.	l.r. Cycles	MSE		Train % correct			Stop % correct			Test % correct			Map % correct			Map statistics			ROC		
		Initial	Final	All	Depos	Non	All	Depos	Non	All	Depos	Non	All	Depos	Non	Chi	rho	D%/A%	D%*D%/A%	D%/A%	ROC
trainlm	0.0 13	0.2388	0.0656	86.97	90.45	83.48	76.14	79.49	73.47	74.07	80.00	69.57	77.39	86.67	616.67	0.98	7.75	90.39		0.90	0.90
trainlm	0.0 12	0.1967	0.0688	84.79	83.65	85.94	76.14	74.36	77.55	72.84	77.14	69.57	81.36	81.67	719.92	1.00	20.27	405.42		0.88	0.88
trainlm	0.0 10	0.1883	0.0880	81.57	83.93	79.20	77.27	82.05	73.47	71.60	77.14	67.39	78.96	82.50	707.28	1.00	35.41	354.05		0.88	0.88
trainlm	0.0 14	0.3969	0.0811	82.33	79.58	85.09	76.14	69.23	81.63	72.84	65.71	78.26	80.70	73.33	757.83	0.98	29.65	444.77		0.85	0.85
trainlm	0.0 14	0.2466	0.0558	88.39	93.95	82.81	78.41	87.18	71.43	77.78	82.86	73.91	78.06	90.00	698.40	1.00	13.19	439.65		0.90	0.90
trainlm	0.0 13	0.2802	0.0631	86.50	82.23	90.79	76.14	58.97	89.80	75.31	68.57	80.43	86.55	74.17	580.10	0.98	9.85	114.96		0.88	0.88
trainlm	0.0 10	0.2757	0.0835	83.56	81.76	85.38	72.73	61.54	81.63	69.14	62.86	73.91	80.60	70.83	489.23	0.97	16.20	188.98		0.85	0.85
trainlm	0.0 12	0.2892	0.0731	86.74	91.49	81.96	65.91	64.10	67.35	71.60	68.57	73.91	73.39	78.33	537.07	1.00	18.25	273.82		0.86	0.86
trainlm	0.0 12	0.1871	0.0558	88.92	88.37	89.46	77.27	64.10	87.76	69.14	62.86	73.91	83.10	75.00	820.74	0.98	20.91	592.43		0.87	0.87
trainlm	0.0 14	0.2648	0.0659	86.50	93.19	79.77	79.55	84.62	75.51	76.54	82.86	71.74	77.65	90.00	711.77	0.98	15.03	400.77		0.89	0.89
Average	12	0.2569	0.0745	84.30	83.08	85.52	75.00	68.46	80.20	73.09	69.71	75.65	81.05	76.50	635.61	0.93	17.88	321.49		0.87	0.87

Table H.100. MLP 10-20-1, 10 input layers (categories), Normally distributed random noise 40%

Training set size		Training: 2111 patterns (1058 deposits, 1053 barren), training-stop: = 88 (39 deposits, 49 barren), test = 81 (35 deposits, 46 barren)																								
Training set type		Randomly selected cells, approximately equal numbers of patterns from each rock type																								
Geology input format		Fuzzy membership values																								
Learn.	l.r.	Cycles	MSE		Train % correct				Stop % correct				Test % correct				Map % correct				Map statistics					
			Initial	Final	All	Depos	Non	All	Depos	Non	All	Depos	Non	All	Depos	Non	All	Depos	Non	Chi	rho	D%/A%	D%*D%/A%	ROC		
trainlm	0.0	12	0.2232	0.0716	85.65	90.55	80.72	78.41	82.05	75.51	77.78	82.86	73.91	74.88	87.50	391.88	0.98	8.87	110.84	0.87						
trainlm	0.0	12	0.1885	0.0800	83.14	87.15	79.11	78.41	76.92	79.59	72.84	82.86	65.22	73.53	82.50	477.30	0.98	14.71	147.09	0.86						
trainlm	0.0	17	0.2208	0.0447	91.57	91.59	91.55	80.68	69.23	89.80	69.14	60.00	76.09	82.21	76.67	395.99	0.98	7.27	115.04	0.85						
trainlm	0.0	27	0.3969	0.0706	85.36	84.40	86.32	84.09	82.05	85.71	70.37	68.57	71.74	78.76	77.50	466.82	0.98	12.47	176.65	0.85						
trainlm	0.0	12	0.2701	0.0766	84.79	85.92	83.67	75.00	74.36	75.51	69.14	74.29	65.22	75.12	77.50	404.14	1.00	16.81	210.08	0.84						
trainlm	0.0	12	0.2490	0.0717	84.60	79.11	90.12	77.27	61.54	89.80	69.14	65.71	71.74	87.72	67.50	461.66	0.97	14.51	133.05	0.86						
trainlm	0.0	11	0.2771	0.0785	83.18	80.43	85.94	79.55	69.23	87.76	69.14	65.71	71.74	80.50	70.00	468.46	1.00	24.35	202.95	0.83						
trainlm	0.0	13	0.2555	0.0689	86.12	89.51	82.72	77.27	76.92	77.55	79.01	85.71	73.91	77.88	84.17	395.96	0.97	8.33	152.65	0.87						
trainlm	0.0	11	0.1747	0.0685	85.36	79.40	91.36	71.59	51.28	87.76	67.90	51.43	80.43	82.95	59.17	376.49	1.00	20.89	208.89	0.82						
trainlm	0.0	11	0.2589	0.0762	83.99	84.78	83.19	76.14	74.36	77.55	71.60	82.86	63.04	75.09	80.83	345.35	0.98	11.38	151.74	0.84						
Average		14	0.2535	0.0745	84.18	81.49	86.88	77.05	67.44	84.69	71.23	68.57	73.26	80.39	72.50	412.59	0.93	13.07	149.82	0.84						

Table H.101. MLP 10-20-1, 10 input layers (categories), Normally distributed random noise 80%

Training set size			Training: 2111 patterns (1058 deposits, 1053 barren), training-stop: = 88 (39 deposits, 49 barren), test = 81 (35 deposits, 46 barren)																						
Training set type			Randomly selected cells, approximately equal numbers of patterns from each rock type																						
Geology input format			Fuzzy membership values																						
Learn.	l.r.	Cycles	MSE		Train % correct				Stop % correct				Test % correct				Map % correct				Map statistics				ROC
			Initial	Final	All	Depos	Non	All	Depos	Non	All	Depos	Non	All	Depos	Non	All	Depos	Non	Chi	rho	D%/A%	D%*D%/A%		
trainlm	0.0	9	0.2501	0.0750	84.75	90.55	78.92	68.18	56.41	77.55	69.14	57.14	78.26	79.12	57.50	389.90	1.00	67.83	226.10	0.77					
trainlm	0.0	9	0.2232	0.0780	82.66	93.38	71.89	69.32	74.36	65.31	69.14	65.71	71.74	75.30	71.67	530.83	0.93	36.18	241.20	0.81					
trainlm	0.0	10	0.2884	0.0723	86.45	91.78	81.10	64.77	43.59	81.63	62.96	45.71	76.09	74.02	53.33	141.09	1.00	10.43	52.16	0.70					
trainlm	0.0	11	0.3945	0.0689	87.40	83.27	91.55	69.32	30.77	100.00	59.26	20.00	89.13	89.19	28.33	299.75	0.97	8.95	7.46	0.66					
trainlm	0.0	8	0.2630	0.0923	80.91	81.66	80.15	64.77	41.03	83.67	62.96	42.86	78.26	90.46	44.17	446.51	0.37	0.00	0.00	0.73					
trainlm	0.0	8	0.1965	0.1036	74.09	92.44	55.65	68.18	84.62	55.10	66.67	88.57	50.00	60.03	84.17	507.22	0.98	29.32	268.75	0.80					
trainlm	0.0	12	0.2248	0.0486	91.33	94.23	88.41	69.32	43.59	89.80	65.43	48.57	78.26	86.26	52.50	383.66	0.98	31.31	182.65	0.80					
trainlm	0.0	12	0.1938	0.0432	92.42	91.21	93.64	64.77	28.21	93.88	56.79	20.00	84.78	89.76	30.00	387.29	0.93	42.62	213.11	0.76					
trainlm	0.0	12	0.2490	0.0462	92.04	92.91	91.17	64.77	30.77	91.84	60.49	34.29	80.43	84.41	37.50	153.94	1.00	15.53	51.76	0.76					
trainlm	0.0	11	0.2600	0.0657	86.83	94.61	79.01	68.18	56.41	77.55	69.14	62.86	73.91	76.54	63.33	333.85	0.97	16.32	81.60	0.76					
Average		10	0.2537	0.0729	84.78	86.81	82.74	67.39	47.18	83.47	64.69	47.71	77.61	81.61	51.42	351.79	0.86	19.07	109.87	0.76					

Table H.102. MLP 10-10-1, 10 input layers (categories), Noise, 10%, uni., large train-test data set]

Training set size	Training: 2111 patterns (1058 deposits, 1053 barren), training-stop: = 1792 (897 deposits, 895 barren), test = 81 (35 deposits, 46 barren)																			
Training set type	Randomly selected cells, approximately equal numbers of patterns from each rock type																			
Geology input format	Fuzzy membership values																			
Learn. Algorith.	l.r.	Cycles	MSE		Train % correct			Stop % correct			Test % correct			Map % correct		Map statistics			D%*D%/A%	ROC
			Initial	Final	All	Depos	Non	All	Depos	Non	All	Depos	Non	All	Depos	Chi	rho	D%/A%		
trainlm	0.0	10	0.3680	0.0905	79.11	78.73	79.49	71.43	65.89	76.98	74.07	68.57	78.26	77.90	72.50	556.66	0.93	12.67	147.80	0.85
trainlm	0.0	14	0.3175	0.0862	81.10	84.59	77.59	72.88	69.45	76.31	71.60	80.00	65.22	75.68	79.17	581.67	0.95	21.34	355.72	0.85
trainlm	0.0	14	0.3714	0.0712	84.94	91.12	78.73	77.68	76.37	78.99	62.96	65.71	60.87	77.32	80.00	480.61	0.97	11.10	323.86	0.86
trainlm	0.0	11	0.1585	0.0840	81.34	86.29	76.35	70.37	61.98	78.77	70.37	77.14	65.22	78.10	78.33	496.76	1.00	15.61	273.19	0.86
trainlm	0.0	12	0.3497	0.1201	71.81	63.23	80.44	76.73	72.58	80.89	66.67	57.14	73.91	75.82	65.00	119.29	0.95	2.90	26.59	0.75
trainlm	0.0	12	0.1979	0.0749	82.76	77.60	87.94	73.33	60.42	86.26	74.07	77.14	71.74	85.00	73.33	457.88	0.98	7.72	96.55	0.87
trainlm	0.0	12	0.2772	0.0668	87.07	87.43	86.70	82.76	80.38	85.14	72.84	71.43	73.91	82.68	80.83	468.76	1.00	11.05	174.96	0.88
trainlm	0.0	13	0.1594	0.0750	83.85	93.57	74.07	78.24	83.84	72.63	74.07	74.29	73.91	69.63	85.00	515.21	0.88	13.30	354.61	0.85
trainlm	0.0	12	0.3518	0.0766	82.66	79.96	85.38	74.11	64.55	83.69	72.84	60.00	82.61	80.87	71.67	599.46	0.98	24.60	409.99	0.84
trainlm	0.0	8	0.1631	0.1241	67.46	66.45	68.47	65.51	61.09	69.94	64.20	68.57	60.87	83.76	64.17	470.19	1.00	13.40	212.12	0.85
Average		12	0.2715	0.0869	80.21	80.90	79.52	74.30	69.65	78.96	70.37	70.00	70.65	78.68	75.00	474.65	0.96	13.37	237.54	0.85

