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Mapping Potential Crop Management Zones within Fields: Use of Yield-map Series and Patterns of Soil Physical Properties Identified by Electromagnetic Induction Sensing

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Abstract. Investment in precision farming technologies can be expensive and is not expected to be cost-effective for every farm. Previous research and farm experience has shown that the amount of soil variability across a farm and within a field is of key importance for determining potential benefits from the adoption of precision farming. The research reported here evaluates the analysis of yield map sequences and electro-magnetic induction (EMI) soil sensing as potentially cost-effective methods for identifying and mapping soil-determined "management zones" within fields. Both methods are shown to provide useful information for the provisional delineation of soil type boundaries and crop management zones, though soil examination in the field is still necessary to confirm specific soil characteristics.

Keywords: yield maps, cluster analysis, EMI sensing, soil properties, management zones

Introduction

Precision farming can be defined as "the process of adjusting husbandry practices within a field according to measured spatial variability" (Sylvester-Bradley *et al.*, 1999). As such it may have perceived benefits in the three main areas of (1) improving the economic margins of crop production, (2) reducing the environmental risk from agrochemicals and (3) greater assurance of crop quality and traceability (Godwin *et al.*, 2002). According to Sylvester-Bradley *et al.* (1999), the cost-effectiveness of precision farming depends upon the cost of defining zones within fields, the temporal stability of these zones and the difference in responsiveness (yield and quality) between the zones to differential treatment. The ability to identify such stable management zones effectively is therefore of prime importance for decision making about precision farming.

Two approaches can be taken to identifying zones, either from the spatial variation in crop yield characteristics at a site, or the factors at that site which determine the yield. It has been suggested that zones could be identified from collections of crop yield maps over several years (Steven and Millar, 1997) and indeed recent studies have attempted to do so, either from simple trends across fields (Godwin *et al.*, 2002) or more complex pattern recognition analyses (Grenzedörffer and Gebbers, 2001; Lark, 2001). Alternatively, many previous projects have demonstrated that the variability of soil physical properties within fields is important to assess the potential for variable rate management of some crop inputs (e.g. fertilisers) and for delineating within-field management zones (Stafford *et al.,* 1996). Beckett and Webster (1971) reviewed statistical studies of soil variation and found that the distance over which there is significant spatial correlation between samples is of the order of tens of metres for physical properties and some chemical nutrients, even though up to half the variability of a property may be found within $1\,m^2$. The cost of measuring and mapping this variation by traditional sampling however, is prohibitive, and so remote sensing methods to measure soil spatial variation have been sought (King and Dampney, 1999).

Various authors have concluded that an EMI sensor can provide useful information on the spatial variation of certain soil properties (King and Dampney, 1999), and more general soil patterns within fields (Lück and Eisenreich, 2001). Such patterns have been related to yield maps and maps of soil types within fields, both visually (King and Dampney*,* 2000) and statistically (Anderson-Cook *et al*., 2002), and the technique holds promise for a cost-effective way in which the variation of soil properties can be measured rapidly over large areas. Interpretation of EMI maps of soil for the identification of management zones requires more knowledge of the soil properties that influence the mapped signal of apparent electrical conductivity. The biggest contributor to electrical conductivity is the solute concentration in salt affected soils (Williams and Hoey, 1987), but for most temperate soils (where salt concentrations are small) the major influences are moisture and texture (clay content) (Brevik and Fenton, 2002). EMI sensors such as the Geonics EM38 produce an integrated measurement of the apparent electrical conductivity (EC_a) over a variable depth of soil (depending on parent material) typically to 3 m or so, but most strongly influenced by the surface 0.75–1.5 m depending on mode of operation (McNeill, 1980). This apparent electrical conductivity has been variously correlated with soil moisture and clay contents (Brevik and Fenton, 2002; Johnson *et al*., 2001), and bulk density and surface organic residues (Johnson *et al*., 2001), as well as crop yields (Anderson-Cook *et al*., 2002). It has also been modelled with soil topography (Clay *et al.,* 2001), and Anderson-Cook *et al.* (2002) found they could successfully classify soil to known types using EC_a readings alone with over 85% accuracy.

