1 A role for data richness mapping in exploration decision making.

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7 Abstract

8 Exploration programs involve long, multi-branched decision pathways with many potential outcomes from a
9 single starting point. Critical decisions along this pathway include the choice of the area(s) in which to
10 explore, and the choice to acquire new data sets to assist in exploration. Included in this is a factoring of
11 risks, including the technical risks associated with imperfect data and the value relative to cost of collecting
12 more data. In our experience it is not common practice to explicitly assess and quantify the impact of data
13 on exploration decisions. A better understanding of the opportunity provided by data has the potential to
14 improve the quality and/or ease of decision making. In this study we explore the potential role of data
15 richness mapping as part of a decision making workflow. We outline a method to quantitatively assess data
16 richness following a four level hierarchy, namely presence of data (L1), quality of data (L2) and attributes of
17 data (L3). Measures of these are combined across several data sets to give an overall estimate of data
18 richness (L4). Using this data richness map, along with past exploration records and a prospectivity model,
19 we conduct an illustrative case study for gold exploration in the Bryah Sub-basin (Yerrida Basin) region of
20 Western Australia. The first application is to produce a simple data based classification of regions with
21 different technical risk characteristics. The second application is to combine this with a prospectivity model
22 to better understand exploration potential. The third application uses data richness mapping to understand
23 which data sets are most likely to have an impact on regional exploration. In each case we show how an
24 understanding of data richness can help support exploration decision making.

25 Introduction:

26 Modern exploration often demands the integration of concepts that operate across a variety of scales
27 (Hronsky and Groves, 2008, McCuaig and Hronsky, 2014, McCuaig et al. , 2010) which leads to a long and
28 multi-branched decision pathway (Kreuzer et al. , 2008). To facilitate this process, the number of geoscience
29 data sets used in a typical program has increased substantially. Programs grow in complexity as attempts
30 are made to combine these data sets meaningfully (Czarnota et al. , 2010, Joly et al. , 2012, Lindsay et al. ,
31 2016, Lindsay et al. , 2014, Occhipinti et al. , 2016, Payne et al. , 2015). Compounding the increase in data

types, the method(s) used to generate individual data sets have typically become more advanced over time, often increasing the complexity of each information source. Data sets have become larger as digital collection and storage barriers are less significant (Perrons and Jensen, 2015), increasing the volume of information to be processed. Finally, each data set also possesses a level of uncertainty, including for example, the relative strength of the contained data signal to local background levels, thus all subsequent decisions are inherently uncertain. The propagation of these uncertainties along a multi-branched decision pathway further reduces confidence in the final decision (Kreuzer, Etheridge, 2008, McCuaig et al. , 2007, Yousefi and Carranza, 2015a).

As a consequence, decisions surrounding the geoscientific data sources and analyses used in an exploration workflow have become more complex. Other fields have also faced problems with decision making in the face of increasing data complexity, including petroleum exploration (Binns and Corbett, 2012, Perrons and Jensen, 2015) and environmental science (Bagstad et al. , 2013, Crossman et al. , 2013, Rounsevell et al. , 2012). Under such conditions, traditional decision making based on heuristics can lose touch with the capability of modern data to inform the decision. One approach to assist in this is the development of semi-automated systems which seek to aggregate and refine data into a reduced model. As an example, a variety of techniques can be applied in order to generate models of mineral resource potential (Knox-Robinson, 2000, Porwal et al. , 2003, Rodriguez-Galiano et al. , 2015, Yousefi and Carranza, 2015b).

In this work we consider the role of geoscientific data in exploration decision making processes. We neglect here all other aspects of decision making, for example, infrastructure accessibility, commodity prices and organisational factors, whilst recognising that they are all very substantial (Penney et al. , 2004, Tulcanaza and Ferguson, 2001). We define a multi-level analytical approach to understand spatial variations in the "richness" of geoscience data sets. Combining this with historical exploration data and a prospectivity model, we apply this in three illustrative examples. In the first application we define a simple data based classification approach for ground selection. In the second we incorporate a prospectivity model, to further delimit exploration potential. In the third application we use data richness to assess the value of several data types in both relatively mature and relatively immature exploration settings, with a view to guiding new data acquisition.

The exploration decision cycle

When making any decision, explorers must consider, either implicitly or explicitly, their knowledge of the level of risk and likely reward associated with different exploration strategies or target areas. These risks may include a variety of economic, political, logistical, social and environmental factors (Trench et al. , 2013), but here we focus on the risk associated with imperfect geoscientific data, in particular its distribution and usefulness. These data are associated with risk in the sense that better surveyed regions provide, in the first

65 place, a greater opportunity to understand what mineral resources may be available and, in the second
66 place, a better understanding of where to find them and how. However, in many cases, better surveyed
67 regions possess fewer opportunities for new discoveries (Guj et al. , 2011, Mamuse and Guj, 2011), and so
68 the potential for substantial reward is less than in little surveyed areas. In an exploration context, this
69 difference in opportunity and risk is often reduced to “greenfields” versus “brownfields”. The former is
70 characterised by areas lacking deposits with little supporting infrastructure and many unknowns, whereas
71 the latter is characterised by areas possessing deposits with better known geology and more supporting
72 infrastructure.

73 Good ground selection underpins all successful exploration (Hronsky and Groves, 2008). Consequently, the
74 most fundamental decision is the decision to take up or abandon areas for exploration, or to seek to manage
75 risk through a joint venture with another organisation (Guj, 2011). Fundamentally, the decision maker must
76 separate regions into favourable and unfavourable regions. These regions may vary considerably depending
77 on the needs of the organisation (Whiting and Schodde, 2006). As an example, one company may be seeking
78 relatively low technical risk opportunities in a "brownfields" region, while another company may be willing
79 to accept higher technical risk in a "greenfields" region in the hope of higher reward. In either case,
80 geoscience data define the degree to which the region can be considered “known”, with associated
81 implications for technical risk and reward.

82 The next level of decision, once a region is chosen (or before it is abandoned) is to decide if more data are
83 required, and if so, which data set(s) to acquire. Implicit in this decision is, firstly, a knowledge of the degree
84 to which geology is known, and secondly, an understanding of which data types are most efficient for
85 progressing to the next phase of exploration. Although less fundamental than ground selection, poor choices
86 at this stage are a substantial barrier to exploration success (Kreuzer, Etheridge, 2008). In this case, a
87 judgement must be made regarding the potential for new data to add value relative to the cost of its
88 acquisition (Eidsvik and Ellefmo, 2013, Kreuzer, Etheridge, 2008, Perrons and McAuley, 2015, Vearncombe et
89 al. , 2017).

90 The next stage of the cycle follows any new data collection, and the decision is whether this data has
91 provided enough new information to proceed towards the next exploration phase, or to prompt a change of
92 exploration strategy, or to change the region of exploration focus (Hronsky and Groves, 2008, Kreuzer,
93 Etheridge, 2008). The impact of new data on knowledge is always positive, but depending on the aims of the
94 organisation, the value of the data may vary considerably, and it may of course have either positive or
95 negative implications for the specific exploration program.

96 From the above, it is clear that this decision cycle carries a high level of implied knowledge about both the
97 value of data that has been or will be collected and also of the optimum approach to gain knowledge

98 through new data collection. For robust decision making, it is important that a degree of rigor is applied to
99 defining the level of data richness and the potential to improve it.

100 Methodology

101 Data richness concepts

102 For our purposes we define data richness as the opportunity provided by data to gain useful knowledge that
103 can help make exploration decisions better, or easier to make. We note that data richness does not define
104 the quality of the decision itself, which may be influenced by a wide variety of other factors.

105 Numerous studies have investigated decision making processes in the face of complex data sets. Task
106 complexity can be defined in several ways, considering a number of dimensions, such as the number of task
107 components, ambiguity in task components and relationships between task components (Liu and Li, 2012,
108 Wood, 1986). A simple overarching definition with relevance to geographic problems may be the number of
109 knowledge states that are possible in the task (Swink and Speier, 1999). A complex task, like finding an ore
110 deposit, will be characterised by a long and multi-branched decision tree, with considerable uncertainty
111 associated with each decision (Kreuzer, Etheridge, 2008, McCuaig, Kreuzer, 2007), leading to many possible
112 knowledge states.