Table H.103. MLP 10-20-1, 10 input layers (categories), Normally distributed random noise 10%, large VV

Training set size		Training: 2111 patterns (1058 deposits, 1053 barren), training-stop: = 1792 (897 deposits, 895 barren), test = 81 (35 deposits, 46 barren)																			
Training set type		Randomly selected cells, approximately equal numbers of patterns from each rock type																			
Geology input format		Fuzzy membership values																			
Learn.	l.r.	Cycles	MSE		Train % correct			Stop % correct			Test % correct			Map % correct			Map statistics			D%*D%/A%	ROC
			Initial	Final	All	Depos	Non	All	Depos	Non	All	Depos	Non	All	Depos	Non	Chi	rho	D%/A%		
trainlm	0.0	12	0.2437	0.0715	83.75	89.60	77.87	71.09	61.98	80.22	75.31	71.43	78.26	73.61	76.67	489.03	0.97	15.83	303.49	0.83	
trainlm	0.0	10	0.2057	0.0853	83.14	85.63	80.63	75.50	72.58	78.44	69.14	80.00	60.87	76.31	79.17	417.72	1.00	16.07	174.11	0.86	
trainlm	0.0	13	0.1789	0.0527	91.05	96.79	85.28	78.63	72.46	84.80	74.07	74.29	73.91	79.12	83.33	473.73	0.98	10.37	198.78	0.87	
trainlm	0.0	14	0.3937	0.0633	87.49	88.28	86.70	76.67	68.56	84.80	80.25	80.00	80.43	79.50	80.00	436.47	0.98	12.04	130.44	0.85	
trainlm	0.0	10	0.2517	0.0924	78.16	89.60	66.67	76.12	82.16	70.06	66.67	85.71	52.17	70.93	86.67	604.56	0.95	16.61	401.38	0.87	
trainlm	0.0	14	0.2661	0.0483	91.28	96.60	85.94	78.35	74.36	82.35	76.54	80.00	73.91	78.84	85.00	601.69	0.98	12.60	378.07	0.88	
trainlm	0.0	12	0.2738	0.0666	87.07	87.90	86.23	78.35	72.02	84.69	76.54	77.14	76.09	82.79	80.83	644.31	0.98	16.10	187.81	0.89	
trainlm	0.0	12	0.2670	0.0680	86.40	92.25	80.53	73.21	67.78	78.66	77.78	85.71	71.74	76.41	85.00	517.37	0.98	14.14	259.24	0.87	
trainlm	0.0	13	0.1819	0.0467	91.80	93.76	89.84	77.62	67.56	87.71	69.14	57.14	78.26	84.08	72.50	584.23	1.00	14.52	278.32	0.88	
trainlm	0.0	10	0.2635	0.0849	82.24	78.45	86.04	78.13	69.90	86.37	75.31	74.29	76.09	82.83	76.67	629.80	0.98	21.59	143.93	0.86	
Average		12	0.2526	0.0680	86.24	89.89	82.57	76.37	70.94	81.81	74.07	76.57	72.17	78.44	80.58	539.89	0.98	14.99	245.55	0.87	

Table H.104. MLP 10-20-1, 10 input layers (categories), Uniform random noise 40%, large VV

Training set size		Training: 2111 patterns (1058 deposits, 1053 barren), training-stop: = 1792 (897 deposits, 895 barren), test = 81 (35 deposits, 46 barren)																	
Training set type		Randomly selected cells, approximately equal numbers of patterns from each rock type																	
Geology input format		Fuzzy membership values																	
Learn.	Cycles	MSE			Train % correct			Stop % correct			Test % correct			Map % correct			Map statistics		
Algoth.		Initial	Final	All	Depos	Non	All	Depos	Non	All	Depos	Non	All	Depos	Non	All	Chi	rho	D%/A%
trainlm	0.0 11	0.2358	0.0867	82.85	92.06	73.60	78.46	82.72	74.19	72.84	82.86	65.22	71.48	88.33	614.30	0.97	12.08	352.41	0.89
trainlm	0.0 10	0.2039	0.0848	83.04	90.93	75.12	79.07	85.17	72.96	71.60	88.57	58.70	70.28	90.00	549.13	1.00	15.43	167.19	0.88
trainlm	0.0 11	0.1823	0.0693	85.84	88.37	83.29	79.35	76.37	82.35	74.07	80.00	69.57	79.97	84.17	580.78	1.00	12.93	194.02	0.89
trainlm	0.0 14	0.3954	0.0624	86.83	89.89	83.76	79.13	75.70	82.57	72.84	77.14	69.57	78.34	82.50	686.21	0.98	20.28	354.91	0.87
trainlm	0.0 11	0.2575	0.0793	82.85	86.29	79.39	79.80	80.27	79.33	76.54	85.71	69.57	77.98	87.50	677.99	1.00	14.40	215.96	0.90
trainlm	0.0 11	0.2735	0.0774	83.85	89.04	78.63	78.13	80.60	75.64	72.84	82.86	65.22	72.37	85.00	443.50	0.98	8.26	110.15	0.87
trainlm	0.0 13	0.2905	0.0683	86.07	95.75	76.35	77.18	78.48	75.87	71.60	80.00	65.22	68.52	85.83	672.66	0.93	15.45	489.39	0.86
trainlm	0.0 13	0.2782	0.0594	88.73	95.46	81.96	75.84	71.91	79.78	71.60	68.57	73.91	75.91	79.17	510.09	1.00	12.72	318.08	0.86
trainlm	0.0 17	0.1801	0.0426	92.33	94.23	90.41	79.74	71.13	88.38	75.31	62.86	84.78	86.25	78.33	1166.87	0.98	20.75	605.34	0.88
trainlm	0.0 11	0.2709	0.0708	85.98	92.63	79.30	78.40	78.48	78.32	72.84	77.14	69.57	73.25	85.00	495.41	0.95	11.11	203.65	0.87
Average	12	0.2576	0.0686	85.93	91.22	80.61	77.77	76.01	79.54	73.46	77.43	70.43	75.65	83.42	627.17	0.98	14.72	296.22	0.87

Table H.105. MLP 17-20-1, 17 input layers (categories)

Training set size		Training: 99 patterns (46 deposits, 53 barren), training-stop: = 88 (39 deposits, 49 barren), test = 81 (35 deposits, 46 barren)																	
Training set type		Randomly selected cells, approximately equal numbers of patterns from each rock type																	
Geology input format		Fuzzy membership values																	
Learn.	Cycles	MSE			Train % correct			Stop % correct			Test % correct			Map % correct			Map statistics		
Algoth.		Initial	Final	All	Depos	Non	All	Depos	Non	All	Depos	Non	All	Depos	Non	All	Chi	rho	D%/A%
trainlm	0.0 10	0.2360	0.0789	84.85	71.74	96.23	69.32	53.85	81.63	70.37	71.43	69.57	71.95	65.83	113.66	0.75	0.83	2.08	0.76
trainlm	0.0 10	0.2363	0.0596	85.86	80.43	90.57	71.59	64.10	77.55	65.43	57.14	71.74	61.80	68.33	86.87	0.93	3.24	62.11	0.72
trainlm	0.0 9	0.2001	0.0733	85.86	91.30	81.13	75.00	69.23	79.59	71.60	65.71	76.09	69.51	76.67	467.73	0.98	15.92	172.50	0.83
trainlm	0.0 8	0.2382	0.1170	74.75	63.04	84.91	68.18	51.28	81.63	72.84	62.86	80.43	84.86	59.17	319.94	0.53	0.00	0.00	0.80
trainlm	0.0 9	0.2906	0.0822	82.83	76.09	88.68	69.32	56.41	79.59	66.67	62.86	69.57	72.88	65.83	217.82	1.00	18.66	108.83	0.77
trainlm	0.0 9	0.2561	0.1088	74.75	56.52	90.57	62.50	48.72	73.47	61.73	57.14	65.22	77.51	54.17	131.67	0.73	1.22	2.03	0.76
trainlm	0.0 8	0.2201	0.0929	82.83	80.43	84.91	79.55	76.92	81.63	76.54	88.57	67.39	68.93	81.67	261.06	1.00	9.67	72.51	0.83
trainlm	0.0 8	0.2171	0.0958	77.78	89.13	67.92	69.32	74.36	65.31	74.07	85.71	65.22	58.73	83.33	161.05	0.93	3.01	17.58	0.79
trainlm	0.0 9	0.2640	0.0846	82.83	78.26	86.79	72.73	61.54	81.63	74.07	65.71	80.43	75.62	69.17	313.38	0.97	10.46	43.58	0.80
trainlm	0.0 13	0.3405	0.0566	87.88	80.43	94.34	70.45	56.41	81.63	76.54	71.43	80.43	57.27	70.00	74.30	0.93	1.20	10.03	0.69
Average	9	0.2499	0.0850	82.02	76.74	86.60	70.80	61.28	78.37	70.99	68.86	72.61	69.91	69.42	714.75	0.88	6.42	49.13	0.78

Table H.106. MLP 10-20-1, 10 input layers (D/A)

Training set size		Training: 99 patterns (46 deposits, 53 barren), training-stop: = 88 (39 deposits, 49 barren), test = 81 (35 deposits, 46 barren)															
Training set type		Randomly selected cells, approximately equal numbers of patterns from each rock type															
Geology input format		Fuzzy membership values															
Learn.	l.r. Cycles	MSE		Train % correct		Stop % correct		Test % correct		Map % correct		Map statistics		D%/A%		D%*D%/A%	
Algoth.		Initial	Final	All	Deps	Non	All	Deps	Non	All	Deps	Chi	rho	D%/A%	D%/A%	D%*D%/A%	ROC
trainlm	0.0 9	0.1898	0.0894	81.82	73.91	88.68	73.86	53.85	89.80	66.67	71.43	63.04	72.24	66.67	71.43	63.04	72.24
trainlm	0.0 10	0.2298	0.0955	78.79	71.74	84.91	68.18	58.97	75.51	67.90	68.57	67.39	64.73	66.67	92.03	0.97	3.52
trainlm	0.0 9	0.2888	0.0929	78.79	67.39	88.68	70.45	61.54	77.55	72.84	65.71	78.26	81.97	65.00	298.06	0.95	5.71
trainlm	0.0 16	0.3946	0.1028	76.77	71.74	81.13	76.14	69.23	81.63	71.60	68.57	73.91	71.22	70.00	155.98	0.97	4.17
trainlm	0.0 9	0.3259	0.1389	66.67	34.78	94.34	71.59	46.15	91.84	67.90	45.71	84.78	86.32	41.67	126.00	0.92	4.00
trainlm	0.0 11	0.2798	0.0532	92.93	91.30	94.34	71.59	66.67	75.51	69.14	74.29	65.22	71.80	78.33	258.13	0.95	6.99
trainlm	0.0 10	0.2960	0.0799	81.82	73.91	88.68	68.18	46.15	85.71	70.37	65.71	73.91	80.93	62.50	449.26	1.00	13.26
trainlm	0.0 9	0.2224	0.0874	78.79	63.04	92.45	73.86	56.41	87.76	69.14	54.29	80.43	85.12	58.33	334.91	0.98	9.70
trainlm	0.0 10	0.2096	0.0823	81.82	63.04	98.11	67.05	41.03	87.76	64.20	42.86	80.43	76.68	50.00	79.48	0.88	1.37
trainlm	0.0 12	0.3004	0.0839	81.82	80.43	83.02	68.18	66.67	69.39	67.90	82.86	56.52	64.00	76.67	183.11	1.00	5.72
Average	11	0.2783	0.0896	80.30	68.91	90.19	70.45	56.67	81.43	69.14	64.00	73.04	75.47	63.50	209.06	0.94	5.53