This paper reports results and conclusions from recent research which has investigated the mapping of soil physical properties and yields within fields using automated methods. They are two alternative approaches to identifying and mapping potential management zones for precision farming. First, the use of yield map sequences to subdivide the field into potential management zones was evaluated, and statistical analyses were carried out to determine if the mean values of soil properties within each defined management zone were significantly different. Second, the use of electro-magnetic induction (EMI) for non-intrusive measurement of the apparent soil electrical conductivity (EC_a) was investigated, with the objectives of (1) identifying the main soil factors influencing soil EC_a, (2) studying the stability of EC_a maps under contrasting measurement conditions and (3) assessing their possible contribution to management zone identification.

Materials and methods

Yield mapping, management zones and soil sampling

An extensive collection of yield maps from farms covering a wide range of conditions in England was reviewed and the maps screened for quality of data (Lark *et al.,* 2003). Sequences of yield maps from four fields on contrasting soil types (Table 1) were used in this study. Each series of maps was analysed to identify sub-regions (potential management zones) within each field where yields varied over time in a similar way. Thus a zone might correspond to sites where the yields are always high, or always low, or show some other temporal pattern, perhaps with large yields in all but dry years. It is hypothesised that such sub-regions are likely to be subject to similar limiting factors on yield which will commonly be soil physical properties. If this is the case, then investigation of soil conditions within each zone, by direct sampling, may allow us to plan how each zone is managed.

The strength of evidence for distinct sub-regions was measured by computing a fuzzy cluster analysis on the yield data (Roubens, 1982), searching in turn for 2,3,…,9 classes. The normalised classification entropy statistics (NCE) was computed for each classification, then the plot of NCE against number of classes was interpreted (as described by Lark, 2001; Lark *et al*., 2003) to identify the optimum number of classes for the field. This analysis allowed the subdivision of fields into regions where the recorded yields most closely resembled a particular season-to-season pattern (the so-called "class of maximum membership"), which were treated as potential "management zones". The analysis also records for each location in the field a "membership value" (scale 0–1) which measures how closely the season to season yield variation at that site resembles each of the typical patterns identified. Procedures for the analysis are detailed by Lark (2001) and Lark *et al*. (2003).

The topsoil and sub-soil (100 and 600 mm depth, respectively, were sampled in each field. The fields were sampled at approximately regular grids (about 1 sample ha^{-1}) and at 20 m intervals along fixed transects, which were parallel and approximately 50 m apart. The samples were taken for laboratory analysis of particle size distribution, organic carbon content (OC) and bulk density (BD) (Avery & Bascomb, 1982). Available water (AW) contents were calculated using pedo-transfer functions (Mayr *et al*., 1999). Statistical analyses were carried out to determine if the mean values of soil properties within each defined management zone were significantly different. Regressions of the soil properties on the membership values defined from the yield data were computed using a maximum likelihood method with a spatially correlated error model (Lark, 2000a), then the mean square error of a point prediction of each soil property using the mean value for the management zone or the regression equation, was calculated.

Soil survey by electromagnetic induction sensing

In the four fields detailed in Table 1, the use of a Geonics EM38 EMI sensor was also studied. It was mounted in a metal-free cart and towed at 6-m pass spacings behind an all terrain vehicle at about 15 km h^{-1}.