113 Exploration relevant data are fundamental to selecting which branches to follow, and we consider that good
114 targeting data will, in general, reduce task complexity by eliminating unpromising branches (Kreuzer,
115 Etheridge, 2008). On occasion, new data will prompt a "new" branch to be required. This apparent increase
116 in task complexity comes from the uncovering of considerations that were previously unknown, and so
117 contributes positively to the ability to make a sound decision, although not necessarily an easier one. An
118 abundance of data is an increasingly common problem that can increase the perception of task complexity,
119 or so called "information overload" (Li, 2016, Perrons and McAuley, 2015). However, this is not universal (Li,
120 2016), and can often be overcome through appropriate data selection or aggregation techniques (Perrons
121 and McAuley, 2015, Swink and Speier, 1999) and good presentation (Li, 2016, Speier, 2006). Consequently,
122 we consider the contribution of new data to decision making to be always positive, although it may be very
123 small.

124 Swink and Speier (1999) explored, using spatial data sets, the influence on decision making of problem size,
125 data aggregation and data dispersal. In their study, problem size encompasses the inherent complexity of
126 the problem, with a constant level of data richness and no uncertainty. In the case that these are non-
127 uniform, we can reframe the concept of problem size to include also the amount of data that are available to
128 solve the problem, and the applicability of those data to the problem. Their study indicates that increasing
129 problem size negatively affects both decision time and decision quality. Data aggregation reflects the degree
130 to which raw data are collated and clustered for analysis (e.g. by spatial averaging or binning). In their study,

131 higher levels of data aggregation did not strongly influence the quality of the decision, but it had a significant
132 effect in reducing the decision time. Data dispersal indicates the degree of spread in the data values, with
133 the notion that more dispersed data provides more recognizable patterns. Their results suggest that decision
134 quality was superior with highly varied data, and that there was little effect on decision time.

135 The results of Swink and Speier (1999) suggest that sound decisions are more likely where clear data signals
136 are present for problems that are simple relative to the richness of the data. In the presence of time limited
137 decision making, the ability to aggregate the data meaningfully is of use. However, their study did not assess
138 the problem of data quality, which is fundamental to resource exploration due to the typically imperfect
139 nature of geoscientific data.

140 We consider data to possess a hierarchy of levels that describe its value to a process (Figure 1). For each
141 data set, three levels of value exist that are separate in concept, although in some cases the data does not
142 permit clear separation of the levels. These levels are hierarchical, in that L3 is not relevant without L2, and
143 L2 is not relevant without L1. Not all data sets possess quantifiable descriptions of all three levels, however,
144 so the hierarchy may be truncated at L1 or L2. A fourth level (L4) considers the integration of these data sets,
145 accounting for redundancies and interdependencies.

146

147 *Figure 1: Four levels of data richness. Level 1 considers the presence of nearby data, level 2 considers the*
148 *quality of those data, and level 3 considers the datas' attributes. Level 4 considers how different data sets*
149 *interact. These form the basis of the analyses in this study. Level 4 is considered here on a conceptual basis.*

150 Our first level (L1) describes the presence of data nearby. This component will typically be defined by a
151 numerical measure of either data density or the distance to data. On occasion, presence versus absence
152 may be a good descriptor. At this stage no information is included on the value of the data, merely their
153 existence. However closely the data may be spaced, the likely presence of "bad" or irrelevant data in the
154 data set means that L1 mappings are not yet an adequate descriptor of data richness.

155 Our second level (L2) considers the intrinsic quality of the data, i.e. their precision and relevance to the
156 purpose, but without considering the properties of the data themselves. Data richness as we define it
157 considers the data solely as it is applied to a particular process, and so high quality data can be low richness
158 if it does not help support a decision. Typical descriptors at L2 will include numerical or categorical
159 descriptors of precision or confidence, as well as definitions of applicability or usefulness. For example, we
160 may wish to downgrade observations from geological units of unsuitable age or lithotype regardless of their
161 intrinsic quality. If we consider "problem size" to be defined as task complexity relative to the availability of
162 useful data, L1 and L2 together can be considered the inverse of problem size, so higher data richness at L1
163 and L2 can be expected to lead to more sound decisions, and also to easier decisions in most cases.

164 At L2 the content of the data is not considered. Therefore, our third level (L3) is a consideration of the
165 degree to which the data has the right attributes to be of use in solving our problem. This is similar in
166 concept to the "dispersion" quality of Swink and Speier (1999) in that we promote clear and strong signals
167 over weak or indistinct signals. We do not consider directly the difficulty of the problem that the data
168 content may present, for example due to high geological complexity; we consider only the qualities of the
169 data. High values of data richness at L3 can be expected to contribute to sound decisions, but not
170 necessarily easier decisions.

171 Finally, in a typical exploration decision process several data types are combined, and so we must consider
172 how these data sets interact to form the final decision, including, for example, redundancies and
173 interdependencies between data sets. This constitutes our fourth conceptual level (L4) and is accounted for
174 here in the different weightings of each data set, and form the framework for an overall estimate of data
175 richness. Several methods exist to analyse interdependencies between datasets rigorously (Journel, 2002,
176 Sun et al. , 2013), and we do not explore this element further here. Level 4 is akin to data aggregation, and
177 based on the work of Swink and Speier (1999) we can expect appropriate data aggregation to reduce
178 perceived task complexity and decision time.

179 Mapping approach

180 We use standard Geographic Information System (GIS) tools to quantitatively map data richness, following
181 previously developed data richness mapping methods (Aitken et al. , 2013). Key operators include the
182 following: Proximity is defined using the Euclidean distance operator while spatial data density is defined
183 using the kernel density operator (Silverman, 1986), often weighted by a descriptor of data quality (L2). In
184 addition, raster data sets are combined and modified using a variety of mathematical operators, including
185 arithmetic, logarithmic and trigonometric operators. Most of these operators are contained within the
186 Spatial Analyst module of ArcGIS and many are available as plugins for the open-source Quantum
187 Geographic Information System (QGIS) package. The analyses here were performed in an automated fashion

188 in ArcGIS using the Python-based geoprocessing functionality, which allows the process to be easily repeated
189 in full or in part as new data are obtained. The specific operations for each data type used in our case study
190 are described below and in Table 1. For this analysis we use public domain precompetitive data that are
191 sourced from governmental data providers, including the Geological Survey of Western Australia and
192 Geoscience Australia.

193 Our work in the case study is focused on constraining interpretations of near surface geology for a regional
194 mapping exercise. The resulting maps were used as part of a prospectivity modelling exercise (Occhipinti et
195 al. , in prep). As a practical case study, we focused on methods that provide good spatial knowledge of
196 lithological and stratigraphic variations across the region, and also are commonly used in regional
197 exploration. The main data sets used were outcropping geology, drillcore and geochemistry data, as well as
198 airborne radiometric and magnetic data and regional ground gravity data. Any other data sets of relevance
199 could be included as long as a descriptor of at least level 1 data richness could be defined.

200 For outcrop geology we consider two descriptors of quality (L2), which in this case we base on the geological
201 age of the outcropping rocks, and the scale of the best quality mapping available (Table 1). In this case we
202 are interested in Precambrian geology, and so we weight Archean and Proterozoic rocks to 1. Phanerozoic
203 rocks are lower weighted (0.5), but non-zero due to their potential to provide information of relevance to
204 the older rocks. Cenozoic rocks are predominantly "cover" and are weighted zero (the value of regolith as a
205 geochemical repository is considered separately). Map scale makes a substantial difference to
206 understanding geological complexity (Ford and McCuaig, 2010) and so 1:250 000 scale maps are weighted at
207 0.4 relative to 1:100 000 scale maps (weighted 1). These are combined to give an Outcrop Quality Factor
208 (OQF) for each outcrop (Aitken, Holden, 2013). We do not apply a level 3 descriptor to outcrop geology, as
209 this is hard to define quantitatively at a regional scale. At smaller scales, or for more specific applications, L3
210 could be defined. For example, a numerical ranking of the lithological difference between a polygon and its
211 neighbours could be used. To define the spatial relevance of surface geological data, we choose the spatial
212 density of outcrop within a certain radius. This is defined using a kernel density function operator, each
213 point weighted by its OQF. In this case a 5 km radius is chosen, reflecting the scale of the mapping and the
214 resolution of the desired result.