Table H.107. MLP 17-20-1, 17 input layers (D/A)

Training set size		Training: 99 patterns (46 deposits, 53 barren), training-stop: = 88 (39 deposits, 49 barren), test = 81 (35 deposits, 46 barren)															
Training set type		Randomly selected cells, approximately equal numbers of patterns from each rock type															
Geology input format		Fuzzy membership values															
Learn.	l.r. Cycles	MSE		Train % correct		Stop % correct		Test % correct		Map % correct		Map statistics		D%/A%		D%*D%/A%	
Algoth.		Initial	Final	All	Deps	Non	All	Deps	Non	All	Deps	Chi	rho	D%/A%	D%/A%	D%*D%/A%	ROC
trainlm	0.0 10	0.2447	0.0536	89.90	84.78	94.34	76.14	64.10	85.71	72.84	80.00	67.39	72.42	76.67	245.85	0.98	5.14
trainlm	0.0 8	0.2612	0.0935	78.79	76.09	81.13	71.59	61.54	79.59	69.14	68.57	69.57	72.34	69.17	357.41	0.97	7.79
trainlm	0.0 10	0.2446	0.0682	87.88	86.96	88.68	80.68	82.05	79.59	71.60	74.29	69.57	72.27	81.67	241.91	0.95	2.88
trainlm	0.0 10	0.1756	0.0575	88.89	84.78	92.45	72.73	61.54	81.63	76.54	80.00	73.91	68.16	75.83	205.01	0.97	7.45
trainlm	0.0 9	0.2124	0.0615	89.90	97.83	83.02	73.86	74.36	73.47	74.07	85.71	65.22	58.03	86.67	154.82	1.00	3.90
trainlm	0.0 10	0.2651	0.0517	92.93	93.48	92.45	81.82	74.36	87.76	72.84	74.29	71.74	76.25	81.67	318.85	0.97	5.84
trainlm	0.0 9	0.1710	0.0611	91.92	95.65	88.68	84.09	89.74	79.59	71.60	71.43	71.74	65.76	86.67	199.30	0.95	2.30
trainlm	0.0 9	0.2558	0.0685	84.85	78.26	90.57	80.68	74.36	85.71	74.07	68.57	78.26	78.53	74.17	312.28	0.98	4.44
trainlm	0.0 11	0.2643	0.0265	96.97	100.00	94.34	75.00	61.54	85.71	66.67	68.57	65.22	66.59	78.33	140.73	0.93	3.17
trainlm	0.0 14	0.4001	0.0835	77.78	71.74	83.02	71.59	71.79	71.43	69.14	62.86	73.91	76.45	69.17	246.58	0.98	7.24
Average	10	0.2486	0.0651	87.47	85.65	89.06	76.14	70.51	80.61	71.60	72.57	70.87	70.63	76.92	229.05	0.94	4.58

Table H.108. MLP 10-20-1, 10 input layers (DastD/A)

Training set size		Training: 99 patterns (46 deposits, 53 barren), training-stop: = 88 (39 deposits, 49 barren), test = 81 (35 deposits, 46 barren)																				
Training set type		Randomly selected cells, approximately equal numbers of patterns from each rock type																				
Geology input format		Fuzzy membership values																				
Learn.	l.r.	Cycles	MSE			Train % correct			Stop % correct			Test % correct			Map % correct			Map statistics				
Algoth.			Initial	Final	All	Depos	Non	All	Depos	Non	All	Depos	Non	All	Depos	Chi	rho	D%/A%	D%*D%/A%	ROC		
trainlm	0.0	10	0.1774	0.0740	86.87	86.96	86.79	78.41	82.05	75.51	72.84	74.29	71.74	73.21	81.67	360.83	1.00	14.36	131.63	0.85		
trainlm	0.0	8	0.1804	0.0882	80.81	73.91	86.79	75.00	61.54	85.71	69.14	62.86	73.91	86.64	66.67	507.15	0.98	10.34	34.47	0.86		
trainlm	0.0	14	0.2545	0.0250	95.96	97.83	94.34	81.82	87.18	77.55	75.31	80.00	71.74	71.00	89.17	313.78	0.92	2.21	57.12	0.82		
trainlm	0.0	15	0.4176	0.0920	81.82	73.91	88.68	72.73	61.54	81.63	71.60	65.71	76.09	81.71	67.50	325.33	0.98	7.65	44.62	0.85		
trainlm	0.0	12	0.2812	0.0644	87.88	86.96	88.68	81.82	84.62	79.59	74.07	85.71	65.22	70.90	85.83	547.68	1.00	16.62	387.90	0.86		
trainlm	0.0	11	0.2319	0.0508	88.89	86.96	90.57	77.27	71.79	81.63	72.84	80.00	67.39	74.66	80.00	247.68	0.95	4.76	79.37	0.84		
trainlm	0.0	15	0.2842	0.0368	92.93	86.96	98.11	81.82	74.36	87.76	77.78	82.86	73.91	80.29	81.67	337.92	0.98	5.01	104.46	0.87		
trainlm	0.0	12	0.3029	0.0558	90.91	93.48	88.68	76.14	82.05	71.43	67.90	74.29	63.04	68.30	84.17	208.71	0.97	5.32	75.37	0.82		
trainlm	0.0	10	0.2004	0.0706	84.85	82.61	86.79	72.73	71.79	73.47	72.84	71.43	73.91	73.85	75.83	379.81	1.00	15.93	225.69	0.83		
trainlm	0.0	14	0.3585	0.0487	89.90	89.13	90.57	80.68	82.05	79.59	69.14	77.14	63.04	71.79	83.33	285.59	0.98	5.29	79.31	0.84		
Average		12	0.2748	0.0611	87.88	84.35	90.94	76.93	73.08	80.00	72.10	75.14	69.78	75.11	78.00	326.73	0.95	7.40	109.04	0.84		

Table H.109. MLP 17-20-1, 17 input layers (DastD/A)

Training set size		Training: 99 patterns (46 deposits, 53 barren), training-stop: = 88 (39 deposits, 49 barren), test = 81 (35 deposits, 46 barren)																				
Training set type		Randomly selected cells, approximately equal numbers of patterns from each rock type																				
Geology input format		Fuzzy membership values																				
Learn.	l.r.	Cycles	MSE			Train % correct			Stop % correct			Test % correct			Map % correct			Map statistics			D%*D%/A%	ROC
			Initial	Final	All	Depos	Non	All	Depos	Non	All	Depos	Non	All	Depos	Chi	rho	D%/A%				
trainlm	0.0	9	0.1833	0.0739	83.84	78.26	88.68	75.00	56.41	89.80	74.07	62.86	82.61	86.25	66.67	659.26	1.00	19.39	129.24	0.87		
trainlm	0.0	11	0.2266	0.0578	90.91	91.30	90.57	82.95	79.49	85.71	75.31	82.86	69.57	72.12	85.00	430.03	0.98	13.22	231.37	0.86		
trainlm	0.0	9	0.1883	0.0601	91.92	91.30	92.45	76.14	64.10	85.71	70.37	65.71	73.91	73.39	75.00	276.92	0.98	9.66	64.41	0.81		
trainlm	0.0	8	0.1806	0.0898	82.83	73.91	90.57	75.00	61.54	85.71	70.37	57.14	80.43	85.57	65.00	464.07	0.98	12.49	31.21	0.83		
trainlm	0.0	9	0.1986	0.0784	84.85	84.78	84.91	79.55	76.92	81.63	75.31	71.43	78.26	74.61	78.33	490.30	1.00	12.01	80.09	0.84		
trainlm	0.0	12	0.2764	0.0410	94.95	97.83	92.45	76.14	74.36	77.55	75.31	80.00	71.74	69.01	85.00	309.59	1.00	6.12	183.74	0.84		
trainlm	0.0	10	0.2434	0.0651	88.89	89.13	88.68	78.41	69.23	85.71	74.07	74.29	73.91	75.77	78.33	416.05	1.00	15.13	151.35	0.86		
trainlm	0.0	8	0.2217	0.0898	77.78	71.74	83.02	75.00	69.23	79.59	75.31	71.43	78.26	80.71	70.83	313.32	0.97	6.84	171.02	0.84		
trainlm	0.0	9	0.2117	0.0591	89.90	86.96	92.45	80.68	69.23	89.80	74.07	60.00	84.78	75.97	73.33	273.12	0.88	0.92	1.53	0.81		
trainlm	0.0	11	0.3471	0.0554	90.91	89.13	92.45	80.68	79.49	81.63	70.37	68.57	71.74	73.37	80.00	416.11	0.98	13.19	252.84	0.85		
Average		10	0.2330	0.0675	87.78	84.78	90.38	77.39	69.74	83.47	73.09	70.29	75.22	75.25	75.67	350.32	0.95	9.04	116.96	0.83		

Table H.110. MLP 10-20-1, 10 input layers (*DastD/A* version 2)

Training set size		Training: 99 patterns (46 deposits, 53 barren), training-stop: = 88 (39 deposits, 49 barren), test = 81 (35 deposits, 46 barren)															
Training set type		Randomly selected cells, approximately equal numbers of patterns from each rock type															
Geology input format		Fuzzy membership values															
Learn. Algorith.	l.r. Cycles	MSE		Train % correct			Stop % correct			Test % correct			Map % correct		Map statistics		
		Initial	Final	All	Depos	Non	All	Depos	Non	All	Depos	Non	All	Depos	Chi	rho	D%/A% D%*D%/A% ROC
trainlm	0.0 11	0.1422	0.0375	91.92	95.65	88.68	85.23	82.05	87.76	75.31	74.29	76.09	74.45	85.00	331.15	0.95	75.46 0.86
trainlm	0.0 8	0.1747	0.0706	84.85	69.57	98.11	72.73	48.72	91.84	71.60	51.43	86.96	81.38	57.50	225.12	0.98	9.26 0.80
trainlm	0.0 12	0.3077	0.0556	86.87	78.26	94.34	70.45	56.41	81.63	67.90	62.86	71.74	71.71	66.67	163.63	1.00	5.12 0.78
trainlm	0.0 16	0.3909	0.0339	92.93	100.00	86.79	80.68	76.92	83.67	65.43	77.14	56.52	61.04	85.83	214.37	0.75	3.85 0.82
trainlm	0.0 11	0.3577	0.0833	81.82	82.61	81.13	72.73	64.10	79.59	76.54	77.14	76.09	73.89	75.00	456.61	1.00	11.44 0.83
trainlm	0.0 7	0.2175	0.1145	69.70	41.30	94.34	65.91	30.77	93.88	70.37	34.29	97.83	96.60	35.83	674.92	0.98	56.49 0.80
trainlm	0.0 10	0.2452	0.0797	85.86	89.13	83.02	72.73	71.79	73.47	70.37	80.00	63.04	68.54	80.83	352.73	0.98	9.84 0.85
trainlm	0.0 12	0.2595	0.0376	94.95	97.83	92.45	75.00	74.36	75.51	66.67	71.43	63.04	65.22	82.50	152.89	0.88	2.12 0.78
trainlm	0.0 8	0.2080	0.0811	81.82	86.96	77.36	75.00	74.36	75.51	70.37	71.43	69.57	61.96	78.33	460.18	0.98	13.89 0.81
trainlm	0.0 9	0.3701	0.0761	84.85	84.78	84.91	71.59	69.23	73.47	69.14	74.29	65.22	65.77	76.67	232.73	1.00	7.93 0.80
Average	10	0.2767	0.0711	84.85	80.22	88.87	72.61	62.05	81.02	69.88	67.14	71.96	71.81	70.50	304.68	0.93	12.08 0.80

