Wong M. T. F., S. Asseng, M. J. Robertson and Y. Oliver 2008. Mapping subsoil acidity and shallow soil across a field with information from yield maps, geophysical sensing and the grower. Precision Agriculture 9, 3-15.

Mapping subsoil acidity and shallow soil across a field with information from yield maps, geophysical sensing and the grower

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Abstract

Management decisions, such as subsoil liming or varying fertilizer inputs to take account of soil depth and anticipated yields require knowledge of where subsoil constraints to root growth occur across the field. We used selected yield maps based on criteria derived from crop simulation, apparent soil electrical conductivity (EC_a), gamma-ray emission maps and a soil type map drawn by the grower to predict the spatial distribution of subsoil acidity and shallow soil across a field. Yield maps

integrate the effects of variation in soil and climate, and it was only under specific seasonal conditions that subsoil constraints depressed yields. We used crop simulation modelling to select yield maps with a large information content on the spatial distribution of these constraints and to omit those with potentially misleading information. Yield and other spatial data layers were used alone or in combination to develop subsoil mapping options to accommodate differences in data availability, access to precision agriculture techniques and the grower's aptitude and preference. One option used gamma-ray spectrometry and EM38 survey as a dual-sensing system to improve data interpretation. Gamma-ray spectrometry helped to overcome the inability of current EC_a -based methods to sense soil depth in highly weathered sandy soil over cemented gravel. A feature of the approaches presented here is the use of grower and agronomist knowledge and experience to help interpret the spatial data layers and to evaluate which approach is most suitable and likely to be adopted to suit an individual.

Keywords: Agricultural Production Systems Simulator (APSIM) · EC_a · Gamma-ray spectrometry · pH · Soil depth

Introduction

Precision agriculture techniques, such as yield, EM38 and gamma-ray emission mapping together with the farmers' and agronomists' knowledge, provide an opportunity to predict the distribution of subsoil constraints such as subsoil acidity and shallow soil at a high spatial resolution. Subsoil acidity is common across the world and 3300 Mha is estimated to have a subsoil pH <4.5 in water (Sumner and Noble,

2003). In Western Australia (WA), about a third of its 18 Mha of arable land is estimated to have an acid subsoil (Davies et al., 2006). Treatment of subsoil acidity by the deep placement of lime uniformly across the whole field is often too expensive and would also induce micro-nutrient deficiencies and loss of yield at mildly acidic to alkaline sites that often occur within the same field. It is important therefore that deep placement of lime is targeted precisely to where it is needed. Direct field measurement and mapping of subsoil properties to allow the targeted application of lime is likely to be impractical and too expensive to be adopted. The spatial structure of these soil properties is often less than 100 m (Mulla and McBratney, 2000). In addition, the engineering challenges to adapt on-the-go technology to map soil pH and lime requirement (Adamchuk et al., 2007) have not been resolved for the management of subsoil acidity. Similar problems occur in characterizing the spatial distribution of shallow soil in some landscapes to adjust inputs such as seed and fertilizer rates according to soil depth.

Current technology to estimate soil depth to a root-impeding layer is problematic in some commonly occurring landscapes. In non-saline shallow soil, an EC_a survey can be used to estimate soil depth to the root-impeding layer if there is sufficient contrast in electrical conductivity between the surface soil and the underlying material. It has been used successfully to estimate for example, depth of a silt loam over a clay pan (Doolittle et al., 1994). Cemented lateritic gravel underlying shallow sandy soil is common in highly weathered landscapes in Australia and elsewhere (McKenzie et al., 2004). The above approach cannot be used in these landscapes as both sandy soil and lateritic gravels have similarly low electrical conductivities in the order of $0\text{--}10\text{ mS m}^{-1}$.

There is, therefore, a need to develop new techniques to locate both subsoil acidity and shallow soil within fields to aid management. These soil conditions often occur as multiple subsoil constraints across the same field.

Yield maps could be used to locate multiple subsoil constraints. A simulation model, such as the Agricultural Production Systems Simulator (APSIM) for crop growth and yield (Keating et al., 2003, <http://www.apsim.info/apsim/>) might provide criteria to enable the selection of yield maps based on years when subsoil acidity and shallow soil are expected to have the greatest depressing effects on grain yields. Simulations by APSIM indicate that in a water-limited Mediterranean-type climate, subsoil constraints have the greatest depressing effect on yield in wet years when there is sufficient rainfall to wet the subsoil, but this water is inaccessible due to limitations on root growth (Wong and Asseng, 2006a, Wong and Asseng, 2007). Yield maps from such years are likely to mirror the spatial distribution of these subsoil constraints. In drier years, the field usually performs more uniformly albeit poorly as there is insufficient water to wet the subsoil. There is less spatial variation and less benefit in roots potentially growing into the subsoil in dry seasons.