215 For drillcore, only publicly available cores are used, and not exploration holes from companies, although at
216 appropriate scales these could easily be included. As a suitable L2 descriptor we consider the maximum
217 depth of the core. We do not apply a level 3 descriptor here as this is hard to define numerically without
218 accessing the core, but there is obviously scope to define such a measure based on the contents of the
219 drillcore log. As with outcrop we define combined L1/L2 data richness using a weighted kernel density
220 operator with a radius of 5 km.

221 For geochemistry, we consider both hard rock and regolith geochemistry samples. A level 2 descriptor is
222 defined based on the type of sample, and on the likelihood that the sample is representative of the
223 underlying region. Regolith (excluding sand) is weighted 2, as in this region it has largely been found to form
224 as a product of in-situ regolith weathering processes (Thorne et al. , 2018). These data are considered more
225 likely to be representative of a substantial area than the "spot" data from hard rock samples (weighted 1).
226 Sand is assigned 0.25 as transported cover. No L3 descriptor is used here, but in less general cases this could
227 involve, for example, particular element ratios that define a characteristic of specific value. We define
228 combined L1/L2 data richness using a weighted kernel density operator with a radius of 5 km.

229 Data richness for airborne radiometric data is defined from L1 to L3. The properties of the data itself (L3) are
230 considered through two measures: First we define the radiometric slope, which indicates the spatial rate of
231 change of each of the three channels (U, Th, K). Each channel is normalised, the slope calculated, and the
232 three slopes added together. This measure provides high values for what might be perceived in a ternary
233 image as an "edge" in colour contrast, perhaps associated with a geological boundary. Another L3 measure
234 is defined as the radiometric distance. For this measure we define, in U-Th-K space, the distance of a
235 measurement from the centroid of the normalised data space. This measure provides high values for what
236 might be perceived in a ternary image as a "peak" or "trough" in one or more channels, perhaps associated
237 with a linear geological feature, such as a dyke or fault alteration zone. These normalised slope and distance
238 measures are added, focusing on edges in this case (Table 1). For L2, a sample quality descriptor is not
239 directly considered, as sampling methods and technologies are similar throughout and detection limits are
240 low. However, the radiometric signal is only as relevant as the rocks it traverses. Therefore we multiply the
241 L3 products by the OQF (excluding the mapping scale adjustment). Level 1 data richness is defined, on a cell-
242 by-cell basis, by the inverse of the line spacing of the highest resolution survey to intersect that cell. This is
243 multiplied by the combined L2/L3 data richness to yield total radiometric data richness.

244 Data richness for magnetic data is defined using similar principles to those applied to the radiometric data.
245 L3 descriptors describe the total gradient magnitude using the analytic signal, and its arc-tangent. The
246 former accounts for the use of amplitude dependent images (e.g. vertical derivative (Hood, 1965)), whereas
247 the latter accounts for the use of amplitude independent images (e.g. tilt (Miller and Singh, 1994)). These are
248 combined with equal weighting in this case. For L2, a sample quality descriptor is not directly considered, as
249 sampling methods and technologies are similar throughout and detection limits are low. Level 1 data
250 richness is defined by the inverse of the line spacing of the highest resolution survey to intersect that cell.
251 This is multiplied by the combined L2/L3 data richness to yield total magnetic data richness.

252 Finally, we consider regional ground gravity data. For L3 we use the analytic signal as in magnetic data but
253 omit the amplitude independent arctangent operator. For L2 we must consider the accuracy of the gravity

254 data which have been collected over several decades and with differing technologies. The Geophysical
 255 Archive Data Delivery System (GADDs) database includes a station error (Wynne and Bacchin, 2009), and we
 256 use this to describe the quality of individual measurements. For L1 we use the kernel density operator,
 257 weighted by station error, with a radius of 20 km. The data density of the gravity data shows a log-normal
 258 distribution, with very detailed surveys around some mining areas, and > 10 km spaced data in others, and
 259 so the logarithm was taken. This composite L1/L2 product was multiplied by the L3 gradient magnitude to
 260 provide the full gravity data richness map.

Category	Proxy Map	Basis	Quality Assignment	Process	Sub-weight	Overall weight
Outcrop Geology	OQF	Presence and relevance of outcrop	OQF: Archean /Proterozoic = 1; Paleozoic/Mesozoic = 0.5; Cenozoic = 0 Map Scale: 100K: OQF x 1; 250K: OQF x 0.4	Kernel density of OQF points R = 5 km	1	0.45
Drillcore Geology		Presence and usefulness of drillcore	Depth-proportional	Kernel density of core locations R = 5 km	1	0.05
Geochemistry		Presence and usefulness of geochemistry data	By sample type: Regolith (ex Sand) = 1; Hard-Rock = 0.5; Sand = 0.25	Kernel density of sample locations R = 5 km	1	0.05
Radiometrics	Slope	Overall rates of radiometric changes	NA	"Slope" function applied to normalised U, Th and K channels and added together	0.75	0.1
	Distance	Deviation from mean	NA	Cumulative "distance" from the U-Th-K centroid	0.25	
	Line Spacing	Amount of data per unit area	Select Highest Resolution Survey at each location	Inverse of Line Spacing Multiply by combined Slope + Distance	1	
	Outcrop Mask	Null values where no outcrop	Outcrops as per OQF, without map scale component.	Multiply by OQF	1	
Magnetics	Gradient Magnitude	High gradient magnitude indicates interpretable signal	Analytic signal describes gradient content (amplitude dependent) Analytic signal arctangent describes gradient content (amplitude independent)	Analytic signal added according to weighting factor Analytic signal arctangent added according to weighting factor	0.5 0.5	0.25
	Line Spacing	Amount of data per unit area	Select Highest Resolution Survey at each location	Inverse of Line Spacing Multiply by Gradient Magnitude	1	
Gravity	Data Density	Amount of data and its precision per unit area	Quality assigned by station error from GADDs	Kernel Density of station locations, R= 20 km Log applied	1	0.1
	Gradient Magnitude	High gradient magnitude indicates interpretable signal	Analytic Signal describes gradient content (amplitude dependent)	Multiply by Data Density	1	

261

262 *Table 1: Basis, assignment, and processing of data richness products for each data type used in this study.*

263 The final process is to aggregate all of these data richness indicators for individual data streams into a single
 264 image. This aggregation could use methods such as fuzzy logic or machine learning should the data sets and
 265 purpose warrant these methods. For example, redundancies between data sets might warrant a fuzzy OR
 266 operator whereas interdependent data sets might warrant a fuzzy AND operator. Following Aitken (2013),
 267 we consider in this case that our data sets are sufficiently independent that a weighted sum was adequate.
 268 Weightings were defined on the level of usefulness of these data to define near surface geology. Outcrop,
 269 where it exists, is considered the premium data set and is weighted at 0.45. Magnetic data is considered
 270 very valuable in mapping beneath cover, and is assigned a weighting of 0.25, whereas radiometric data is
 271 reduced to 0.1 due to its limitations in areas lacking outcrop, and partial redundancy with outcrop data.
 272 Gravity is given a weighting of 0.1 due to low resolution through most of the study area. For this regional
 273 mapping exercise, drillcore and geochemistry were given low weightings (0.05) due to the sparseness of core
 274 in the former case, and the limited correlation with "geology" in the latter. Of course these may be weighted
 275 differently in studies undertaken with a different purpose.