Table 1. Details of study fields

Field	Location	Size of study area	Cropping	Parent material	Relationship between soils and topography
1	Lincolnshire	7.5 ha	1997 (Winter Wheat), 2000 (Winter Wheat)	Jurassic limestone	Deep clay soils at east of field on plateau, shallow soils over limestone in west and centre on sides and tops of dry valleys, deep sandy soils in floor of dry valleys.
2	Oxfordshire	18 ha	1996 (Winter Wheat), 1998 (Spring Beans), 2000 (Winter Wheat)	Cretaceous chalk	Shallow clayey soils over chalk over gently sloping field, some deeper more flinty soils on higher plateau-like ground in east.
3	Bedfordshire	6 ha (approx)	1999 (Winter Wheat), 2000 (Winter Wheat)	Cretaceous sands and clays	Clayey soils in south falling away on gentle slopes to medium loamy soils in a basin-like feature in centre and deep sandy soils in east on rising ground.
4	Bedfordshire	12 ha (approx)	1994 (Winter Wheat), 1998 (Winter Barley), 1999 (Winter Wheat)	Cretaceous sands and clays	Clayey soils in north on flat land with moderate slopes up to deep sandy soils on a ridge in the south.

Principal component analysis was conducted on measured soil properties from the intensive survey, to define a new set of uncorrelated soil variables that account for most of the soil variation. An initial principal component analysis was conducted on all the data from all four fields combined, because not all fields had sufficient data of every variable to support a separate analysis. A plot of the first two principal components showed that Fields 1–3 could be combined into a single dataset, and results from the analysis of these data are presented here. Principal components were obtained for this combined set of data. Most of these could be interpreted; for example, one principal component might have large values for generally wet soils of heavy texture and large organic content. Soil EC_a data were then regressed on these principal components using a maximum likelihood method (King *et al.*, 2003), in order to show which of these components appeared to account for significant variation in EC_a. Since the principle components are uncorrelated, it is legitimate to interpret their relative significance in the regression model, then relate this to the initial interpretation of each component.

Additionally in each field, measurements on passes of 6-m intervals were compared when carried out under dry (summer) and wet (winter) soil moisture regimes. Most measurements were taken with the EM38 in vertical mode. Robustly estimated variograms of the EC_a data were used to determine the pass spacing that would allow EC_a to be mapped with a specified precision by ordinary kriging. Multivariate spatial and cluster analysis was used in order to assess the stability of EC_a patterns with time.

These analyses enabled us to identify the specific soil properties that were most influential in determining the soil variation measured by EMI. They also help in determining whether it has potential as a surrogate means of identifying management zones and thus site suitability for variable rate management.

Results

Yield mapping, management zones and pedological survey

Figure 1 shows the normalised classification entropy (NCE) class centres of Field 3 as an example of the output from the fuzzy cluster analyses of sequences of yield maps (where possible 3 years or more). The results for all analyses on all fields can be found in Lark *et al.* (2003). The cluster analysis of yield maps for each of the four fields reported in this paper identified 4 class centres, and those from Field 3 are shown on Figure 1(a). They were distributed across the field as shown in Figure 1(b). Regression modelling of soil properties (Table 2) showed that the subsoil clay content and subsoil sand content were significantly related to the class of maximum membership. This might be expected as these soil properties have a major influence on the soil AW. Yields were highest in class 4 and the subsoil in sub-regions of this class had a high clay and low sand content. In areas of low yield (class 1), the subsoil had a low clay content and high sand content. There were no significant relationships with the other measured soil properties.

Table 2 summarises the regression statistics and statistics for the comparison of class means. In Field 1, data is given for two areas within the field : area "A" had yield map and EC_a data but had limited soil variability, area "B" just had EC_a data but more soil variability. For each field, the variation of at least one of the soil

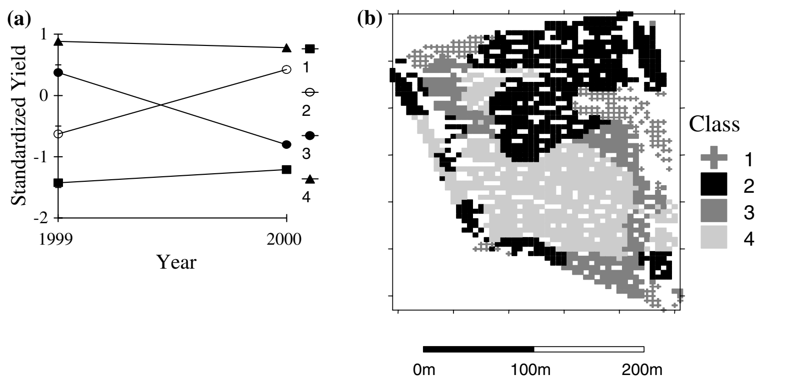

Figure 1. (a) NCE class centres for yields for the two years 1999 and 2000 of Field 3, (b) Distribution of the class of maximum membership in Field 3.