Table H.111. MLP 17-20-1, 17 input layers (*DastD/A* version 2)

Training set size		Training: 99 patterns (46 deposits, 53 barren), training-stop: = 88 (39 deposits, 49 barren), test = 81 (35 deposits, 46 barren)															
Training set type		Randomly selected cells, approximately equal numbers of patterns from each rock type															
Geology input format		Fuzzy membership values															
Learn. Algorith.	l.r. Cycles	MSE		Train % correct			Stop % correct			Test % correct			Map % correct		Map statistics		
		Initial	Final	All	Depos	Non	All	Depos	Non	All	Depos	Non	All	Depos	Chi	rho	D%/A% D%*D%/A% ROC
trainlm	0.0 12	0.2933	0.0304	94.95	95.65	94.34	76.14	71.79	79.59	74.07	82.86	67.39	67.06	84.17	189.47	0.97	3.79 0.81
trainlm	0.0 9	0.2682	0.1009	73.74	97.83	52.83	67.05	82.05	55.10	71.60	88.57	58.70	40.24	90.00	307.77	0.92	10.74 0.78
trainlm	0.0 9	0.2226	0.0783	79.80	73.91	84.91	77.27	61.54	89.80	70.37	62.86	76.09	78.24	66.67	300.19	0.95	4.05 0.79
trainlm	0.0 10	0.1439	0.0576	87.88	89.13	86.79	79.55	74.36	83.67	70.37	71.43	69.57	72.12	79.17	375.03	1.00	214.11 0.84
trainlm	0.0 8	0.2447	0.0775	81.82	76.09	86.79	79.55	71.79	85.71	79.01	77.14	80.43	74.05	75.00	244.93	1.00	8.00 0.83
trainlm	0.0 9	0.2504	0.0588	89.90	86.96	92.45	81.82	76.92	85.71	74.07	80.00	69.57	68.24	81.67	294.41	0.95	3.11 0.83
trainlm	0.0 10	0.2145	0.0710	83.84	86.96	81.13	70.45	64.10	75.51	70.37	71.43	69.57	60.35	75.00	188.22	1.00	6.43 0.77
trainlm	0.0 9	0.2321	0.0534	89.90	89.13	90.57	79.55	71.79	85.71	71.60	74.29	69.57	70.83	79.17	359.25	1.00	11.89 0.82
trainlm	0.0 10	0.2686	0.0817	84.85	73.91	94.34	77.27	61.54	89.80	65.43	51.43	76.09	83.39	63.33	239.34	0.93	4.35 0.82
trainlm	0.0 11	0.3772	0.0784	85.86	82.61	88.68	73.86	71.79	75.51	72.84	71.43	73.91	74.48	75.83	285.64	0.98	13.23 0.83
Average	10	0.2458	0.0737	84.24	82.83	85.47	75.57	68.97	80.82	71.60	72.00	71.30	69.39	75.17	270.84	0.95	7.38 0.81

Table H.112. MLP 25-20-1, 25 input layers (all layers)

Training set size		Training: 99 patterns (46 deposits, 53 barren), training-stop: = 88 (39 deposits, 49 barren), test = 81 (35 deposits, 46 barren)																
Training set type		Randomly selected cells, approximately equal numbers of patterns from each rock type																
Geology input format		Fuzzy membership values																
Learn. Algorith.	l.r. Cycles	MSE		Train % correct			Stop % correct			Test % correct			Map % correct			Map statistics		
		Initial	Final	All	Deps	Non	All	Deps	Non	All	Deps	Non	All	Deps	Non	Chi	rho	D%/A% D%*D%/A%
trainlm	0.0 13	0.2222	0.0386	96.97	97.83	96.23	77.27	69.23	83.67	65.43	65.71	65.22	71.25	79.17	65.22	212.45	0.95	2.57 12.86
trainlm	0.0 11	0.2420	0.0477	90.91	84.78	96.23	79.55	74.36	83.67	71.60	68.57	73.91	73.86	76.67	73.91	290.55	1.00	7.84 91.48
trainlm	0.0 8	0.2182	0.0790	87.88	86.96	88.68	72.73	64.10	79.59	74.07	77.14	71.74	74.28	76.67	74.28	424.91	0.97	10.15 25.38
trainlm	0.0 10	0.2314	0.0598	87.88	89.13	86.79	77.27	79.49	75.51	70.37	82.86	60.87	60.04	84.17	209.17	209.17	0.95	4.81 80.22
trainlm	0.0 9	0.2925	0.0761	87.88	84.78	90.57	77.27	71.79	81.63	74.07	71.43	76.09	74.34	76.67	344.51	344.51	0.38	0.00 0.00
trainlm	0.0 10	0.2360	0.0689	85.86	86.96	84.91	72.73	71.79	73.47	65.43	71.43	60.87	69.93	77.50	241.78	241.78	0.98	3.32 27.63
trainlm	0.0 11	0.3069	0.0573	91.92	86.96	96.23	72.73	64.10	79.59	67.90	57.14	76.09	77.17	70.83	189.21	189.21	0.98	8.27 41.34
trainlm	0.0 9	0.3578	0.0821	85.86	91.30	81.13	75.00	69.23	79.59	69.14	71.43	67.39	71.56	78.33	375.62	375.62	0.98	6.78 56.51
trainlm	0.0 9	0.1815	0.0486	91.92	91.30	92.45	64.77	51.28	75.51	71.60	80.00	65.22	59.32	75.00	86.99	86.99	0.92	1.95 17.89
trainlm	0.0 9	0.1908	0.0702	84.85	73.91	94.34	72.73	61.54	81.63	71.60	65.71	76.09	84.48	67.50	454.21	454.21	1.00	14.71 171.60
Average	10	0.2479	0.0628	89.19	87.39	90.75	74.20	67.69	79.39	70.12	71.14	69.35	71.62	76.25	282.94	282.94	0.91	6.04 52.49

Table H.113. MLP 10-20-1, 10 input layers (categories), inverse distance

Training set size		Training: 99 patterns (46 deposits, 53 barren), training-stop: = 88 (39 deposits, 49 barren), test = 81 (35 deposits, 46 barren)																
Training set type		Randomly selected cells, approximately equal numbers of patterns from each rock type																
Geology input format		Fuzzy membership values																
Learn. Algorith.	l.r. Cycles	MSE		Train % correct			Stop % correct			Test % correct			Map % correct			Map statistics		
		Initial	Final	All	Deps	Non	All	Deps	Non	All	Deps	Non	All	Deps	Non	Chi	rho	D%/A% D%*D%/A%
trainlm	0.0 12	0.2097	0.0419	91.92	91.30	92.45	77.27	69.23	83.67	62.96	71.43	56.52	49.29	76.67	51.32	51.32	0.93	2.02 53.89
trainlm	0.0 9	0.2025	0.0934	80.81	65.22	94.34	76.14	53.85	93.88	71.60	54.29	84.78	93.88	53.33	531.30	531.30	0.85	10.16 50.81
trainlm	0.0 9	0.1914	0.0770	82.83	78.26	86.79	72.73	56.41	85.71	71.60	77.14	67.39	74.69	68.33	314.02	314.02	0.90	3.12 25.97
trainlm	0.0 13	0.4233	0.0777	86.87	86.96	86.79	82.95	71.79	91.84	70.37	68.57	71.74	82.52	74.17	416.76	416.76	0.97	6.92 23.07
trainlm	0.0 11	0.2369	0.0755	85.86	78.26	92.45	81.82	69.23	91.84	69.14	62.86	73.91	88.27	70.00	561.11	561.11	0.92	9.78 163.08
trainlm	0.0 11	0.2080	0.0682	86.87	84.78	88.68	78.41	74.36	81.63	64.20	62.86	65.22	50.93	80.00	82.49	82.49	0.93	3.34 47.26
trainlm	0.0 11	0.2603	0.0479	91.92	89.13	94.34	81.82	71.79	89.80	66.67	68.57	65.22	54.96	75.83	143.78	143.78	0.85	4.60 84.28
trainlm	0.0 14	0.3709	0.0292	95.96	95.65	96.23	79.55	71.79	85.71	61.73	71.43	54.35	61.35	77.50	162.40	162.40	0.70	4.15 131.56
trainlm	0.0 10	0.1985	0.0645	86.87	80.43	92.45	80.68	74.36	85.71	62.96	57.14	67.39	70.60	68.33	282.50	282.50	0.95	6.36 143.01
trainlm	0.0 11	0.2433	0.0526	87.88	86.96	88.68	78.41	71.79	83.67	69.14	71.43	67.39	64.67	72.50	199.98	199.98	0.68	3.82 54.14
Average	11	0.2545	0.0628	87.78	83.70	91.32	78.98	68.46	87.35	67.04	66.57	67.39	69.12	71.67	274.57	274.57	0.87	5.43 77.71

Table H.114. MLP 10-20-1, 10 input layers (categories), log distance

Training set size		Training: 99 patterns (46 deposits, 53 barren), training-stop: = 88 (39 deposits, 49 barren), test = 81 (35 deposits, 46 barren)																				
Training set type		Randomly selected cells, approximately equal numbers of patterns from each rock type																				
Geology input format		Fuzzy membership values																				
Learn.	l.r.	Cycles	MSE			Train % correct			Stop % correct			Test % correct			Map % correct			Map statistics				
Algoth.			Initial	Final	All	Depos	Non	All	Depos	Non	All	Depos	Non	All	Depos	Chi	rho	D%/A%	D%*D%/A%	ROC		
trainlm	0.0	12	0.2485	0.0356	93.94	86.96	100.00	81.82	74.36	87.76	70.37	65.71	73.91	59.08	76.67	97.51	0.93	1.57	35.24	0.70		
trainlm	0.0	10	0.2528	0.0513	90.91	89.13	92.45	77.27	66.67	85.71	70.37	74.29	67.39	76.38	71.67	232.85	0.98	4.88	77.23	0.82		
trainlm	0.0	11	0.2125	0.0408	93.94	93.48	94.34	71.59	76.92	67.35	65.43	77.14	56.52	64.41	79.17	193.51	0.97	5.58	134.76	0.79		
trainlm	0.0	19	0.3988	0.0537	88.89	86.96	90.57	76.14	74.36	77.55	72.84	68.57	76.09	74.59	72.50	258.19	0.98	7.75	174.30	0.79		
trainlm	0.0	13	0.2613	0.0293	94.95	91.30	98.11	78.41	74.36	81.63	66.67	62.86	69.57	72.85	70.83	186.11	0.92	4.91	143.18	0.76		
trainlm	0.0	12	0.2524	0.0670	85.86	76.09	94.34	84.09	74.36	91.84	69.14	62.86	73.91	62.75	74.17	92.22	0.97	2.89	62.69	0.73		
trainlm	0.0	11	0.2168	0.0635	84.85	78.26	90.57	77.27	64.10	87.76	66.67	60.00	71.74	79.19	69.17	248.23	0.97	6.26	73.02	0.82		
trainlm	0.0	8	0.2241	0.0942	78.79	69.57	86.79	70.45	56.41	81.63	65.43	51.43	76.09	67.95	59.17	332.30	0.80	10.41	26.02	0.70		
trainlm	0.0	11	0.2226	0.0688	86.87	82.61	90.57	80.68	76.92	83.67	66.67	62.86	69.57	68.91	72.50	135.22	0.93	3.43	94.20	0.75		
trainlm	0.0	12	0.3059	0.0608	89.90	84.78	94.34	77.27	64.10	87.76	66.67	65.71	67.39	71.41	75.00	203.98	0.98	5.32	164.00	0.79		
Average		12	0.2557	0.0571	88.69	84.35	92.45	77.05	69.74	82.86	67.28	65.71	68.48	68.77	72.08	193.39	0.94	5.34	100.33	0.76		