276 Data Richness in the Capricorn Orogen

277 The mapping process described above provides an image of data richness within the Capricorn Orogen of
278 central Western Australia (Figure 2). This map is targeted to the process of producing a revised regional map
279 of near surface geology (Figure 3), and describes, to an extent, the opportunity provided to the interpreters
280 to make correct interpretations. Low data richness implies that the map was made from few relevant data,
281 or data of low quality, whereas high data richness indicates an abundance of good and useful data.

282
283 *Figure 2: Relative data richness in the Capricorn Orogen region, including richness estimates for outcrop*
284 *geology, geochemistry, magnetic, radiometric, gravity and drillcore data (see Table 1). The white line*
285 *indicates the boundary of the remapped region (Fig. 3). The black box indicates the Bryah Sub-basin case*
286 *study area (Fig 4).*

287 The Pilbara Craton, Gascoyne Province and Bryah Sub-basin regions are all relatively data rich, whereas the
288 Yilgarn Craton and the Ashburton and Earaheedy Basins have more variable data richness, ranging from
289 quite low to locally high. The Bangemall Basin in the central orogen is less well served by current data sets,
290 especially in the east. The Phanerozoic Officer and Carnarvon Basins also have low data richness in this
291 analysis due to the lack of information pertaining to Proterozoic basement geology although this does not
292 imply low data richness in general.

Figure 3: Simplified interpreted bedrock geology of the Capricorn Orogen. The black box indicates our Bryah Sub-basin case study area (Fig 4)

Applications: Data Richness in exploration decision making

Based on the exploration decision process and the concepts outlined above, exploration success demands, in the first phase, sound judgements of the level of risk and potential reward associated with areas for exploration and, in the second phase, a sound judgement regarding which data types are most likely to lead to improved knowledge.

In this section we demonstrate an approach that combines data richness with past exploration data and also a prospectivity model to assist in these two phases of decision making. We apply this mapping method in a case study of the Bryah Sub-basin region, which has relatively high data richness. We focus on gold exploration for which there is a suitable history of past and current exploration (Fig. 4). Although we use real data, our purpose is to illustrate the method, rather than to provide a genuine assessment of exploration potential, for which our data sets are not sufficiently detailed.

Figure 4. Reclassified past exploration data in the Bryah Sub-basin Region. Interpreted bedrock geology is coloured using the same legend as Figure 3. MINEDEX entries (gold only) were selected with the 1:100 000 map sheets shown (red boxes) and are reclassified as described in the text. Sizes of all symbols indicate known endowment, including current resource and reserve estimates and past production. Italicised letters indicate particular projects: L - Labouchere; F - Fortnum; PH - Peak Hill; NS - North Star; H - Hermes.

Past exploration data in the Bryah Sub-basin region

A common approach to understanding belt-scale mineral endowment is to conduct a power-law analysis to predict whether there is "missing" endowment relative to the largest deposit, which is often among the first discovered (Fallon et al. , 2010, Guj, Fallon, 2011, Lisitsin et al. , 2014, Lisitsin et al. , 2010, Yigit, 2012). In our case we are mapping spatial variations in endowment within a belt, and so a different approach is needed. To conduct this analysis, we use the public domain mines and mineral deposits database, MINEDEX (GSWA, 2018) to define resources within the belt. We select only entries listed with gold as the target commodity and limit the area to the following 1:100 000 scale map sheets: Moorarie, Padbury, Milgun, Jamindi, Bryah, Glengarry, Doolgunna (Fig. 4)

MINEDEX separates the record of resources and their development into several categories, including occurrences, prospects, deposits and mines. Occurrences and prospects represent two stages of exploration; an occurrence being recorded where economic minimum cut-off limits for minerals are exceeded, and a prospect being recorded in the case of a number of significant intersections of mineralisation. Once a

327 maiden resource has been released by a company, the prospect is upgraded to a deposit. Mines include a
328 number of stages, including proposed, under development, operating, care and maintenance, and shut.

329
330 *Figure 5 Resource Rate within the Bryah Sub-basin Region as defined from MINEDEX data. MINEDEX symbols*
331 *are coloured as per Figure 4. This measure indicates the rate of resource discovery (E) relative to exploration*
332 *activity (n).*

333 For our analysis, we reclassify the MINEDEX entries into four categories that describe the intensity of past
334 exploration and the level of success recorded within any particular area. The first category, "Fire",
335 represents evidence of ongoing exploration success, whereas the second, "Smoke", indicates evidence of
336 potential future success, but not current success. The third, "Ashes", represents evidence of past exploration
337 success, whereas the fourth, "Cinders", represents evidence of past activity but not at substantial levels.
338 Thus, we consider "Fire" and "Ashes" representative of recent and past success, respectively, whereas
339 "Smoke" and "Cinders" are representative of exploration activity (recent and past, respectively).

340 "Fire" includes deposits and mines with an unmined resource estimate exceeding 200 kg contained Au
341 (approximately 7000 oz). Resource estimates include gold contained within resources and reserves from
342 MINEDEX. The cut-off value is defined by the deposit with the lowest resource estimate (the Blake deposit,
343 part of the Hermes Project), and excludes the small leftover resources associated with some shut mines. This
344 yields 31 "Fire" sites including at Hermes, Peak Hill, and Fortnum (Fig 4). These have a cumulative

345 endowment of 106 071 kg Au. "Smoke" includes all prospects and occurrences, as well as deposits with no
 346 resource estimate. A total of 190 smoke records are generated (Fig 4).

347 "Ashes" includes all significant past production from care and maintenance or shut mines. A cut-off of
 348 significant production is imposed at 1400 kg Au (50,000 oz). Within all of MINEDEX, this cut-off includes the
 349 top 210 mines (thus excluding the remaining 9421 locations), from which 93% of past production was
 350 derived. In the case study, four records are included in the ashes category, namely Fortnum (18 477 kg Au),
 351 Labouchere (6 949 kg Au), Peak Hill (20 572 kg Au) and North Star (7 017 kg Au). "Cinders" includes all other
 352 past production from care and maintenance or shut mines, with 227 records returned (Fig 4). The cinders
 353 category has a cumulative past production of 3 430 kg Au.

Descriptor	Conceptual Basis	Derivation
Resource Rate	Resource endowment relative to activity.	$RR = \frac{E}{n}$
Strike Rate	Ratio of success to activity	$SR = \frac{F + A}{n}$
Currency	Ratio of recent activity to total activity	$C = \frac{F + S}{n}$
Positivity	Ratio of recent success to recent activity	$P = \frac{F}{F + S}$
Freshness	Ratio of "in ground" resources relative to all resources	$Fr = \frac{E_F}{E}$
Resource Potential Rate	Ratio of "in ground" resources relative to activity	$RPR = \frac{E_F}{n}$

354 *Table 2: Descriptors of resource endowment and past exploration history from reclassified MINEDEX data. E -*
 355 *resource endowment from all sites, n – number of sites, F – number of Fire sites, A – number of Ashes sites, S*
 356 *– number of Smoke sites, E_F – resource endowment within Fire sites.*

357 From these reclassified MINEDEX entries, we derive several descriptors of resource potential (Table 2).
 358 These are calculated for defined areas, and in this case we use a 5 km by 5 km graticule. Firstly, we define
 359 the *Resource Rate* (Figure 5) as the total endowment (E - including all production, plus resources and
 360 reserves; see Supplementary Figure 1) divided by the number of MINEDEX entries (hereafter, *n*; see
 361 Supplementary Figure 2). This parameter describes the overall rate of resource discovery relative to activity,
 362 and is highest in frontier regions with few entries.