Table 2. Summary statistics of class means and from regressions of class membership and EC_a with soil physical properties

	Class means[a]		Class membership[b]		EC_a	
	Variance[c]	*P*	Residual variance	*P*	Residual variance	*P*
Field 1 (area A)						
Topsoil clay	74.03	ns	72.69	ns	72.01	ns
Topsoil sand	304.6	ns	308.4	ns	320.6	ns
Topsoil org. C	0.09	ns	0.09	ns	0.093	ns
Topsoil AW	0.0009	*	0.001	ns	0.001	ns
Subsoil clay	354.3	*	391.4	ns	836.7	ns
Subsoil sand			700.3	ns	794.8	ns
Subsoil org. C	0.048	ns	0.051	ns	0.051	ns
Subsoil AW	0.0007	***	0.0008	**	0.002	ns
AW (1 m)	456.7	***	581.0	***	1260.0	ns
Field 1 (area B)						
Topsoil clay					40.35	***
Topsoil sand					173.6	***
Topsoil org. C					0.147	ns
Topsoil AW						
Subsoil clay					255.7	**
Subsoil sand					825.7	*
Subsoil org. C					0.073	ns
Subsoil AW					0.001	*
AW (1 m)					1159.0	ns
Field 2						
Topsoil clay	50.87	ns	50.86	ns	52.18	ns
Topsoil sand	56.87	*	59.32	ns	34.33	***
Topsoil org. C	1.74	ns			1.645	***
Topsoil AW	0.001	ns	0.0012	*	0.0011	***
Subsoil clay	92.41	ns	91.95	ns	87.71	ns
Subsoil sand	75.98	ns	77.54	ns	63.11	***
Subsoil org. C	0.663	*	0.665	*	0.660	*
Subsoil AW	0.0005	*	0.0006	ns	0.0006	ns
AW (1 m)	437.9	ns	456.8	ns	436.4	ns
Field 3						
Topsoil clay	73.44	ns	77.6	ns	44.98	***
Topsoil sand	267.6	ns	271.0	ns	145.9	***
Topsoil org. C	0.212	ns	0.233	ns	0.105	**
Topsoil AW	0.001	ns	0.001	ns	0.001	ns
Subsoil clay	222.0	ns	184.6	***	207.6	**
Subsoil sand	621.5	**	517.0	***	625.9	**
Subsoil org. C	0.046	ns	0.466	ns		
Subsoil AW	0.001	ns	0.001	*	0.001	*
AW (1 m)	988.2	ns	782.6	*	845.2	*
Field 4						
Topsoil clay	16.58	***	16.5	***	20.1	***
Topsoil sand	90.14	***	88.6	***	102.6	***
Subsoil clay	26.7	***	26.0	***	27.8	**
Subsoil sand	85.65	***	83.4	***	85.9	***

[a]Four classes were determined in each field, though this is fortuitous and not pre-determined.
[b]Dominant classes only, minor classes were not included in the regression analyses.
[c]Within class variance comparable directly with the residual variance for the regressions.

properties was significantly related to the classification on the yield data, suggesting that analysis of yield maps was useful for identifying potential management zones based on soil physical properties. Texture (sand and clay content) and AW seemed to be the main properties predicted.

Soil survey by electromagnetic induction sensing

EMI surveys were carried out across the four fields at two times in the year, when the soil was at field capacity and also after harvest when it was near maximum dryness. The resulting map of apparent electrical conductivity (EC_a) for Field 3 at field capacity is given as an example in Figure 2(a) (also in King *et al.*, (2003)), and after harvest in Figure 2(b).