Table H.115. MLP 10-20-1, 17 input layers (categories), distance & strike narrow buffers

Training set size			Training: 99 patterns (46 deposits, 53 barren), training-stop: = 88 (39 deposits, 49 barren), test = 81 (35 deposits, 46 barren)																			
Training set type			Randomly selected cells, approximately equal numbers of patterns from each rock type																			
Geology input format			Fuzzy membership values																			
Learn.	l.r.	Cycles	MSE			Train % correct			Stop % correct			Test % correct			Map % correct			Map statistics			D%*D%/A%	ROC
			Initial	Final	All	Depos	Non	All	Depos	Non	All	Depos	Non	All	Depos	Non	All	Depos	Chi	rho		
trainlm	0.0	13	0.2367	0.0369	92.93	93.48	92.45	81.82	76.92	85.71	67.90	71.43	65.22	59.55	81.67	223.23	0.95	5.18	220.31	0.79		
trainlm	0.0	12	0.3270	0.0967	81.82	67.39	94.34	70.45	58.97	79.59	60.49	54.29	65.22	87.19	60.83	481.18	0.92	12.99	227.39	0.77		
trainlm	0.0	12	0.2424	0.0659	88.89	80.43	96.23	76.14	64.10	85.71	66.67	62.86	69.57	85.71	70.00	455.93	0.98	9.84	254.16	0.85		
trainlm	0.0	16	0.3793	0.1258	71.72	39.13	100.00	72.73	41.03	97.96	65.43	25.71	95.65	95.27	35.83	293.03	0.87	8.85	177.02	0.71		
trainlm	0.0	14	0.2549	0.0538	87.88	80.43	94.34	77.27	64.10	87.76	66.67	65.71	67.39	83.88	70.83	498.03	0.93	9.81	261.64	0.82		
trainlm	0.0	10	0.2242	0.0689	84.85	78.26	90.57	76.14	58.97	89.80	71.60	62.86	78.26	87.40	67.50	620.34	0.93	13.14	229.91	0.82		
trainlm	0.0	9	0.2107	0.1019	76.77	54.35	96.23	77.27	58.97	91.84	67.90	42.86	86.96	93.76	52.50	726.26	1.00	17.00	467.59	0.86		
trainlm	0.0	15	0.2299	0.0433	90.91	91.30	90.57	79.55	71.79	85.71	66.67	77.14	58.70	69.37	80.83	375.98	0.93	5.96	218.45	0.83		
trainlm	0.0	15	0.2320	0.0426	92.93	86.96	98.11	84.09	74.36	91.84	70.37	80.00	63.04	79.74	80.83	396.07	0.98	6.61	209.46	0.85		
trainlm	0.0	11	0.3183	0.0899	79.80	71.74	86.79	75.00	61.54	85.71	65.43	54.29	73.91	81.03	63.33	876.84	0.97	17.62	205.52	0.79		
Average		13	0.2629	0.0731	84.75	74.13	93.96	76.59	62.31	87.96	66.42	59.71	71.52	81.26	65.92	477.50	0.95	10.38	230.50	0.80		

Table H.116. MLP 10-20-1, 10 input layers (categories), distance & strike wide buffers,

Training set size		Training: 99 patterns (46 deposits, 53 barren), training-stop: = 88 (39 deposits, 49 barren), test = 81 (35 deposits, 46 barren)																			
Training set type		Randomly selected cells, approximately equal numbers of patterns from each rock type																			
Geology input format		Fuzzy membership values																			
Learn. Algorith.	l.r. Cycles	MSE			Train % correct			Stop % correct			Test % correct			Map % correct			Map statistics				
		Initial	Final	All	Deps	Non	All	Deps	Non	All	Deps	Non	All	Deps	Non	Chi	rho	D%/A%	D%*D%/A%	ROC	
trainlm	0.0 10	0.2289	0.0469	89.90	86.96	92.45	82.95	92.31	75.51	67.90	68.57	67.39	71.55	83.33	255.44	0.92	5.56	74.17	0.82		
trainlm	0.0 17	0.3225	0.0145	97.98	97.83	98.11	80.68	79.49	81.63	62.96	68.57	58.70	69.51	83.33	433.71	0.92	7.95	384.16	0.86		
trainlm	0.0 10	0.1961	0.0736	83.84	89.13	79.25	79.55	79.49	79.59	61.73	54.29	67.39	77.56	75.83	260.79	0.98	5.24	126.70	0.83		
trainlm	0.0 17	0.3942	0.1440	77.78	82.61	73.58	67.05	76.92	59.18	54.32	60.00	50.00	58.19	74.17	87.88	0.90	1.62	64.97	0.68		
trainlm	0.0 11	0.2734	0.0958	77.78	82.61	73.58	70.45	74.36	67.35	64.20	65.71	63.04	73.52	75.00	262.90	0.93	6.00	165.11	0.82		
trainlm	0.0 11	0.2718	0.0455	93.94	95.65	92.45	72.73	69.23	75.51	60.49	54.29	65.22	66.48	75.00	290.13	0.65	6.98	244.28	0.77		
trainlm	0.0 13	0.2021	0.0284	94.95	95.65	94.34	73.86	69.23	77.55	62.96	60.00	65.22	65.80	76.67	254.06	0.97	5.92	143.17	0.80		
trainlm	0.0 10	0.2055	0.0655	84.85	76.09	92.45	73.86	61.54	83.67	67.90	51.43	80.43	84.15	64.17	348.17	0.97	9.36	54.62	0.83		
trainlm	0.0 13	0.2432	0.0340	92.93	89.13	96.23	68.18	61.54	73.47	60.49	60.00	60.87	76.45	71.67	501.82	0.92	3.80	34.84	0.83		
trainlm	0.0 12	0.3015	0.0404	90.91	84.78	96.23	77.27	71.79	81.63	64.20	51.43	73.91	75.11	70.83	323.76	0.90	8.66	202.08	0.79		
Average	13	0.2620	0.0584	88.69	88.48	88.87	74.09	71.28	76.33	62.22	59.71	64.13	69.61	74.33	281.45	0.91	5.76	147.38	0.79		

Table H.117. MLP 10-20-1, 10 input layers (categories), contrast layers with narrow buffers

Training set size		Training: 99 patterns (46 deposits, 53 barren), training-stop: = 88 (39 deposits, 49 barren), test = 81 (35 deposits, 46 barren)																				
Training set type		Randomly selected cells, approximately equal numbers of patterns from each rock type																				
Geology input format		Fuzzy membership values																				
Learn.	l.r.	Cycles	MSE			Train % correct			Stop % correct			Test % correct			Map % correct			Map statistics			D%*D%/A%	ROC
			Initial	Final	All	Deps	Non	All	Deps	Non	All	Deps	Non	All	Deps	Non	Chi	rho	D%/A%			
trainlm	0.0	8	0.2251	0.0944	81.82	71.74	90.57	71.59	64.10	77.55	69.14	68.57	69.57	71.78	68.33	292.68	1.00	15.26	88.99	0.78		
trainlm	0.0	11	0.2117	0.0692	82.83	76.09	88.68	78.41	69.23	85.71	66.67	62.86	69.57	75.93	70.00	307.78	0.97	11.93	149.10	0.81		
trainlm	0.0	11	0.1955	0.0721	87.88	93.48	83.02	71.59	84.62	61.22	69.14	74.29	65.22	67.98	85.00	241.43	0.95	6.80	175.75	0.81		
trainlm	0.0	19	0.4228	0.0420	87.88	76.09	98.11	78.41	66.67	87.76	70.37	57.14	80.43	82.11	67.50	375.56	0.93	8.17	258.67	0.84		
trainlm	0.0	9	0.2652	0.0827	82.83	71.74	92.45	78.41	69.23	85.71	69.14	60.00	76.09	79.03	67.50	511.81	0.98	11.00	64.17	0.82		
trainlm	0.0	10	0.2527	0.0617	88.89	86.96	90.57	73.86	66.67	79.59	66.67	71.43	63.04	71.05	75.83	444.83	0.98	16.76	279.41	0.82		
trainlm	0.0	13	0.2403	0.0645	86.87	86.96	86.79	71.59	69.23	73.47	69.14	68.57	69.57	69.99	75.83	145.09	0.95	4.09	51.09	0.78		
trainlm	0.0	9	0.2554	0.0926	78.79	69.57	86.79	65.91	61.54	69.39	70.37	62.86	76.09	76.59	65.00	638.70	0.95	17.57	117.11	0.80		
trainlm	0.0	11	0.1934	0.0468	92.93	95.65	90.57	69.32	74.36	65.31	61.73	77.14	50.00	66.94	83.33	260.84	0.98	5.70	123.50	0.81		
trainlm	0.0	13	0.2840	0.0395	93.94	91.30	96.23	78.41	76.92	79.59	64.20	60.00	67.39	74.05	77.50	312.34	1.00	7.81	156.24	0.83		
Average		12	0.2531	0.0613	87.47	83.91	90.57	74.32	70.77	77.14	67.04	66.57	67.39	71.30	74.42	328.97	0.96	9.19	142.89	0.80		

Table H.118. MLP 14-20-1, 14 input layers (substitutes for geology)

Training set size		Training: 99 patterns (46 deposits, 53 barren), training-stop: = 88 (39 deposits, 49 barren), test = 81 (35 deposits, 46 barren)															
Training set type		Randomly selected cells, approximately equal numbers of patterns from each rock type															
Geology input format		Fuzzy membership values															
Learn. Algorith.	l.r. Cycles	MSE		Train % correct			Stop % correct			Test % correct			Map % correct		Map statistics		
		Initial	Final	All	Depos	Non	All	Depos	Non	All	Depos	Non	All	Depos	Chi	rho	D%/A% D*D%/A% ROC
trainlm	0.0 9	0.3210	0.1042	73.74	54.35	90.57	70.45	46.15	89.80	67.90	51.43	80.43	88.88	50.83	476.90	0.97	13.16 32.90 0.82
trainlm	0.0 10	0.3089	0.0634	86.87	86.96	86.79	69.32	66.67	71.43	71.60	77.14	67.39	69.08	77.50	315.74	0.95	10.29 197.14 0.81
trainlm	0.0 11	0.3052	0.0559	88.89	82.61	94.34	75.00	64.10	83.67	70.37	60.00	78.26	81.46	70.00	294.25	0.93	8.16 54.43 0.82
trainlm	0.0 9	0.2132	0.0809	80.81	63.04	96.23	69.32	43.59	89.80	67.90	57.14	76.09	78.49	55.00	176.51	0.38	0.00 0.00 0.73
trainlm	0.0 9	0.2222	0.0834	84.85	76.09	92.45	73.86	71.79	75.51	66.67	65.71	67.39	74.86	71.67	501.96	0.98	13.70 79.89 0.82
trainlm	0.0 11	0.2842	0.0263	97.98	95.65	100.00	75.00	79.49	71.43	69.14	74.29	65.22	68.46	84.17	427.64	1.00	10.94 337.47 0.82
trainlm	0.0 12	0.2334	0.0846	80.81	65.22	94.34	76.14	64.10	85.71	66.67	62.86	69.57	69.96	64.17	159.36	0.95	6.44 134.22 0.74
trainlm	0.0 11	0.3321	0.0845	80.81	86.96	75.47	70.45	71.79	69.39	69.14	80.00	60.87	45.34	80.00	141.86	0.92	4.73 149.82 0.73
trainlm	0.0 10	0.2716	0.0631	86.87	84.78	88.68	71.59	69.23	73.47	71.60	71.43	71.74	73.36	75.83	500.72	0.95	15.86 224.71 0.82
trainlm	0.0 9	0.2957	0.0755	83.84	73.91	92.45	69.32	58.97	77.55	67.90	65.71	69.57	73.65	66.67	310.67	0.97	13.08 108.98 0.77
Average	11	0.2717	0.0663	86.56	80.63	91.70	72.93	66.34	78.16	69.35	69.08	69.57	70.20	72.67	311.48	0.90	9.12 148.66 0.79