363 In addition we define several measures that describe the state of past exploration in the area. *Strike Rate*
 364 (Supplementary Figure 3) is defined by the number of successes ("Fire" and "Ashes" entries) divided by *n*.
 365 This describes the overall rate of success relative to activity. *Currency* (Supplementary Figure 4) is defined by

366 the number of recent sites ("Fire" and "Smoke" entries), divided by n . This is intended to describe the
 367 amount of recent exploration activity relative to past activity. *Positivity* (Supplementary Figure 5) is defined
 368 by the number of "Fire" entries divided by the number of recent sites ("Fire" and "Smoke" entries) indicating
 369 the rate of success in recent times. *Freshness* (Supplementary Figure 6) is defined by the resources contained
 370 within "Fire" entries divided by the total resources, E . This descriptor indicates the degree to which
 371 significant resources remain, with potential to be mined. Finally, we define *Resource Potential Rate*
 372 (Supplementary Figure 7) as the *Resource Rate* multiplied by the *Freshness*, to indicate the areas with the
 373 greatest amount of unmined resources relative to overall activity.

374
 375 *Figure 6 Overall data richness in the Bryah Sub-basin Region, also showing MINEDEX data, coloured as per*
 376 *Figure 4.*

377 These descriptors of past exploration activity define only what has been done, and it is important to
 378 recognise the degree to which this may have been enabled or inhibited by the availability of useful data. In
 379 our first application of data richness mapping, we consider how combining the record of past exploration
 380 with data richness may provide a meaningful tool to assist in ground selection.

381 [Application 1: A simple data based classifier for ground selection](#)

382 As a simple decision making tool we propose the following classification scheme for ground selection, based
 383 on a) data richness and b) the degree of past success relative to exploration activity (the *Resource Rate*) (Fig

384 7). Although many schemes could be used to classify this, we define four conceptual zones, defined as
385 follows:

- 386 1. Little explored: Low data richness and low resource rate (or no exploration data)
387 2. Under explored: Low data richness and high resource rate
388 3. Well explored: High data richness and high resource rate
389 4. Over explored: High data richness and low resource rate (or no exploration data)

390

391 *Figure 7 A simple 2D ground classification based on resource endowment rate and data richness*

392 The first category has high potential for new data to aid discovery, and may be highly rewarding should there
393 be a large deposit. However the probability of success is low, and low knowledge levels lead to an
394 exploration environment containing high technical risk. The second category is potentially the most
395 promising, with a large opportunity for new data to aid discovery, but also with some demonstrated success.
396 This can be used to establish an exploration strategy characterised by lower technical risk of failure, although
397 the largest deposits are commonly discovered in the early stages (Guj, Fallon, 2011). The third category has
398 more limited potential for new data to aid decision making and discovery, although it may provide low
399 technical risk opportunities with good data already available, and so may provide success over a relatively
400 short term. The last provides limited opportunity for new data to aid discovery, and has not demonstrated
401 success in the past. In this last case, it is possible that, despite high data richness, the region may not have
402 been explored thoroughly for the commodity of interest, and so may preserve potential. This may occur as a
403 consequence of a focus on a narrow mineralisation style or a specific commodity, or due to a cultural or
404 administrative restriction on exploration. We do not consider these influences here, although we note that
405 they could be accounted for in most cases.

406

407 Data richness in the Bryah Sub-basin region (Fig 6) has a positive skewed and weakly bimodal distribution,
 408 and we set the cut-off for high data richness at the higher modal peak (0.5). This limits the "data rich" areas
 409 to quite a small proportion of the map area (16%). For Resource Rate, the distribution is close to a power-
 410 law distribution and the cut-off was set at the onset of significant upward curvature (~ 40). This limits the
 411 resource rich areas to a very small proportion of the map area (2 %).

412 The resulting classification (Fig 8) indicates much of the map is classified as "little explored". It is appropriate
 413 for such regions to consider new data collection to support predictive targeting approaches as part of a
 414 "greenfields" exploration strategy. Along the main ranges, which have substantial outcrop, the region is
 415 predominantly classified as "over explored". New data collection for such regions is perhaps not warranted
 416 and it may be preferable to release such ground. Any data collection should focus on supporting a predictive
 417 approach (Hronsky and Groves, 2008).

418
 419 *Figure 8: A simple classification of resource potential and data richness in the Bryah Sub-basin Region.*
 420 *MINEDEX data are shown with the same colouring as Figure 4.*

421 A few small areas are classified as "well explored", notably the regions around Fortnum and Peak Hill.
 422 Opportunities for new gold deposits in these regions may be limited, but it is appropriate to consider new
 423 data collection to support a "brownfields" exploration strategy. Finally the classification highlights a few
 424 regions which are "under explored" including around Hermes, in the Horseshoe Range and in the extended

regions of Labouchere, Fortnum, and Peak Hill. It is appropriate for such regions to consider new data collection to support the transition from prediction based to detection based targeting (Hronsky and Groves, 2008, McCuaig and Hronsky, 2014, McCuaig, Beresford, 2010).

Application 2: Coupling data richness with prospectivity analysis for enhanced classification

It is becoming common practice to include quantitative models of mineral prospectivity within the exploration workflow, and so we consider here how this might be combined with the data based classification above. Mineral resources data, data richness and prospectivity modelling are complementary methods and should be analysed in a coupled fashion, but with clear separation. We achieve this by considering each an axis of a 3 dimensional model space (Fig 10). Although there is an implicit orthogonality between these axes, interdependencies and redundancies will exist between them. Not least is the requirement that good data is needed for an accurate prospectivity analysis, with the consequence that low resolution data will underestimate variations in prospectivity, and show less correlation with mineralisation (Ford and McCuaig, 2010, Lindsay, Aitken, 2016). In addition, data is likely to be clustered around existing deposits, and knowledge from those deposits is often used in defining the prospectivity model workflow (Porwal and Kreuzer, 2010).

440

Figure 9: 3D classification based on data richness, modelled prospectivity and mineral resources data. Each face defines a knowledge plane with four classes. The data plane classes are LE – Little Explored, OE – Over Explored, UE- Under Explored, WE – Well Explored (see Fig 7); the prospectivity plane classes are LP – Low Prospectivity, URP – Unrealised Prospectivity, UXP – Unexplained Prospectivity, RP – Realised Prospectivity (Supplementary Figure 8); finally, the exploration plane classes are KL – Knowledge Limited; DL – Data Limited, PL – Prospectivity Limited, and EL – Exploration Limited (Supplementary Figure 9). These combine to give eight categories of exploration potential. See text for discussion of these and the categories defined.

448 Adding a prospectivity model to the classification, leads to three distinct planes (Fig 9), which we define as
449 the data plane, the prospectivity plane and the exploration plane. The data plane describes the extent to
450 which the region is known from data, and it is defined and classified as in the previous application (Figure 7).
451 The prospectivity plane describes prospectivity from models and data, and is comparable to conventional
452 methods for interpreting prospectivity models relative to endowment. Classes describe the relationship
453 between the prospectivity model and the exploration data (Supplementary Figure 8). The exploration plane
454 describes the limiting factors for further exploration success. The four states defined are knowledge limited,
455 where knowledge level is too low to define possibilities; data limited, where the availability of exploration
456 relevant data is the dominant limiting factor; prospectivity limited, where lack of apparent potential (or poor
457 model knowledge) is the dominant limiting factor; and exploration limited, where neither data nor model
458 prospectivity limits potential, but exploration opportunities may be limited by other factors (Supplementary
459 Figure 9).

460 From this, eight classes can be defined for a more thorough description of exploration potential (Fig 9). The
461 lower tier lacks mines and deposits (at least relative to prospects/occurrences) and can be categorised as
462 follows:

- 463 1. Undefined potential describes regions where little is known, and basic data collection may be
464 needed to better understand the mineral system and its opportunities.
- 465 2. Unrealised potential describes regions where, despite low data richness and few known resources,
466 high potential is suggested by the prospectivity model. This region may present good opportunities
467 for new discoveries.
- 468 3. Low potential describes regions where, despite high data richness, prospectivity is low and known
469 resources are few. Unconventional opportunities may exist, however.
- 470 4. Undeveloped potential indicates regions with high data richness and high model prospectivity, but
471 few known resources. Exploration activity may be restricted, or these regions may be characterised
472 by subeconomic mineralisation.