Many growers do not have yield maps, but have access to maps of soil type on their land. Grain yield and nitrate leaching are both related to soil type (Godwin and Miller, 2003, Wong et al., 2006) and associated with acidification of the soil (Wong et al., 2004a). In addition, pH buffering capacity also varies with soil type due to differences in clay and organic matter content (Lund et al., 2005). Risk of acidification is likely to vary with soil type. For growers who do not have access to yield or soil type maps,

geophysical sensing commonly used by the mining industry in Western Australia (WA), provides another means of identifying areas of potential subsoil constraint. In deep soil without superficial salt and gravels, EC_a measured by EM38 sensing and gamma-ray emission from the natural ^{40}K abundance of the soil profile are related to clay content in highly weathered soil (Lück et al., 2005, McBratney et al., 2005, Wong and Harper, 1999). Clay content in sandy soil controls plant available soil water capacity (PAWC) and yields (Wong and Asseng, 2006b). It also controls soil pH buffering capacity and the rate of acidification by nitrate leaching and the removal of basic cations in the harvested crop. Our hypothesis is that selected yield maps, maps of soil type and geophysical sensing could be interpreted by the agronomist in collaboration with the grower to locate areas affected by subsoil acidification.

Gamma-ray spectrometry might provide a means of locating shallow soil when EC_a -based methods cannot be used. Soil profiles contain natural radioactive isotopes of potassium, uranium and thorium. Gamma-ray emissions by these radioisotopes can be sensed by ground and airborne instruments and have been used to infer the spatial distribution of soil-forming materials (Cook et al., 1996), soil potassium and clay contents (Wong and Harper, 1999). Lateritic gravels have a small potassium content, reflecting the intense weathering to which the material has been subjected, but are enriched with thorium because of sorption by iron oxide. Sandy soil in these landscapes consists mostly of quartz and has little radioactivity (Cook et al., 1996). We expect that the thorium contents of gravels and sandy soil would provide enough gamma-radiometric contrast to locate shallow soil. The sandy soil layer attenuates gamma-ray emission from the gravel layer and each ~10 cm layer (its half thickness) is

expected to decrease radiation measured at the soil surface by half (Spielberg, 1975). Our second hypothesis is that selected yield maps and gamma-ray emission maps could be interpreted to locate shallow soils.

The aim of this work is to test the two hypotheses mentioned here that (1) selected yield maps, maps of soil type and geophysical sensing could be interpreted by the agronomist in collaboration with the grower to locate areas affected by subsoil acidification and (2) selected yield maps and gamma-ray emission maps could be interpreted to locate shallow soils.

Materials and Methods

The 200 ha experimental field is 350 km north of Perth, at Buntine, WA (116.57°E, 29.99°S). The average (1954-2003) annual rainfall for Buntine is 333 mm, of which 238 mm falls in May to October (growing season). The crops are usually sown in autumn (May-June) and harvested in summer (November-December). The main crops grown were wheat in rotation with lupin and canola. A pasture phase was included in the rotation about every five years. Grain yield was monitored across the field for the period 1996 to 2005. A yield monitor (AgLeader) recorded yield data at intervals of 3 s. The point data were de-spiked and then kriged with the exponential local variogram option of Vesper (Minasny et al., 1999) and the kriged values were imported as a grid into ArcView for viewing and export as images. Vesper computes variograms and was used for all our kriging work. The field was planted with wheat in 1996, 1999, 2001, 2003 and 2005 and given 60 kg N ha⁻¹ at the time of sowing. The May to October

rainfall in Buntine was 285 mm in 1996, 360 mm in 1999, 200 mm in 2001, 250 mm in 2003 and 230 mm in 2005.