Figure 2 shows an example of EC_a readings taken in vertical mode at a high data density. A visual comparison of the above EC_a map with a relevant soil map, such as that shown in Figure 3 (soils described by Wright, 1987), indicated a clear pattern of larger EC_a readings in the parts of the field dominated by the heavier clay loam soils, compared with smaller values from the lighter soils. This pattern held true in general at both wet and dry times of the year suggesting that a large part of the signal from this field was governed by the clay content of the soil. This is also suggested by the fact that the site mean EC_a was only marginally smaller in the summer compared with the winter, and leads to the identification of two distinct classes of response for this field. Site hydrology also shaped the pattern however, as the valley feature in the

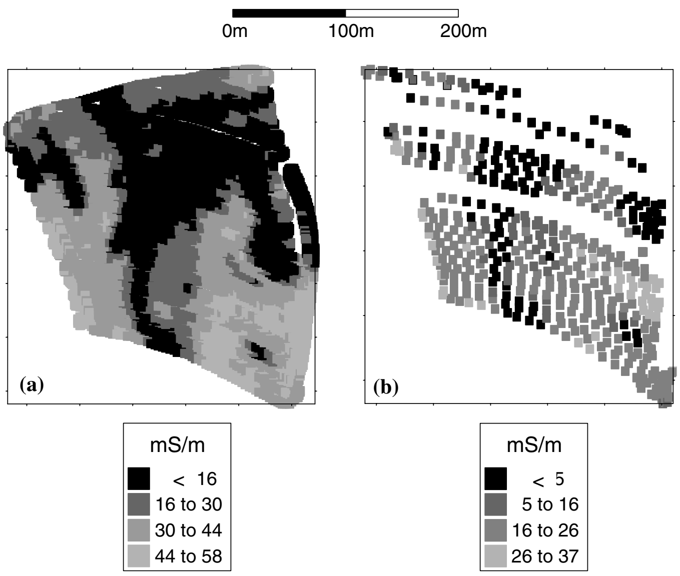

Figure 2. Map of the distribution of EC_a (in vertical mode) across Field 3; (**a**) measured when soil was at field capacity in the spring (March), and (**b**) measured when the soil was near maximum dryness after harvest (August).

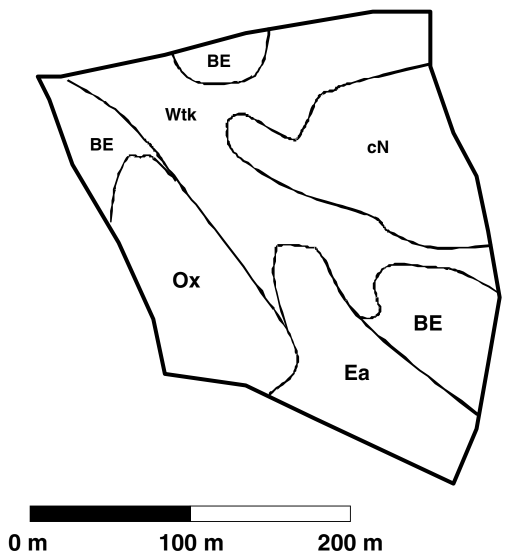

Figure 3. The soils mapped on Field 3. Ea = Evesham; BE = Bearsted; Wtk = Waterstock; cN = Cot-Cottenham; Ox = Oxpasture (Wright, 1987).

top left of the figure shows as an area of marginally higher readings, and was probably due to subsoil moisture. Similar maps for the other fields can be related to changes in soil type and hydrology across each site, and also demonstrate a basic stability of pattern across wet and dry seasons.