473 In the upper tier, substantial deposits exist. Categories in the upper tier are as follows:

- 474 5. Unexplained potential is where existing deposits are not well described by the prospectivity model,
475 but are in areas with low data richness. In this case data collection should focus on delineating the
476 components of the existing mineral system
- 477 6. Unsupported potential is where high prospectivity is associated with deposits, but data richness is
478 low. In these cases new data are needed to build support for the discovery of new deposits
- 479 7. Anomalous potential indicates deposits that exist despite low prospectivity and high data richness.
480 In these cases a better model of the mineral system is needed.

481 8. Realised potential indicates where all elements are high, indicating a mature exploration region.

482 Opportunities may exist for brownfields exploration and satellite deposits.

483 Recent studies have undertaken prospectivity analyses for the Bryah Basin region (Occhipinti, Lindsay, in
484 prep), using a knowledge based method similar to previous works (Lindsay, Aitken, 2016, Occhipinti,
485 Metelka, 2016). From this study we extract a gold prospectivity analysis suitable for the Bryah Sub-Basin gold
486 mineral system. We consider this analysis to be representative of the potential of the region to have
487 experienced ore forming processes, but not necessarily the capacity for economic deposits to be present.
488 Within each 5 km cell, we take the maximum value of the prospectivity model found in that cell to represent
489 its value. Then, for classification, we apply a cut-off at 0.14, representing half the maximum observed value
490 within the analysis, and classify into high and low prospectivity on that basis.

491 Application of this 3D classification to the Bryah Sub-Basin region (Figure 10) provides further definition of
492 the exploration opportunities within the region. Mineral exploration potential over three quarters of the
493 region is classified as “undefined” with “low potential” also common in several parts of the region.

494 Unrealised potential is found in some areas, often in regions with existing deposits, but also in some new
495 areas. Undeveloped potential is also found, associated with better exposed regions with many prospects
496 and occurrences, but few deposits (Fig 10).

497 In areas with deposits, realised potential is found at Peak Hill and at Nathans, whereas unsupported
498 potential is found in regions around Hermes, Fortnum, Horsehoe Range, Wilgeena, Harmony and Harrods
499 (Fig 10). A few unexplained and anomalous potential results are returned, mostly associated with small
500 deposits (e.g. Homestead, Bloodstone, Durack) but also the large mine at Labouchere. All these are located
501 on the fringes of the basin, close to large regions of extensive cover, low data richness, and undefined
502 potential (Fig 10). These anomalous results may therefore be explained by the limited resolution and
503 accuracy of the prospectivity model in low data richness areas, rather than any systemic deficiency in the
504 model.

Figure 10: 3D classification applied to the Bryah Basin region, including a prospectivity model. Eight categories are defined showing exploration opportunities within the region, see text for definitions. L – Labouchere, N – Nathans, F – Fortnum, HR - Horseshoe Range, PH – Peak Hill, He – Hermes, Ho – Homestead, Hd – Harrods, Ha - Harmony, D – Durack, W – Wilgeena, B – Bloodstone. The Yellow Box indicates the Peak-Hill/Hermes Region (see Figure 11)

Application 3: A tool for data value comparison

A key question remains as to the types of new data that are most likely to lead to further success. The data richness mapping approach can be used to define, within potential target areas, which data sets are below the regional standard. As an example, we examine the components of data richness in the Peak Hill – Hermes region (Fig 11), which preserves a contrast between the historic Peak Hill exploration area and some frontier regions, including the sizeable deposit at Hermes. With our public domain data, drillcore data richness is limited to one cell. The impact of new drilling is not discussed further here, although drilling programs are of course a substantial component of undercover exploration. Gravity data have relatively consistent spacing (2 km), and most of the variability is due to contrasts in L3 data richness. New data would potentially be of benefit in high signal strength regions in the south and north.

The Peak Hill region contains the largest historic gold production within the region, from a main mine group and a number of smaller satellite mines and deposits. The data richness around Peak Hill is high, owing to

523 abundant outcrop and high quality airborne geophysical data with strong signals. Consequently, the
 524 immediate surrounds of the Peak Hill region are classified as "well explored" (Figure 8) and have "realised
 525 potential" (Figure 10), consistent with an exploration history extending back to 1897 (Armstrong et al. ,
 526 1970).

528 *Figure 11: Ensemble of data richness elements in the Peak Hill/Hermes region. Top Row: a) overall data*
 529 *richness with a colour scale as per Figure 6 b) Resource Rate with a colour scale as per figure 5 c) 3D*
 530 *classification, with colour scale as per Figure 10. MINEDEX data are shown on a), b) and c) with colours as per*
 531 *Figure 4. Middle Row: d) outcrop data richness, with outcrop outlines in black e) geochemistry data richness*
 532 *with sample locations shown including weighting (W), f) drillcore data richness with collar locations (stars).*
 533 *The relative magnitudes of d, e, and f each use the colour scale at the right hand side. Bottom Row: g)*
 534 *radiometric data richness with outcrop outlines in black, h) magnetic data richness, i) gravity data richness.*
 535 *Classified magnitudes of g,h, and i each use the colour scale at the right hand side. See Fig 10 for location. Ha*
 536 *- Harmony Mine (shut), E - Enigma deposit, D - Durack deposit, PH -Peak Hill Group, W - Wilgeena Mine*
 537 *(shut), H - Hermes Group*

538 Both data richness and exploration success reduce away from Peak Hill leading to areas that are "little
 539 explored", with "unrealised potential" and for which new data might benefit exploration. Most of the
 540 reduction in data richness reflects reducing outcrop, and a corresponding increase in Cenozoic cover,
 541 perhaps causing the reduction in exploration success. The region to the south and west hosts the Harmony

mine (Resource – 3 566 kg Au), the Enigma deposit (Resource – 2 069 kg Au) and the Durack deposit (Resource – 3 484 kg Au). Harmony is situated within an "under explored" region with "unsupported potential". Durack and Enigma occur in regions classified as "well explored" and with "anomalous potential" and "realised potential" respectively. It should be noted that with data richness values of 0.52 and 0.55, respectively, they are very close to the cut-off. Data collection within the immediate vicinity of deposits may focus on more directed targeting datasets, not considered here, consistent with their classification (Fig 11). The large region to the southwest is classified as "little explored" and with "undefined potential". This southwestern frontier is fairly well served by geophysical surveys but has in places low data richness due to weak signals (Fig 9h,i). Low data richness exists for geochemistry data due to poorly distributed sampling, and improvements to that data set are likely to be most beneficial to regional exploration in this area.

The region north and east of Peak Hill possesses no deposits and low data richness, but is in part classed with "unrealised potential". This region has little outcrop, and is served only by low resolution magnetic and radiometric data (400m), although geochemical and gravity data richness are each relatively high. Therefore, for this region, improvements to the airborne geophysical data coverage may be of most benefit to regional exploration.

In the south of the region, Wilgeena mine (Resource - 1543 kg Au) sits in a region classified as "under explored" with "unsupported potential". Data richness is 0.49 so, like Durack and Enigma, this is close to the threshold. The surrounding region is classified with "undeveloped potential" to the east and west, but "unrealised potential" to the north. Data richness is moderate for outcrop and is mixed for magnetic and radiometric data, with 50m spacing in the south but just 400m spacing in the north. Geochemistry data richness is low due to a lack of samples. Further regional exploration in this region, in particular the region to the north, might benefit most from upgrading the airborne geophysical and geochemistry data coverage.

The Hermes region is different to Peak Hill in that there is no significant historic production, but there is a significant group of deposits, with a combined MINEDEX resource estimate exceeding 19 000 kg Au (approx. 670 000 oz). Data richness is high in the southeast, where substantial outcrops and high resolution airborne geophysical surveys (50 m) both exist, and the region is classified with "undeveloped potential". Hermes itself is situated within an area of low data richness, classified as "under explored" and with "unsupported potential". In the context of new data, the deposit proximal region has good geophysical coverage, but overall low magnetic data richness due to fairly weak gradients, and low radiometric data richness due to lack of outcrop. Chemistry data richness is also low, with few data within the region. It is likely, therefore, that the most valuable data to improve data richness within the deposit proximal region is additional geochemistry.