We used the crop model APSIM (Keating et al., 2003) to determine the type of season when subsoil constraints, such as acidity and shallow soil over a root-impeding layer, have the greatest limiting effect on wheat yields at such locations. The aim was to select the most informative yield map to locate these constraints across the field. APSIM simulates daily root and shoot growth, and grain yields based on information on daily weather and soil property data. This model simulated wheat yields successfully for different rates of N fertilizer on soil affected by both subsoil compaction and acidity (Asseng et al., 1998, Tang et al., 2003). The model deals with subsoil constraints in general by modifying the rate of root elongation and root length density development. This is achieved by modifying root hospitality factors at specific layers in the affected subsoil (Asseng et al., 1998, Tang et al., 2003, Wong and Asseng, 2007). The root hospitality factors (R_h) decrease potential root growth rates according to the severity of the subsoil constraint. This approach enables APSIM to simulate root growth of wheat at four contrasting locations in WA with measured root depths ranging from 0.05 to 1.3 m. The root mean square deviation (RMSD) of the root depth simulations was 0.13 m across the four sites (Asseng et al., 1998). The corresponding RMSD of simulated wheat yields was 0.4 t ha^{-1} with measured yields ranging from 1.0 to 4.0 t ha^{-1} .

The APSIM simulations for Buntine used long-term daily weather records (1954-2003) to investigate seasonal variation in the effect of medium (R_h decreased to 25% of control) to severe (R_h decreased to 2.5% of control) levels of subsoil constraints.

Details of the simulation experiments and justification for using these R_h values are given by Wong and Asseng, (2007).

The grower produced a map of soil types based on field observations and his knowledge with five readily observable soil types which he named: good sand (loamy sand), medium sand (yellow sand), poor sand (deep white sand), gravels and red clay (red clayey soil). The terrain slopes to a salty creek which diagonally bounds the north west of the field, which is mapped as good sand. He used a GPS to locate soil and field boundaries approximately. This soil mapping approach was chosen because these soil types are easily recognised by local growers because of their colour and the behaviour of the crop that they support.

We measured apparent soil electrical conductivity (EC_a) across the field with electromagnetic induction equipment (*Geonics* EM38) in its vertical dipole mode. Details of the measurements are given in Wong and Asseng (2006b). The EC_a survey was carried out on a 30 m line spacing with a quad bike in June 2004 when the soil was moist with 75 mm rain since the previous month. This line spacing, equivalent to three header widths, minimized interpolation errors during kriging (O'Leary et al., 2004). The EC_a data and exponential local variograms computed by Vesper were used to kriged values to a 5 m grid to produce a map of EC_a . The gamma-ray emission survey was also carried out on 30 m line spacing with an *Exploranium* gamma-ray spectrometer with a large (8 l) thallium activated sodium iodide crystal scintillation detector. This survey was also done on a quad bike, but in February 2004 when the soil was dry to minimise gamma-ray attenuation (Carroll, 1981). The site received only 22 mm rain in

the previous 5 months to February and maximum monthly rainfall was 9 mm. The gamma-ray emission spectra in the range of 0.4 to 2.82 MeV were recorded at 3 s intervals. The spectra were resolved into the individual emissions from potassium, thorium and uranium according to their characteristic peaks. The individual emission data were kriged as above to map the surface counts from potassium, uranium and thorium.

Soil pH in calcium chloride was measured at 83 locations and soil depth at 65 locations across the field from 0 to 200 cm wherever possible and at 10 cm intervals in areas with yields, EC_a and gamma-emission values ranging from low to high. Selection of the locations of soil pH and soil depth measurements was done separately and independently by technical staff and they do not overlap. The pH values reported here were the lowest acidic or highest alkaline values occurring in the 20-40 cm layer. In addition, the topsoil (0-10 cm) at 25 sites was sampled across the field and analysed for bicarbonate extractable phosphorus and potassium and total nitrogen contents.

Results

The effect of a subsoil constraint on wheat yield depends on seasonal rainfall. The smallest effects occur in dry years. In these years, the difference in simulated average wheat yields between the control, medium and severe subsoil constraints is small (Fig. 1). In this low rainfall Mediterranean-type environment, subsoil constraints cause the greatest loss of yield in relation to the control in wet seasons. It is in years with wet seasons that low-yielding areas are more likely to be correlated with areas with subsoil

constraints. A wet year occurred in 1999 (360 mm May to October rainfall) during the period of yield monitoring. We selected the yield map for that year to locate low yielding areas.

Figure 1. Trends of simulated average yields of wheat given 60 kgN ha⁻¹ with seasonal rainfall for control, medium and severe subsoil constraints in Buntine (for details see Wong and Asseng, 2007).