Table H.119. MLP 33-20-1, 10 input layers (1-of-n coded geology)

Training set size		Training: 99 patterns (46 deposits, 53 barren), training-stop: = 88 (39 deposits, 49 barren), test = 81 (35 deposits, 46 barren)															
Training set type		Randomly selected cells, approximately equal numbers of patterns from each rock type															
Geology input format		Fuzzy membership values															
Learn. Algorith.	l.r. Cycles	MSE		Train % correct			Stop % correct			Test % correct			Map % correct		Map statistics		
		Initial	Final	All	Depos	Non	All	Depos	Non	All	Depos	Non	All	Depos	Chi	rho	D%/A% D*D%/A% ROC
trainlm	0.0 16	0.2510	0.0458	93.88	91.11	96.23	79.31	73.68	83.67	72.50	76.47	69.57	67.36	81.67	286.08	0.97	8.00 199.99 0.82
trainlm	0.0 24	0.2615	0.0514	91.84	91.11	92.45	79.31	78.95	79.59	62.50	67.65	58.70	63.38	80.83	228.16	0.98	7.25 151.02 0.80
trainlm	0.0 15	0.2478	0.0447	91.84	91.11	92.45	83.91	78.95	87.76	68.75	73.53	65.22	68.03	82.50	302.59	1.00	8.95 231.30 0.82
trainlm	0.0 16	0.1943	0.0595	90.82	86.67	94.34	73.56	63.16	81.63	72.50	67.65	76.09	67.77	74.17	213.16	0.92	4.01 36.75 0.79
trainlm	0.0 13	0.3187	0.0749	83.67	82.22	84.91	77.01	71.05	81.63	71.25	67.65	73.91	75.13	75.00	340.37	1.00	8.98 112.30 0.83
trainlm	0.0 15	0.3085	0.0695	84.69	82.22	86.79	74.71	71.05	77.55	68.75	67.65	69.57	73.97	75.00	410.45	1.00	12.59 136.39 0.84
trainlm	0.0 9	0.1749	0.0925	81.63	82.22	81.13	74.71	68.42	79.59	65.00	73.53	58.70	64.56	74.17	285.71	1.00	13.76 160.48 0.77
trainlm	0.0 14	0.2021	0.0669	83.67	86.67	81.13	77.01	76.32	77.55	71.25	76.47	67.39	65.27	80.83	308.73	0.95	11.40 161.48 0.81
trainlm	0.0 17	0.2350	0.0552	89.80	88.89	90.57	85.06	81.58	87.76	67.50	70.59	65.22	68.80	81.67	259.98	1.00	8.08 175.04 0.81
trainlm	0.0 11	0.2364	0.0700	86.73	95.56	79.25	77.01	78.95	75.51	65.00	73.53	58.70	59.70	84.17	201.64	0.95	7.30 109.54 0.78
Average	15	0.2430	0.0630	87.86	87.78	87.92	78.16	74.21	81.22	68.50	71.47	66.30	67.40	79.00	283.69	0.98	9.03 147.43 0.81

Table H.122. MLP 17-20-1, 17 input layers (categories, fuzzy inputs)

Training set size		Training: 99 patterns (46 deposits, 53 barren), training-stop: = 88 (39 deposits, 49 barren), test = 81 (35 deposits, 46 barren)																
Training set type		Randomly selected cells, approximately equal numbers of patterns from each rock type																
Geology input format		Fuzzy membership values																
Learn. Algorith.	l.r. Cycles	MSE		Train % correct			Stop % correct			Test % correct			Map % correct			Map statistics		
		Initial	Final	All	Depos	Non	All	Depos	Non	All	Depos	Non	All	Depos	Non	Chi	rho	D%/A% D%*D%/A%
trainlm	0.0 11	0.3433	0.0573	90.91	80.43	100.00	76.14	64.10	85.71	70.37	54.29	82.61	86.93	67.50	371.41	0.92	4.96	16.55
trainlm	0.0 8	0.2119	0.0964	77.78	78.26	77.36	72.73	74.36	71.43	64.20	68.57	60.87	78.85	74.17	233.73	0.92	2.99	19.96
trainlm	0.0 9	0.1747	0.0666	84.85	76.09	92.45	72.73	61.54	81.63	64.20	54.29	71.74	86.75	65.00	409.31	1.00	9.64	96.42
trainlm	0.0 8	0.2403	0.0775	84.85	86.96	83.02	68.18	56.41	77.55	64.20	57.14	69.57	77.47	68.33	295.61	0.95	7.10	94.66
trainlm	0.0 10	0.2310	0.0527	91.92	93.48	90.57	76.14	76.92	75.51	70.37	68.57	71.74	80.44	80.83	801.37	1.00	21.64	540.97
trainlm	0.0 9	0.2806	0.0758	82.83	69.57	94.34	71.59	66.67	75.51	61.73	45.71	73.91	80.21	61.67	192.24	0.90	1.87	4.68
trainlm	0.0 8	0.2251	0.0774	85.86	78.26	92.45	72.73	64.10	79.59	67.90	57.14	76.09	84.79	67.50	431.02	0.98	7.52	31.35
trainlm	0.0 8	0.2965	0.0881	77.78	67.39	86.79	75.00	64.10	83.67	66.67	54.29	76.09	85.87	62.50	323.35	0.95	13.20	44.00
trainlm	0.0 10	0.2734	0.1087	73.74	93.48	56.60	71.59	79.49	65.31	54.32	60.00	50.00	54.03	79.17	110.43	0.88	4.44	85.14
traingd	0.0 619	0.3508	0.0900	76.77	73.91	79.25	71.59	66.67	75.51	64.20	54.29	71.74	79.15	65.83	241.92	0.98	4.44	33.26
Average	70	0.2627	0.0791	82.73	79.78	85.28	72.84	67.44	77.14	64.81	57.43	70.43	79.45	69.25	341.04	0.95	7.78	96.70

Table H.123. MLP 17-20-1, 17 input layers (D* D/A, fuzzy inputs)

Training set size		Training: 99 patterns (46 deposits, 53 barren), training-stop: = 88 (39 deposits, 49 barren), test = 81 (35 deposits, 46 barren)																
Training set type		Randomly selected cells, approximately equal numbers of patterns from each rock type																
Geology input format		Fuzzy membership values																
Learn. Algorith.	l.r. Cycles	MSE		Train % correct			Stop % correct			Test % correct			Map % correct			Map statistics		
		Initial	Final	All	Depos	Non	All	Depos	Non	All	Depos	Non	All	Depos	Non	Chi	rho	D%/A% D%*D%/A%
trainlm	0.0 13	0.2506	0.0449	92.93	100.00	86.79	72.73	76.92	69.39	70.37	77.14	65.22	76.13	85.83	410.45	0.98	7.18	329.29
trainlm	0.0 7	0.2468	0.1118	71.72	52.17	88.68	75.00	53.85	91.84	70.37	48.57	86.96	90.69	51.67	420.58	1.00	14.70	24.51
trainlm	0.0 9	0.2110	0.0834	80.81	65.22	94.34	76.14	51.28	95.92	64.20	40.00	82.61	90.64	53.33	457.63	0.93	6.21	31.06
trainlm	0.0 9	0.1614	0.0438	93.94	97.83	90.57	76.14	74.36	77.55	66.67	62.86	69.57	80.28	80.00	377.53	1.00	7.93	105.75
trainlm	0.0 11	0.2884	0.0290	96.97	95.65	98.11	76.14	79.49	73.47	61.73	65.71	58.70	76.74	81.67	353.44	0.98	7.07	182.62
trainlm	0.0 11	0.3350	0.0200	96.97	97.83	96.23	78.41	74.36	81.63	69.14	68.57	69.57	77.32	81.67	376.72	0.92	5.25	153.11
trainlm	0.0 9	0.1930	0.0371	93.94	93.48	94.34	80.68	66.67	91.84	79.01	71.43	84.78	84.00	78.33	638.35	0.97	15.55	349.88
trainlm	0.0 10	0.3199	0.0521	89.90	84.78	94.34	75.00	56.41	89.80	77.78	68.57	84.78	83.89	70.83	346.80	0.90	4.16	31.21
trainlm	0.0 10	0.2852	0.0299	95.96	95.65	96.23	79.55	82.05	77.55	69.14	77.14	63.04	77.33	85.83	368.66	0.98	5.84	155.62
traingd	0.0 3067	0.3598	0.0547	89.90	86.96	92.45	80.68	69.23	89.80	71.60	68.57	73.91	84.53	75.83	627.05	0.98	14.98	287.08
Average	315	0.2744	0.0519	90.10	85.00	94.53	77.39	67.18	85.51	70.00	62.57	75.65	83.24	72.67	433.82	0.96	8.67	133.74

Appendix I

Results of Fuzzy Systems Experiments: Kalgoorlie Case Study

Results of Fuzzy Systems Experiments: Kalgoorlie Case Study

Table I.1. Fuzzy, 10 input layers (categories)

Number of inputs		10																			
Selection criteria		Categories: at least one of each type of input GIS layer is represented																			
Inputs		f1, f4, f20, f30, f36-1, f37-1, f42, f43, f44, f46																			
Gamma value	MSE	Train % correct				Stop % correct				Test % correct				Map % correct				Map statistics			
		Initial	Final	All	Deps	Non	All	Deps	Non	All	Deps	Non	All	Deps	Non	All	Deps	Chi	rho	D%/A%	D*D%/A%
$\gamma = 0.90$	n.a.	n.a.	n.a.	55.56	6.52	98.11	57.95	5.13	100.00	59.26	5.71	100.00	99.90	5.83	100.00	99.90	5.83	2399.40	0.52	655.23	1092.05
$\gamma = 0.91$	n.a.	n.a.	n.a.	55.56	6.52	98.11	59.09	7.69	100.00	59.26	5.71	100.00	99.86	6.67	100.00	99.86	6.67	2025.13	0.53	481.79	802.98
$\gamma = 0.92$	n.a.	n.a.	n.a.	55.56	6.52	98.11	61.36	15.38	97.96	60.49	8.57	100.00	99.78	10.00	100.00	99.78	10.00	1845.84	0.53	390.02	650.03
$\gamma = 0.93$	n.a.	n.a.	n.a.	62.63	21.74	98.11	68.18	30.77	97.96	60.49	8.57	100.00	99.48	20.83	100.00	99.48	20.83	1705.19	0.95	364.02	606.69
$\gamma = 0.94$	n.a.	n.a.	n.a.	62.63	21.74	98.11	71.59	38.46	97.96	65.43	22.86	97.83	98.80	27.50	100.00	98.80	27.50	1815.40	0.95	348.53	580.88
$\gamma = 0.95$	n.a.	n.a.	n.a.	65.66	32.61	94.34	76.14	56.41	91.84	61.73	28.57	86.96	96.62	39.17	100.00	96.62	39.17	1535.87	0.98	292.51	487.52
$\gamma = 0.96$	n.a.	n.a.	n.a.	69.70	69.57	69.81	73.86	79.49	69.39	67.90	65.71	69.57	85.80	71.67	100.00	85.80	71.67	1243.78	1.00	160.60	267.66
$\gamma = 0.97$	n.a.	n.a.	n.a.	58.59	84.78	35.85	60.23	87.18	38.78	56.79	94.29	28.26	60.99	88.33	100.00	60.99	88.33	1284.00	0.98	95.79	159.66
$\gamma = 0.98$	n.a.	n.a.	n.a.	56.57	100.00	18.87	48.86	100.00	8.16	48.15	97.14	10.87	35.98	99.17	100.00	35.98	99.17	1014.82	0.98	51.08	127.71
$\gamma = 0.99$	n.a.	n.a.	n.a.	46.46	100.00	0.00	44.32	100.00	0.00	43.21	100.00	0.00	0.01	100.00	100.00	0.01	100.00	861.62	0.95	51.90	432.53
$\gamma = 1.00$	n.a.	n.a.	n.a.	46.46	100.00	0.00	44.32	100.00	0.00	43.21	100.00	0.00	0.01	100.00	100.00	0.01	100.00	151.97	0.90	2.63	214.82