574 The region to the west is classified as “little explored” with “unrealised potential” and is perhaps
575 prospective. This region is strongly deficient in several data types, including geochemistry, for which there is
576 a distinct data gap, and high resolution airborne geophysical data are not available (existing data are 400 m
577 spaced). Improvements to these data types are likely to be of most benefit to exploration in this region.

578 The decision to collect new data includes, as outlined above, the option to collect more detailed, more
579 extensive or higher accuracy surveys of the same data types already analysed. In these cases, the existing
580 data richness map can be used to guide the collection of the new survey. Moreover, the mapping process
581 can be repeated to quantify the influence of new data collection. Alternatively, options exist to collect other
582 data types that were not used in the original analysis. Strictly, the current data richness map provides no
583 information on these new data types, and to include them the mapping process must be reconfigured at
584 level 4 to take account of the new data, their value, and relationships with other datasets. In practice,
585 redundancies and interdependencies between data types may allow data richness to be used to avoid
586 redundancy and maximise benefit during planning.

587 Conclusion

588 Successful exploration is contingent upon some key decisions including ground selection and the choice of
589 data to collect in an attempt to improve baseline knowledge, to develop predictive capacity, and/or to
590 improve detection capability. Each of these decisions depends on a knowledge of existing data and its
591 quality, as well as what data might be most useful to build further knowledge. In our experience of
592 exploration practice such matters are implicitly considered from a heuristic standpoint, but it is not common
593 to approach this process in an explicit and numerically rigorous manner.

594 Here we have demonstrated an approach for semi-automated mapping of data richness that can be applied
595 without undue difficulty and using commonly available GIS tools. Using a case study of gold exploration in
596 the Bryah Sub-basin, Western Australia, we demonstrate three ways in which this approach can be used to
597 support decision making. The first application is as a simple data based classifier for ground selection,
598 considering both data richness and past exploration data. The second application combines this with a
599 prospectivity model to further characterise exploration potential in the region. The third is a data value
600 comparison that highlights those data sets that are relatively deficient, with a view to collecting the most
601 effective additional data.

602 Due to the static natures of the regional data sets used here, we were not able to map changes in data
603 richness and endowment through time. However, the data richness mapping process could easily be used in
604 a time-lapse manner, with repeated analyses following data collection programs, so long as the data set
605 types remained constant. This would allow the growth of knowledge surrounding the project to be mapped
606 through time, and might help identify data streams that are, or are not, proving effective. Indeed, at least

for L1 and L2 data richness, this step could be applied prior to a data collection program to help determine the optimum spacing and target precision. Adding completely new data types, or combining or splitting data richness elements, require a reconfiguration of the mapping process based on the value of the new data and its interdependencies and redundancies with other data types.

In each of these applications, a role is presented for data richness mapping that can support decision making. The first exploration phase involves selecting favourable and unfavourable regions according to the requirements of the organisation. Our case study demonstrates how this process can be aided by comparing the potential benefit of new data collection against the past record of resource discovery and models of prospectivity. The second phase involves collecting the data most likely to be of benefit to exploration, perhaps emphasising prediction or detection depending on the scale of the study and the maturity of the region. With our approach, deficiencies in data can be recognised and, if deemed worthwhile, rectified. Following or even preceding data collection programs, the impact of these data on data richness can be compared with the cost of collection, and the effectiveness of different methods can be enumerated. When combined with other indicators of exploration risk and potential reward these measures have a significant role to play in making sound exploration decisions more easily.

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References

- Aitken ARA, Holden EJ, Dentith MC. Semiautomated quantification of the influence of data richness on confidence in the geologic interpretation of aeromagnetic maps. *Geophysics*. 2013;78:1-13.
- Armstrong A, Armstrong F, Wilson L. The biography of William John Wilson : discoverer of the Peak Hill Goldfields, Western Australia; and, Early history of Peak Hill.1970.
- Bagstad KJ, Semmens DJ, Waage S, Winthrop R. A comparative assessment of decision-support tools for ecosystem services quantification and valuation. *Ecosystem Services*. 2013;5:e27-e39.
- Binns P, Corbett P. Risk and uncertainty from frontier to production - A review. *First Break*. 2012;30:57-64.
- Crossman ND, Burkhard B, Nedkov S, Willemsen L, Petz K, Palomo I, et al. A blueprint for mapping and modelling ecosystem services. *Ecosystem Services*. 2013;4:4-14.
- Czarnota K, Blewett RS, Goscombe B. Predictive mineral discovery in the eastern Yilgarn Craton, Western Australia: An example of district scale targeting of an orogenic gold mineral system. *Precambrian research*. 2010;183:356-77.

642 Eidsvik J, Ellefmo SL. The Value of Information in Mineral Exploration Within a Multi-Gaussian Framework.
643 Mathematical Geosciences. 2013;45:777-98.

644 Fallon M, Porwal A, Guj P. Prospectivity analysis of the Plutonic Marymia Greenstone Belt, Western
645 Australia. Ore Geol Rev. 2010;38:208-18.

646 Ford A, McCuaig TC. The effect of map scale on geological complexity for computer-aided exploration
647 targeting. Ore Geol Rev. 2010;38:156-67.

648 GSWA. MINEDEX. Perth, Western Australia: Department of Mines, Industry Regulation and Safety,
649 Government of Western Australia; 2018.

650 Guj P. A practical real option methodology for the evaluation of farm-in/out joint venture agreements in
651 mineral exploration. Resources Policy. 2011;36:80-90.

652 Guj P, Fallon M, McCuaig TC, Fagan R. A Time-Series Audit of Zipf's Law as a Measure of Terrane Endowment
653 and Maturity in Mineral Exploration. Economic Geology. 2011;106:241-59.

654 Hood P. Gradient Measurements in Aeromagnetic Surveying. Geophysics. 1965;30:891-902.

655 Hronsky JMA, Groves DI. Science of targeting: Definition, strategies, targeting and performance
656 measurement. Australian Journal of Earth Sciences. 2008;55:3-12.

657 Joly A, Porwal A, McCuaig TC. Exploration targeting for orogenic gold deposits in the Granites-Tanami
658 Orogen: Mineral system analysis, targeting model and prospectivity analysis. Ore Geol Rev. 2012;48:349-83.

659 Journel AG. Combining knowledge from diverse sources: An alternative to traditional data independence
660 hypotheses. Mathematical Geology. 2002;34:573-96.

661 Knox-Robinson CM. Vectorial fuzzy logic: A novel technique for enhanced mineral prospectivity mapping,
662 with reference to the orogenic gold mineralisation potential of the Kalgoorlie Terrane, Western Australia.
663 Australian Journal of Earth Sciences. 2000;47:929-41.

664 Kreuzer OK, Etheridge MA, Guj P, McMahon ME, Holden DJ. Linking Mineral deposit models to quantitative
665 risk analysis and decision-making in exploration. Economic Geology. 2008;103:829-50.

666 Li CY. The more, the better? Why abundant information leads to unanticipated outcomes. Telematics and
667 Informatics. 2016;33:834-47.

668 Lindsay M, Aitken A, Ford A, Dentith M, Hollis J, Tyler I. Reducing subjectivity in multi-commodity mineral
669 prospectivity analyses: Modelling the west Kimberley, Australia. Ore Geol Rev. 2016;76:395-413.

670 Lindsay MD, Betts PG, Ailleres L. Data fusion and porphyry copper prospectivity models, southeastern
671 Arizona. Ore Geol Rev. 2014;61:120-40.

672 Lisitsin VA, Dhnaram C, Donchak P, Greenwood M. Mossman orogenic gold province in north Queensland,
673 Australia: regional metallogenic controls and undiscovered gold endowment. Mineralium Deposita.
674 2014;49:313-33.