The size and location of low yielding areas measured in Buntine varies temporally (Fig. 2). In the wet year of 1999 when a subsoil constraint was expected to have the greatest yield depressing effect, the fifth lowest-yielding area (0.6-1.3 t ha⁻¹) occurs in the southern part of the field (Fig. 2). This area coincides broadly with areas mapped as poor sand and gravel by the grower (Fig. 2). Only one of the two gravel sites was lowest-yielding in that year. This southern gravel site was consistently low-yielding throughout the period of yield monitoring. The second wettest season was in 1996

(285 mm May to October rainfall). The coefficient of variation of grain yield across the field decreases from 38% in 1999 to 17% in 1996 when subsoil constraints are expected to have less effect on yields. The contrast in yields from the low to high yielding areas is less in 1996 than in 1999, but the low yielding areas are still discernable in 1996 and they also coincide broadly with poor sand and the southern gravel. In 2001, there was little difference in yields on the medium sand, poor sand and gravel which produced the lowest yields for the year. The area of red clayey soil changes from high yielding in 1999, 2001 and 2005 to the lowest yielding in 2003. This lowest yielding area stretches across the red clayey and southern gravel soil in 2003. In contrast to 1999, some of the highest yields ($2.0\text{--}2.5\text{ t ha}^{-1}$) are on poor sand in the dry year of 2003. Soil test values for the low yielding areas in 1999 were adequate for potassium ($>65\text{ mg kg}^{-1}$) and phosphorus ($>20\text{ mg kg}^{-1}$) and nitrogen was applied to each crop.

Figure 2. Wheat yields measured in 1996 to 2005 (a to e) and soil map of the field (f) produced by the grower. May to October rainfalls were 285 mm in 1996, 360 mm in 1999, 200 mm in 2001, 250 mm in 2003 and 230 mm in 2005.

The spatial patterns of EC_a and gamma-emissions from potassium (K) and thorium (Th) are shown in Fig. 3. The low gamma-emission from ^{40}K (<60 counts $100s^{-1}$) typically measured on deep sandy areas are not matched by low EC_a values typical of sands (<15 $mS\ m^{-1}$) along the north-west boundary of the field. This area was bounded by a saline creek and was affected by salt. Gamma-ray emission from ^{40}K is not affected by salt and therefore located sandy soil more accurately.

Figure 3. Apparent soil electrical conductivity measured by EM38 (a), gamma-ray emission from potassium (b) and thorium (c) measured across the field. Areas where apparent soil electrical conductivity <10 $mS\ m^{-1}$ overlapped gamma-ray emission from potassium <40 counts $100s^{-1}$ assumed to represent very coarse sandy soil are shown in (d).

Areas of low EC_a values $< 10 \text{ mS m}^{-1}$ occur in the center north and center south of the field and are not matched by low gamma-emission from ^{40}K . This area contains superficial gravels characterized by large thorium emissions (Fig. 3c) and confirms the grower's knowledge of the field. The coarsest textured sand approximately mapped as "poor sand" by the grower occurs where areas of low EC_a values ($< 10 \text{ mS m}^{-1}$) coincide with areas of low gamma-emission from ^{40}K (0-40 counts 100s^{-1}) (Fig 3d). These areas are more prone to acidification than others because of more nitrate leaching and low pH buffer capacity. The area mapped as "medium sand" by the grower has EC_a values up to 15 mS m^{-1} and gamma-emission from ^{40}K counts up to 80 counts 100s^{-1} . The clayey soil has larger EC_a values ($> 20 \text{ mS m}^{-1}$) coinciding with high gamma-emission from ^{40}K (> 80 counts 100s^{-1}).

The fitted exponential global variogram for subsoil pH has a zero nugget, a sill of 3.25 and range of 253 m. Subsoil pH ranges from very acid (pH 3.7 in CaCl_2) over the sandy soil to alkaline (pH 8.8 in CaCl_2) over the clayey soil (Fig. 4a). The most acidic subsoil occurs as expected across the coarse sandy area mapped by the grower as "poor sand". The combined use of EC_a and gamma-ray emission from potassium identifies the areas with the most acidified subsoil by locating the coarsest textured sand across the field (Fig. 3d). In addition to identifying the approximate area mapped by the grower as "poor sand", this dual-sensor method also identifies two additional small very acid-prone areas that are not on the grower's map (Fig. 3d). These areas have current subsoil pH values of 4.2-4.7 and are also not readily noticeable on the yield map for 1999. We assume that these areas represent imminent risks for yield loss by subsoil acidification. This early diagnostic capability enables preventative treatment of subsoil acidity before

yield losses occurs and the problem becomes more serious and difficult and costly to treat.