Table I.2. Fuzzy, 10 input layers (D* D/A)

Number of inputs		10																	
Selection criteria		D×D/A: % of total deposits / % of total area represented by the highest prospectivity class																	
Inputs		f44, f43, f46, f42, f2.5, f39, f14, f4, f22, f45																	
Gamma value	MSE	Train % correct			Stop % correct			Test % correct			Map % correct			Map statistics			D%*D%/A%	ROC	
	Initial	Final	All	Deps	Non	All	Deps	Non	All	Deps	Non	All	Deps	Chi	rho	D%/A%			
γ = 0.90		n.a.	n.a.	61.62	19.57	98.11	69.32	35.90	95.92	62.96	25.71	91.30	99.14	24.17	1536.21	0.97	64.36	214.55	0.89
γ = 0.91		n.a.	n.a.	61.62	21.74	96.23	72.73	43.59	95.92	65.43	31.43	91.30	98.73	27.50	1834.93	0.98	59.35	197.83	0.89
γ = 0.92		n.a.	n.a.	65.66	34.78	92.45	71.59	46.15	91.84	66.67	37.14	89.13	97.85	32.50	1608.36	0.98	52.50	175.01	0.89
γ = 0.93		n.a.	n.a.	64.65	45.65	81.13	72.73	51.28	89.80	69.14	48.57	84.78	95.84	43.33	1413.48	0.98	45.50	151.67	0.89
γ = 0.94		n.a.	n.a.	67.68	58.70	75.47	72.73	69.23	75.51	70.37	62.86	76.09	91.30	58.33	1391.13	1.00	68.17	397.67	0.89
γ = 0.95		n.a.	n.a.	72.73	76.09	69.81	73.86	84.62	65.31	65.43	80.00	54.35	81.76	75.00	1477.67	0.98	88.50	811.26	0.89
γ = 0.96		n.a.	n.a.	58.59	93.48	28.30	56.82	97.44	24.49	62.96	100.00	34.78	58.76	95.00	1585.87	0.96	87.40	1019.63	0.89
γ = 0.97		n.a.	n.a.	49.49	100.00	5.66	48.86	100.00	8.16	48.15	100.00	8.70	24.79	100.00	1346.10	0.92	65.55	928.68	0.89
γ = 0.98		n.a.	n.a.	48.48	100.00	3.77	46.59	100.00	4.08	44.44	100.00	2.17	13.39	100.00	811.29	0.85	29.82	546.66	0.89
γ = 0.99		n.a.	n.a.	46.46	100.00	0.00	44.32	100.00	0.00	43.21	100.00	0.00	0.03	100.00	362.13	0.77	5.87	381.62	0.88
γ = 1.00		n.a.	n.a.	46.46	100.00	0.00	44.32	100.00	0.00	43.21	100.00	0.00	0.01	100.00	52.02	0.65	1.43	143.35	0.67

Table I.3. Fuzzy, 17 input layers (categories)

Number of inputs		17																
Selection criteria		Categories: at least one of each type of input GIS layer is represented																
Inputs		f1, f4, f14, f20, f22, f30,f34, f36.1, f37.1, f37.3, f38, f39, f42, f43, f44, f45, f46																
Gamma value	MSE	Train % correct			Stop % correct			Test % correct			Map % correct			Map statistics			D%*D%/A%	ROC
	Initial	Final	All	Deps	Non	All	Deps	Non	All	Deps	Non	All	Deps	Chi	rho			
$\gamma = 0.90$	n.a.	n.a.	53.54	0.00	100.00	55.68	0.00	100.00	56.79	0.00	100.00	99.99	0.00	2522.40	0.40	0.00	0.00	0.89
$\gamma = 0.91$	n.a.	n.a.	53.54	0.00	100.00	55.68	0.00	100.00	56.79	0.00	100.00	99.99	0.00	2011.30	0.40	0.00	0.00	0.89
$\gamma = 0.92$	n.a.	n.a.	53.54	0.00	100.00	55.68	0.00	100.00	58.02	2.86	100.00	99.99	0.83	2462.57	0.38	0.00	0.00	0.89
$\gamma = 0.93$	n.a.	n.a.	55.56	4.35	100.00	55.68	0.00	100.00	58.02	2.86	100.00	99.98	2.50	1694.20	0.47	0.00	0.00	0.89
$\gamma = 0.94$	n.a.	n.a.	54.55	4.35	98.11	56.82	2.56	100.00	59.26	5.71	100.00	99.96	4.17	2212.83	1.00	744.58	620.48	0.89
$\gamma = 0.95$	n.a.	n.a.	55.56	6.52	98.11	61.36	15.38	97.96	60.49	8.57	100.00	99.88	10.00	2519.39	1.00	744.58	1240.96	0.89
$\gamma = 0.96$	n.a.	n.a.	58.59	13.04	98.11	65.91	25.64	97.96	64.20	20.00	97.83	99.38	19.17	1849.63	1.00	321.19	535.32	0.89
$\gamma = 0.97$	n.a.	n.a.	71.72	54.35	86.79	76.14	64.10	85.71	70.37	51.43	84.78	94.28	56.67	1810.78	0.98	266.35	887.84	0.89
$\gamma = 0.98$	n.a.	n.a.	51.52	95.65	13.21	53.41	100.00	16.33	53.09	100.00	17.39	42.74	98.33	1285.42	0.92	109.45	547.24	0.89
$\gamma = 0.99$	n.a.	n.a.	46.46	100.00	0.00	44.32	100.00	0.00	43.21	100.00	0.00	0.03	100.00	687.36	0.85	24.83	537.88	0.89
$\gamma = 1.00$	n.a.	n.a.	46.46	100.00	0.00	44.32	100.00	0.00	43.21	100.00	0.00	0.01	100.00	50.41	0.77	1.43	141.88	0.67

Appendix J

Explanation of ArcView GIS Layer Names

J.1 Explanation of ArcView GIS Layer Names

The directory “polygon.layers” contains vector data stored as grid files (suffix: .grd). The directory raster.layers contains raster data stored as shape files (suffix: .shp). Files with a “.avl” suffix are legend files and provide data used to colour the maps.

Table J.1: Explanation of ArcView GIS Layer Names

Layer Name	Description
Polygon Layers (shape files)	
Augers	Geochemistry; 13,503 hand-held auger drill holes, regolith, max. Au & As assays (ppb)
AuAs	Geochemistry; 112,366 percussion drill holes, max. Au & As (ppb) at bottom of hole
Data_extent	Study area; geology clipped to area
Deps_all	Deposits: orogenic gold, 2603 mines, deposits and occurrences (1443 in study area)
Deps_all_clip	Deposits: as above but coverage is clipped to size of study area
Deps_1000tcg	Deposits; as above but only deposits with total contained gold $\geq$ 1000 kg are shown
D1	Faults: crustal-scale NNW
D2	Faults: regional-scale NNW

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Table J.1: *continued*

Layer Name	Description
D3	Faults: regional-scale NE
D4	Faults: regional-scale E-W, oriented clipped to study area
D123	Faults: crustal-scale NNW, regional-scale NNW, and regional-scale NE
Faults	Faults: all (not clipped to study area)
Struct_types	Faults: all with NNW-trending structures emphasized
Folds	Ground traces of anticlinal and synclinal axes (not clipped to study area)
Folds_clipped	Ground traces of anticlinal and synclinal axes (clipped to study area)
Geology	Solid geology, all Goldfields Pty Ltd lease areas (completed 16.11.00). 108 rock types
Mineout-51	Mine outlines including open pits and mine dumps
Ozchem	AGSO OZCHEM whole-rock geochemistry database for Eastern Goldfields
Raster Layers (grid files)	
L1.l.ass-t25	Solid geology with a simplified 25 rock-type legend
L1.l.ass-t55	Solid geology with a simplified 55 rock-type legend
L1favgeol25pr	Favourability of host rock-type based on $P(Deposit)$, fuzzy membership values
L2.l.rh1b	Rock strength - subjective estimate, fuzzy membership values
L2.l.rh2b	Rock strength - subjective estimate, 10 classes
L2.l.rh3	Rock strength - Young's modulus, compilation by Hatheway (1989)
L2.l.rh4	Rock strength - Youngs modulus, AMC Pty Ltd (Lee, 2000; unpublished data)
L2.l.rh5	Rock strength - Uniaxial compressive strength
L2.l.rh6	Rock strength - Uniaxial tensile strength
L2.l.rh7	Rock strength - Fracture Toughness
L3.l.ch1	Chemical ratio - $Fe_{total}(wt\%) \times Fe/(Fe+Mg+Ca)$, second factor; elemental wt%
L3.l.ch2	Chemical ratio - $Fe/(Fe+Mg+Ca)$, elemental wt% ratio
L3.l.ch3	Chemical ratio - $Fe_2O_3/(Fe_2O_3 + FeO)$
L3.l.ch4	Chemical ratio - Fe_2O_3/FeO
L3.l.ch5	Chemical ratio - Fe^{3+}/Fe^{2+} , elemental wt% ratio
L4.l.pf	Lithology; binary layer: porphyritic felsic intrusive rocks
L4.l.pf.dist	Lithology; distance to nearest porphyritic felsic intrusive (rock types grouped; feldspar

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Table J.1: *continued*

Layer Name	Description
	<p>porphyry, feldspar quartz biotite porphyry, feldspar quartz hornblende porphyry, feldspar</p> <p>quartz porphyry, plagioclase +/- hornblende porphyry</p>
L5_m_rtp	Airborne magnetic survey data; TMI, RTP, Kalgoorlie area
L6_m_lvd	Airborne magnetic survey data; first vertical derivative
L7_m_2vd	Airborne magnetic survey data; second vertical derivative
L8_r_k	Airborne radiometric survey data; K-channel
L9_r_th	Airborne radiometric survey data; Th-channel
L10_r_tot	Airborne radiometric survey data; Th-channel
L11_r_u	Airborne radiometric survey data; Th-channel
L12_grav	Gravity; AGSO Bouguer gravity anomaly grid, Kalgoorlie area
L13_lsar_tm	Landsat Thematic Mapper satellite image (composite)
L14_m_z	Magnetic anomalies; z-scores for each rock type; $z = (x - \text{mean})/s$
L14_mz-1_dist	Magnetic anomalies; z-score ≤ -1 ; distance to nearest magnetic anomaly
L14_mz-1_bn01	Magnetic anomalies; z-score ≤ -1 ; binary layer; values; 0, 1
L14_mz-1bn1nl	Magnetic anomalies; z-score ≤ -1 ; binary layer; values; null, 1
L14_mz1_dist	Magnetic anomalies; z-score $\geq +1$; distance to nearest magnetic anomaly
L14_mz1_lt1	Magnetic anomalies; z-score $\geq +1$; distance to nearest anomaly < 1000 m
L14_mz1_lt15	Magnetic anomalies; z-score $\geq +1$; distance to nearest anomaly < 1500 m
L14_mz1_lt2	Magnetic anomalies; z-score $\geq +1$; distance to nearest anomaly < 2000 m
L14_mz1_bn01	Magnetic anomalies; z-score $\geq +1$; binary layer; values; 0, 1
L14_mz1bn1nl	Magnetic anomalies; z-score $\geq +1$; binary layer; values; null, 1
L14_mz2_dist	Magnetic anomalies; z-score ≥ 2 ; distance to nearest anomaly
L14_mz2dist15	Magnetic anomalies; z-score $\geq +2$, distance to nearest anomaly < 1500 m
L14_mz2dist2	Magnetic anomalies; z-score $\geq +2$, distance to nearest anomaly < 2000 m
L14_mz2dist25	Magnetic anomalies; z-score $\geq +2$, distance to nearest anomaly < 2500 m
L14_mz2bn1nul	Magnetic anomalies; z-score $\geq +2$, binary layer; values; null, 1
L15_m_zint	Magnetic anomalies; rounded to integers
L16_as_int	Auger drill hole arsenic (ppb), max. at bottom of hole; interpolation method 1