675 Lisitsin VA, Moore DH, Olshina A, Willman CE. Undiscovered orogenic gold endowment in Northern Victoria,
676 Australia. Ore Geology Reviews. 2010;38:251-69.

677 Liu P, Li Z. Task complexity: A review and conceptualization framework. International Journal of Industrial
678 Ergonomics. 2012;42:553-68.

679 Mamuse A, Guj P. Rank statistical analysis of nickel sulphide resources of the Norseman-Wiluna Greenstone
680 Belt, Western Australia. Mineralium Deposita. 2011;46:305-18.

681 McCuaig C, Hronsky J. The Mineral System Concept: The Key to Exploration Targeting. Building Exploration
682 Capability for the 21st Century: Society of Economic Geologists, Inc.; 2014. p. 153-75.

683 McCuaig TC, Beresford S, Hronsky J. Translating the mineral systems approach into an effective exploration
684 targeting system. Ore Geol Rev. 2010;38:128-38.

685 McCuaig TC, Kreuzer OP, Brown WM. Fooling Ourselves - Dealing with Model Uncertainty in a Mineral
686 Systems Approach to Exploration. Digging Deeper, Vols 1 and 2. 2007:1435-8.

687 Miller HG, Singh V. Potential field tilt - a new concept for location of potential field sources. Journal of
688 Applied Geophysics. 1994;32:213-7.

689 Occhipinti SA, Lindsay ML, Aitken ARA, Metelka V, Pirajno F, Joly A, et al. Prospectivity analysis of the
690 Capricorn Orogen, Western Australia – using a Mineral Systems Approach, GSWA Report XXX. Perth:
691 Geological Survey of Western Australia; in prep. p. xx.

692 Occhipinti SA, Metelka V, Lindsay MD, Hollis JA, Aitken ARA, Tyler IM, et al. Multicommodity mineral systems
693 analysis highlighting mineral prospectivity in the Halls Creek Orogen. Ore Geol Rev. 2016;72:86-113.

694 Payne CE, Cunningham F, Peters KJ, Nielsen S, Puccioni E, Wildman C, et al. From 2D to 3D: Prospectivity
695 modelling in the Taupo Volcanic Zone, New Zealand. Ore Geol Rev. 2015;71:558-77.

696 Penney SR, Allen RM, Harrisson S, Lees TC, Murphy FC, Norman AR, et al. A global-scale exploration risk
697 analysis technique to determine the best mineral belts for exploration. Transactions of the Institutions of
698 Mining and Metallurgy, Section B: Applied Earth Science. 2004;113:B183-B96.

699 Perrons RK, Jensen JW. Data as an asset: What the oil and gas sector can learn from other industries about
700 “Big Data”. Energy Policy. 2015;81:117-21.

701 Perrons RK, McAuley D. The case for “n«all”: Why the Big Data revolution will probably happen differently in
702 the mining sector. Resources Policy. 2015;46:234-8.

703 Porwal A, Carranza EJM, Hale M. Knowledge-driven and data-driven fuzzy models for predictive mineral
704 potential mapping. Natural Resources Research. 2003;12:1-25.

705 Porwal AK, Kreuzer OP. Introduction to the Special Issue: Mineral prospectivity analysis and quantitative
706 resource estimation. Ore Geol Rev. 2010;38:121-7.

707 Rodriguez-Galiano V, Sanchez-Castillo M, Chica-Olmo M, Chica-Rivas M. Machine learning predictive models
708 for mineral prospectivity: An evaluation of neural networks, random forest, regression trees and support
709 vector machines. Ore Geol Rev. 2015;71:804-18.

710 Rounsevell MDA, Pedroli B, Erb KH, Gramberger M, Busck AG, Haberl H, et al. Challenges for land system
711 science. Land Use Policy. 2012;29:899-910.

712 Silverman BW. Density estimation for statistics and data analysis. New York: Chapman and Hall; 1986.

713 Speier C. The influence of information presentation formats on complex task decision-making performance.
714 International Journal of Human-Computer Studies. 2006;64:1115-31.

715 Sun Y, Tong C, Trainor-Guitton WJ, Lu C, Mansoor K, Carroll SA. Global sampling for integrating physics-
716 specific subsystems and quantifying uncertainties of CO₂ geological sequestration. International Journal of
717 Greenhouse Gas Control. 2013;12:108-23.

718 Swink M, Speier C. Presenting geographic information: Effects of data aggregation, dispersion, and users'
719 spatial orientation. Decision Sciences. 1999;30:169-93.

720 Thorne RL, Spinks SC, Anand RR, Metelka V, Davis A, Ibrahimi T, et al. Regolith landform processes and
721 geochemical exploration of the Capricorn Orogen, Western Australia. EP 183025 CSIRO, Australia P95. 2018.

722 Trench A, Packey D, Sykes J. Chapter 7. Non-Technical Risks and Their Impact on the Mining Industry.
723 Australian Institute of Mining & Metallurgy Monograph 30 Second Edition 2013. p. 605-18.

724 Tulcanaza E, Ferguson GA. The value of information: A guide to the strategic development of projects
725 founded on mineral resource categorization. Transactions of the Institutions of Mining and Metallurgy,
726 Section B: Applied Earth Science. 2001;110:B126-B35.

727 Vearncombe J, Riganti A, Isles D, Bright S. Data upcycling. Ore Geol Rev. 2017;89:887-93.

728 Whiting T, Schodde R. Why do brownfields exploration? The International Mine Management Conference.
729 Melbourne, Victoria, Australia: Australian Institute of Mining & Metallurgy 2006. p. 41-50.

730 Wood RE. Task complexity: Definition of the construct. Organizational Behavior and Human Decision
731 Processes. 1986;37:60-82.

732 Wynne P, Bacchin M. Index of Gravity Surveys (Second Edition). Geoscience Australia Record 2009/07. 2009.

733 Yigit O. Discovered and undiscovered gold endowment of Turkey: a quantitative mineral resource
734 assessment using GIS and rank statistical analysis. Mineralium Deposita. 2012;47:521-34.

735 Yousefi M, Carranza EJM. Fuzzification of continuous-value spatial evidence for mineral prospectivity
736 mapping. Computers and Geosciences. 2015a;74:97-109.

737 Yousefi M, Carranza EJM. Geometric average of spatial evidence data layers: A GIS-based multi-criteria
738 decision-making approach to mineral prospectivity mapping. Computers and Geosciences. 2015b;83:72-9.

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742 Supplementary Figure 1 - Gold endowment, E (kg), for the 5 km graticule over the Bryah Sub-basin region.

743 Includes past mine production, as well as estimated resources and reserves for mines and deposits.

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746 Supplementary Figure 2 – MINEDEX entries (n) for the 5 km graticule over the Bryah Sub-basin region.

747 Includes all entries with “gold” as target commodity. Gold resources contained in other styles of deposits are
748 not considered.

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750

751 Supplementary Figure 3 – Strike Rate (see Table 2 for definition) for the 5 km graticule over the Bryah Sub-
 752 basin region.

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755 Supplementary Figure 4 – Currency (see Table 2 for definition) for the 5 km graticule over the Bryah Sub-
 756 basin region.

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759 Supplementary Figure 5 – Positivity (see Table 2 for definition) for the 5 km graticule over the Bryah Sub-
 760 basin region.

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763 Supplementary Figure 6 – Freshness (see Table 2 for definition) for the 5 km graticule over the Bryah Sub-
 764 basin region.

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767 Supplementary Figure 7 – Resource Potential Rate (see Table 2 for definition) for the 5 km graticule over the
 768 Bryah Sub-basin region.

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770 Supplementary Figure 9 – Four way classification in the prospectivity plane for the 5 km graticule over the
 771 Bryah Sub-basin region. Red shading shows region with model prospectivity above the cut off value, set at
 772 half the maximum value.

773

774 Supplementary Figure 9 – Four way classification in the exploration plane for the 5 km graticule over the
 775 Bryah Sub-basin region. Red shading shows region with model prospectivity above the cut off value, set at
 776 half the maximum value.