The second most acidic subsoil occurs as expected on the next finer textured sand. This covers an approximate area mapped by the grower as “medium sand” and has subsoil pH values of 4.2-4.7 (Fig 4.a). The finer texture of this sand results in higher apparent electrical conductivity and gamma ray emission than the “poor sand”. It is mostly located where EC_a values are $<15 \text{ mS m}^{-1}$ and gamma-emission from ^{40}K counts are $<100 \text{ counts } 100\text{s}^{-1}$ (Fig. 3a and 3b). There are 32 subsoil pH measurements across the acidification prone areas identified with these geophysical characteristics. All 32 subsoil pH values are < 5.0 and 26 of these measurements have values of 4.7 or less. The most and second most acidification prone areas identified by combined use of EC_a and gamma-ray emission from potassium were in good accord with kriged estimates of subsoil pH.

Figure 4. Sample locations (stars and dots) and kriged subsoil pH in CaCl_2 (a) and soil depth (b).

The fitted exponential global variogram for soil depth had a nugget variance of 255, a sill of 3760 and range of 222 m. Soil depth over cemented gravels (penetrometer-resistance > 5 MPa) varied from 10 cm to over 200 cm (Fig. 4b). Thorium emissions with >75 counts 100s^{-1} were associated with soil depths typically < 50 cm (Fig. 5). This method located two areas of shallow soil that coincided with the grower's soil map for gravel (Fig 2f) and matched soil depth measurements.

Figure 5. Soil depth and thorium emission measured across the field.

Variation in wheat yield in 1999 identifies only one of the two areas of shallow soil. Lupin yield was measured in the northern part of the field in 2000. Yield monitoring broke down in the rest of the field. This partial yield map shows an area of low yield in the south-east quadrant that matched the second area of shallow soils to the north of the field (Fig. 6). It is assumed that the second area had less tightly packed cemented

gravels that did not affect wheat roots but impeded the growth of the much thicker lupin roots through the limited space between the gravels.

Figure 6. Lupin yield in 2000 showing an area of low yield in the south-east quadrant that matched an area of shallow soils.

Discussion

The usefulness of individual yield maps to locate subsoil constraints should be evaluated carefully. A yield map selected on the basis of crop simulation and complementary soil measurements indicated successfully the location of subsoil acidity and shallow soil. This is a change in approach from the common practice of combining yield maps from different years with other spatial data to produce zones of differing yield behaviour and management needs. Targetting specific yield maps for locating subsoil constraints was made possible through recent developments in crop modelling

which allowed us to develop an insight into soil-crop-weather-management situations in which crops would be most sensitive to subsoil constraints (Wong and Asseng, 2007). This approach helped us to avoid combining yield maps with strong information content on the spatial distribution of subsoil constraints (for example a map for the wet year of 1999) with yield maps with potential disinformation on the location of these constraints (for example a map for the dry year of 2003). Potential disinformation might occur through the misinterpretation of yield maps in situations when locations with subsoil constraints outyield other locations. For example, subsoil constraints restrict vegetative growth and hence decrease leaf area and water requirement under some seasonal conditions. The advantage of a smaller water requirement enables the crop to yield more than a crop grown without subsoil constraints which tend to fail more dramatically in years with water shortage during the later part of the growing season (Delroy and Bowden, 1986, Wong and Asseng, 2007). The generic sensitivity of root growth and yield response to subsoil constraints enabled us to use selected yield maps and targeted soil sampling to identify multiple subsoil constraints occurring in the same field.

Combining yield maps to identify zones of a field for situations when there is a strong interaction between crop-soil-season does not help because the same area can be the highest or lowest yielding depending on the soil and season. The subsoil acidic site shown in Fig. 4 was the lowest yielding in the wet season of 1999 but was one of the highest yielding in the dry year of 2003 (Fig. 2). Anecdotal evidence suggests that large seasonal variation in yields is the norm. This suggests a need to maintain the integrity of both the spatial and temporal dimensions of variability by avoiding the indiscriminate combining of yield maps and loss of temporal detail. A compromise to

limit the number of yield maps that the agronomist would need to deal with to capture seasonal and spatial variations might be to represent grain yield over a range of season types of interest (for example, see Wong and Asseng, 2006b). The use of crop modelling to integrate soil and weather data now helps in managing spatial variability for the specific season in question and anticipated size of crop (Oliver et al., 2006, Robertson et al., 2007, Stoorvogel and Bouma, 2005, Wong et al., 2001).