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Table J.1: *continued*

Layer Name	Description
L16_as_fint	Auger drill hole arsenic (ppb); max. at bottom of hole; interpolation method 2 (filtered)
L17_au_int	Auger drill hole gold (ppb); max. at bottom of hole; interpolation method 1
L18_l_mdql	Lithology; binary layer: quartz dolerite and leucocratic dolerite
L18_l_mdql-dist	Lithology; distance to nearest quartz dolerite and leucocratic dolerite
L19_l_gsy	Lithology; binary layer: syenite and syenodiorite units
L19_l_gsy-dist	Lithology; distance to nearest syenite and syenodiorite unit
L20_f1_dist	Faults; distance to nearest crustal-scale NNW fault
L20_s_crust	Faults; crustal-scale NNW faults (raster format)
L21_s_shear	Faults; regional-scale NNW faults (raster format)
L21_f2_dist	Faults; distance to nearest regional-scale NNW fault
L22_d3_ns	Faults; binary layer; regions north & south of the nearest NE-trending regional-scale fault
L22_s_ftt_ne	Faults; regional-scale NE faults (raster format)
L22_d3_dist	Faults; distance to nearest regional-scale NE fault
L23_s_ftt_ne	Faults; regional-scale E-W faults (raster format)
L23_d4_dist	Faults; distance to nearest regional-scale E-W fault
L24_d_all_bin	Deposits; binary layer, all deposits
L24_d_allbn_nd	Deposits; binary layer, all deposits, areas of Nodata excluded
L24_d_bin1000	Deposits; binary layer, deposits with total contained gold ≥ 1000 kg
L24_d_bin3000	Deposits; binary layer, deposits with total contained gold ≥ 3110 kg (100000 oz)
L24_d_freq	Deposits; number of deposits in each 100×100 m grid cell
L25_d_tcg2	Deposits; Total Contained Gold (TCG) per 100×100 m grid cell
L25dtcg2_bak	Deposits; Total Contained Gold (TCG) per cell (Nodata areas shown in black)
L25_d_oreton	Deposits, tonnes (1000 kg) of ore per 100×100 m grid cell
L25_f1c1_int	Deposits: Gaussian filter, TCG/cell, central cell = original value, converted to integers
L25_f1s1_int	Deposits: Gaussian filter, TCG/cell, window sum = original value, converted to integers

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Table J.1: *continued*

Layer Name	Description
L25_f2c1.int	Deposits: directional Gauss. filter TCG/cell, central cell = original value, converted to int.
L25_f2s1.int	Deposits: directional Gauss filter TCG/cell, window sum = original value, converted to int.
L25_tcg_f1c1	Deposits: Gaussian filter TCG per cell, central cell = original value, floating point data
L25_tcg_f1s1	Deposits: Gaussian filter TCG per cell, window sum = original value, floating point data
L25_tcg_f2c1	Deposits: directional Gauss. filter TCG/cell, central cell value = original value
L25_tcg_f2s1	Deposits: directional Gauss filter TCG/cell, window sum = original value, floating pt. data
L26_anom_dst	Radiometric: distance to log10(K/Th) anomalies
L26_kdivth_lg	Radiometric: log10(K/Th)
L26_kth_anom	Radiometric: derived from L26_kdivth_lg anomalies in range [1.13-2.21] = 1, rest = 0
L26_kthanombn	Radiometric: binary anomalies = 1, rest = 0
L26_kthlg_dt5	Radiometric: distance to L26_kdivth_lg anomalies in range [1.13-2.21], buffer limit = 5 km
L26_r_kdivth	Radiometric: K/Th
L27_anom_dst	Radiometric: distance to log10(K/total) anomalies
L27_kdivto_lg	Radiometric: log10(K/total)
L27_ktoanombn	Radiometric: binary anomalies = 1, rest = Null
L27_ktolg_dt5	Radiometric: distance to L27_kdivtot_lg anomalies in range [4.68-5.06], buffer limit = 5 km
L27_ktot_anom	Radiometric: derived from L27_kdivtot_lg anomalies in range [4.68-5.06] = 1, rest = 0
L27_r_kdivtot	Radiometric: K/total
L28_s_f1str1k	Structure: strike of crustal-scale NW faults, buffer limit = 1 km
L29_s_f2str	Structure: strike of regional-scale NW faults
L29_s_f2str1k	Structure: strike of regional-scale NW faults, buffer limit = 1 km
L30_s_f3str	Structure: strike of regional-scale NE faults
L30_s_f3str1k	Structure: strike of regional-scale NE faults, buffer limit = 1 km

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Table J.1: *continued*

Layer Name	Description
L31_s.f4str	Structure: strike of regional-scale E-W faults
L31_s.f4str1k	Structure: strike of regional-scale E-W faults, buffer limit = 1 km
L32_s.f2f3	Structure: intersection of regional-scale NW & NE faults
L33_s.f23gdst	Structure: distance to intersection of regional NW & NE faults (grid-based calculation)
L34_s.f23pdst	Structure: distance to intersection of regional NW & NE faults (vector-based calculation)
L35_cnt25_200	Lithology: contact type, 25 rock type legend, buffer limit = 200 m
L35_ct25_1300	Lithology: contact type, 25 rock type legend, buffer limit = 1300 m
L35_l_rt25	Lithology: contact type, 25 rock type legend
L35_l_rt55	Lithology: contact type, 55 rock type legend
L36_l_rh1	Rheology: contrast at lith. contact, percentile of subjective rankings
L36_l_rh11k	Rheology: contrast at lith. contact, percentile of subjective rankings
L36_l_rh2	Rheology: contrast at lith. contact, subjective ranking
L36_l_rh21k	Rheology: contrast at lith. contact, subjective rankings, buffer limit = 1 km
L36_l_rh3	Rheology: contrast at lith. contact, Young's modulus, Hatheway (1989)
L36_l_rh31k	Rheology: contrast at lith. contact, Young's modulus, Hatheway (1989), buffer limit = 1
L36_l_rh4	Rheology: contrast at lith. contact, Young's modulus, Lee (2000)
L36_l_rh41k	Rheology: contrast at lith. contact, Young's modulus, Lee (2000), buffer limit = 1 km
L36_l_rh5	Rheology: contrast at lith. contact, uniaxial compressive strength, Lee (2000)
L36_l_rh51k	Rheology: contrast at lith. contact, uniaxial compressive strength, buffer limit = 1 km
L36_l_rh6	Rheology: contrast at lith. contact, uniaxial tensile strength, Lee (2000)
L36_l_rh61k	Rheology: contrast at lith. contact, uniaxial tensile strength, Lee (2000), buffer = 1 km
L36_l_rh7	Rheology: contrast at lith. contact, fracture toughness, Lee (2000)
L36_l_rh71k	Rheology: contrast at lith. contact, fracture toughness, Lee (2000), buffer limit = 1 km

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Table J.1: *continued*

Layer Name	Description
L37_l_ch1	Chemistry: contrast at lith. contact, $(\text{Fe}^{2+} + \text{Fe}^{3+}) / (\text{Fe}^{2+} + \text{Fe}^{3+} + \text{Mg} + \text{Ca})$, elemental wt%
L37_l_ch11k	Chemistry: contrast at lith. contact, as above but 1 km buffer limit
L37_l_ch2	Chemistry: contrast at lith. contact, $(\text{FeO} + \text{Fe}_2\text{O}_3)$ wt% oxide $\times (\text{Fe}^{2+} + \text{Fe}^{3+}) / (\text{Fe}^{2+} + \text{Fe}^{3+} + \text{Mg} + \text{Ca})$
L37_l_ch21k	Chemistry: contrast at lith. contact, as above but 1 km buffer limit
L37_l_ch3	Chemistry: contrast at lith. contact, $\text{Fe}_2\text{O}_3 / (\text{Fe}_2\text{O}_3 + \text{FeO})$, wt% oxides
L37_l_ch31k	Chemistry: contrast at lith. contact, as above but 1 km buffer limit
L37_l_ch4	Chemistry: contrast at lith. contact, $\text{Fe}_2\text{O}_3 / \text{FeO}$, wt% oxides
L37_l_ch41k	Chemistry: contrast at lith. contact, as above but 1 km buffer limit
L37_l_ch5	Chemistry: contrast at lith. contact, $\text{Fe}^{3+} / \text{Fe}^{2+}$, elemental wt%
L37_l_ch51k	Chemistry: contrast at lith. contact, as above but 1 km buffer limit
L38_c_str	: strike of lithological contacts
L38_c_str1k	Lithology: strike of lithological contacts, buffer limit = 1 km
L39_c_dist	Lithology: distance to lithological contacts
L40_strk_d123	Structure: strike of fault types; 1 (crustal NW), 2 (regional NW), & 3 (regional NE)
L42_f123_comb	Structure: fault types; 1 (crustal NW), 2 (regional NW), & 3 (regional NE)
L42_f1234_cmb	Structure: fault types; 1 (crustal NW), 2 (regional NW), 3 (regional NE), & 4 (regional E-W)
L42_f123den5k	Structure: total length of faults (crustal NE, regional NW, regional NE)
L43_lith_div	Lithology: number of lithological contacts in window 5×5 km around cell
L44favcnt2501	Lithology: favourability of nearest contact type based on $P(\text{Deposit})$, fuzzy m/ship values
L45_l_meta	Lithology: metamorphic grade
L46_dist_anti	Structure: distance to trace of axial plane of anticline
L46_dist_sync	Structure: distance to trace of axial plane of syncline
L46_folddist	Structure: distance to trace of axial plane of anticlines and synclines
L46_foldnear	Structure: 1 = nearest anticline, 2 = nearest syncline

continued on next page

Table J.1: *continued*

Layer Name	Description
L47_grntd_dst	Lithology: distance to granitoid excluding distances = 0 within granitoid itself
L48_g_dst2200	Lithology: distance to granitoid, buffer limit = 2200 m
L49_l_umafic	Lithology: presence of ultramafic rocks (binary)
L49_um_dist	Lithology: distance to ultramafic rocks
L49_umd_st2200	Lithology: distance to ultramafic rocks, buffer limit = 2200 m
L50_gtd_dist	Lithology: distance to granitoid including distances = 0 within granitoid itself
L50_granitoid	Lithology: presence of granitoids (binary)
Mask100	Study area
Num_cell	Cell values = cell number from top left to bottom right, [1,1254,000]
gdx17_10_r2	Neural network prospectivity map; 17-10-1 MLP , adaptive lr rate & momentum (<i>traingdx</i>)
fuz_0510_98	Fuzzy system prospectivity map; 10-inputs, input fuzzy m/ship range [0.5,1.0], ($\gamma = 0.98$)