Regression modelling (Table 2) showed that EC_a was strongly related to topsoil clay and sand but also related to some degree to most other measured soil physical properties in both topsoil and subsoil. Similarly on all fields, the EC_a data detected significant differences in at least some soil properties . In some cases (e.g. Field 1B and Field 3), the yield classification was more closely related to subsoil rather than topsoil properties compared to the EC_a data. This might be expected as yield will tend to integrate the effect of soil properties throughout the rooting depth of the crop which can be over 1 m, whereas the EMI technique will interact with soil independently of the growing crop. Comparing the residual variances over all fields shows that neither yield maps nor EC_a were consistently more useful for predicting soil physical properties.

A principal components analysis of the soil properties data revealed that data from three of the four fields studied behaved in a similar manner and that, within this combined dataset, the variation was accounted for by eight principal components, the first four of which accounted for 90%. The latent vectors and how they relate to the soil properties (positively or negatively) are shown in Table 3. The four most influential components have been plotted against each other in Figure 4. The apparent electrical conductivity (EC_a) was regressed on these principal components and, since the principal components are un-correlated, those which make a significant contribution to explaining variation in EC_a (PC1 > PC6 > PC2 > PC8) could be identified (Table 4).

Table 3. Latent vectors for each principal component. (BD = Bulk density, C = Carbon)

Soil layer	Soil variable	Principle Component							
		PC1	PC2	PC3	PC4	PC5	PC6	PC7	PC8
Top	Clay	−0.438	−0.176	0.107	0.082	0.197	−0.501	−0.468	0.500
	Sand	0.444	0.027	−0.129	−0.081	−0.300	0.419	−0.533	0.479
	Organic C	0.081	−0.837	−0.282	0.050	0.380	0.251	0.045	−0.027
	BD	−0.314	0.233	−0.059	−0.733	0.430	0.328	−0.117	−0.009
Sub	Clay	−0.425	−0.238	−0.014	−0.055	−0.508	0.128	−0.447	−0.534
	Sand	0.432	0.159	0.088	0.132	0.465	−0.200	−0.525	−0.481
	Organic C	0.338	−0.212	−0.233	−0.614	−0.258	−0.581	0.062	−0.052
	BD	−0.158	0.293	−0.909	0.224	0.038	−0.091	−0.045	−0.025

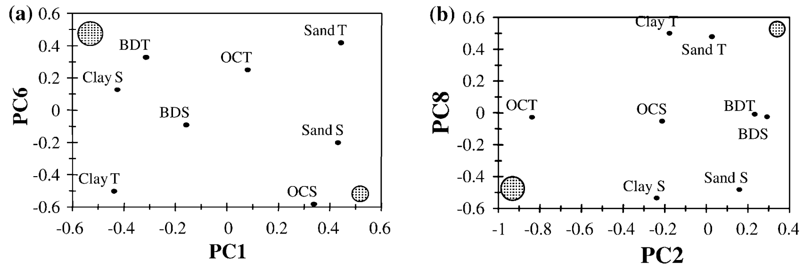

Figure 4. Elements for the latent vectors for: (**a**) PC1 and PC6, and (**b**) PC2 and PC8 of static soil properties in combined datasets from three sites (T = topsoil, S = subsoil, BD = bulk density, OC = organic C).

From Table 4, it can be seen that PC1, PC2 and PC8 were negatively correlated with EC_a values whilst PC6 was positively correlated. Figure 4 shows the weighting of the original soil variables in these four components. The large circular symbols in Figure 4 indicate where large EC_a values are expected in the plot and the small circular symbols show where small EC_a values are to be expected. Hence large clay contents and bulk densities in both topsoil and subsoil are associated with large EC_a (Figure 4(a)). However, large topsoil and subsoil sand content, and large subsoil organic carbon content were associated with low values of EC_a (Figure 4(a)). Less influentially, large topsoil organic carbon content can also contribute to high EC_a values (Figure 4b) and, in some cases, large bulk densities in both topsoil and subsoil can be associated with low EC_a readings as well as high (Figure 4(b)).