Use of gamma-ray spectrometry is relatively new to precision agriculture. It enabled us to overcome the shortcomings of EC_a -based methods to estimate soil depth to root-impeding layer (Doolittle et al., 1994) in a sandy soil over cemented gravel. This type of soil profile is common in highly weathered landscapes such as those in WA (McKenzie et al., 2004). Sands or sandy topsoil overlying clayey subsoils are also common in these landscapes and are termed duplex soils in Australia (Turner, 1992). We anticipate that EC_a -based methods should be applicable on these soils. Gamma-ray spectrometry complements these methods for mapping shallow soil more comprehensively. The cost of gamma-ray and EM38 surveys are similar if carried out separately. These surveys are sometimes carried out simultaneously at little additional cost compared with the use of a single instrument. The theory of gamma-ray attenuation is amenable to development to enable accurate quantitative estimates of soil depth in the 0-45 cm range. This development will be described elsewhere.

Access to both gamma-radiometric and EM38 surveys speeds up data interpretation. Low EM38 values, for example, could mean both deep sandy or shallow soil over gravel. The actual situation those values represent can be resolved by simply asking the

grower or by visiting the site. This approach may be time consuming and not practical for high resolution mapping especially if large areas are being surveyed. The development of simple rules such as those described here and summarized in Fig. 7 to distinguish sandy from shallow soils and salty from clayey soils highlight the additional benefits of accessing both data sets simultaneously. This dual sensor approach was able on its own to locate shallow soil, and currently and potentially yield-limiting acidic subsoils more accurately than yield maps used in conjunction with simulation modelling. Under the conditions of our measurements, low EC_a values $< 15 \text{ mS m}^{-1}$ typically occur on sands and gravels whereas values $> 20 \text{ mS m}^{-1}$ typically occur on clayey soil or on salt affected areas. Low gamma-emission from ^{40}K of $< 80 \text{ counts } 100 \text{ s}^{-1}$ typically occurs on sandy soils whereas emission $> 80 \text{ counts } 100 \text{ s}^{-1}$ typically occurs on shallow soil overlying gravel and on loamy to clayey soil.

Figure 7. Table 1. Rules for interpretation of dual EM38 and gamma-radiometric data

	Low EC_a	High EC_a
Low gamma	Sandy soil	Salt-affected, sandy soil
High gamma	Shallow sandy soil over gravels	Loamy to clayey soil

An important feature of the approaches presented here to map subsoil acidity and shallow soil is the use of a flexible range of data and the knowledge and experience of the agronomist and grower. Targeted soil sampling and analysis for nutrient content, yield maps, field observations and grower interviews enabled us to eliminate common topsoil constraints, weeds and diseases as major limiting factors and to identify subsoil acidity as the major limiting factor in one area and shallow soil in the other. A similar result could be achieved with the grower's soil map or geophysical sensing for EC_a and gamma-emission. The grower's soil map was not essential for the interpretation of yield or geophysical maps and to locate subsoil constraints, but some growers only have soil maps as spatial data for their farms (Wong et al., 2004b). The different options presented here were designed to accommodate differences in data availability, access to precision agriculture techniques, and grower aptitude and preference. Working closely with growers enabled us to evaluate which approach is most suitable and likely to be adopted to suit the individual grower.

Conclusions

Targeting selected yield maps improves their value in locating subsoil constraints across the field. A crop model, such as APSIM, can help in the selection of yield maps with the greatest information content from the diverse set of maps arising from seasonal variability. This process avoids the dilution of information that arises from combining yield maps with varying levels of information and disinformation. In the absence of yield maps, growers' knowledge of the spatial distribution of their soil types could be used with additional interpretation to locate subsoil constraints across a field. A more

comprehensive identification of acidic subsoil areas could be achieved with spatially dense information from both gamma-ray emission from ^{40}K and EC_a . The dual sensor data allowed subsoil acidity to be identified before a yield loss could be detected. This early detection allows for preemptive site-specific treatment of subsoil acidity before the problem becomes more acute and difficult to treat. The dual sensor technique enabled the identification of shallow soil where current EC_a -based methods cannot be used.

Acknowledgements

We are grateful to the GRDC and CSIRO for co-funding this work and Mike Wong's participation at the 6th European Conference on Precision Agriculture. We are grateful to the grower for discussing this work with us and to Mr. N. Khimashia, Ms. K. Wittwer and Mr. T. Parker for technical assistance.

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