The EC_a datasets from the four fields studied here, were all analysed spatially by kriging. Variances were calculated for each dataset according to the most commonly used estimator of the variogram, Matheron's (1962), and three other robust estimators. Figure 5 shows the four estimators for a dataset from field 1, which indicates the difference between the scale of difference between Matheron's and the other three robust estimators. Validation of these estimators for all the datasets according to the cross-validation procedures described by Lark (2000b) and King *et al.* (2001), showed that Matheron's model over-estimated the variogram in most cases (except

Table 4. Regression model of EC_a (vertical, spring) on principal components of soil properties

PC	Coefficient	variance	*t* ratio	*p*
1	−5.221	0.375	−8.53	< 0.001
2	−4.054	1.104	−3.86	< 0.001
3	−1.929	1.399	−1.63	> 0.05
4	−0.553	1.827	−0.41	> 0.05
5	−1.654	2.541	−1.04	> 0.05
6	8.653	3.717	4.49	< 0.001
7	−5.961	10.733	−1.82	> 0.05
8	−15.300	32.027	−2.70	0.01

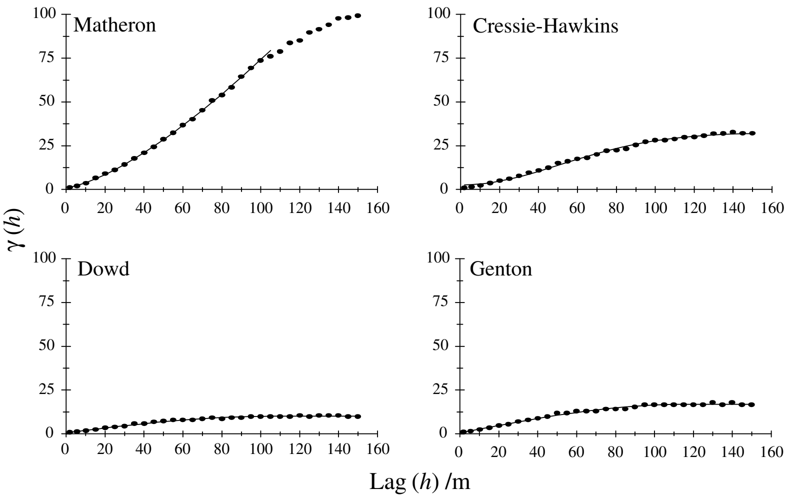

Figure 5. Variograms for data from Field 1 ("wet" soil) for four different estimators. Top left = Matheron (1962); Top right = Cressie-Hawkins (1980); Bottom left = Dowd (1984); Bottom right = Genton (1998).

two), whereas robust indicators were generally acceptable. The full analyses of the variograms is given in King *et al.* (2003), but an important practical implication of this consideration is found in the assessment of the optimal spacing between passes of the EMI sensor across a field.

Variograms were obtained for all datasets (Figure 5) and the cross validation procedure was used to select the most appropriate estimator for each (Table 5). Also given in Table 5 are the spacing between passes necessary to give an estimation error (range of ± 1 s.e.) which is no more than 10% of the mean of the signal across the whole field (or 25% if the former cannot be achieved at > 5 m). Choice of estimator is important in this analysis as the use of Matheron's estimator for Field 1 would have indicated the need for twice as many passes as Dowd's, which described the data better.

The data in Table 5 also indicate that little change in spacing is required on different occasions and, indeed, kriged estimates of the change in EC_a between

Table 5. Pass spacing (m) required for an error of < 10% of the mean (< 25% in brackets)

Field	Date	Mode	Estimator	Point Kriging	Block Kriging (10 m block)
Field 1	1	V	Dowd	19	42
	1	H	Dowd	< 5 (15)	11
	2	V	Dowd	< 5 (16)	11
	2	H	Matheron	< 5 (< 5)	13
Field 2	1	V	Matheron	< 5 (> 60)	32
	1	H	Cressie-Hawkins	< 5(< 5)	10
	2	V	Genton	< 5(44)	17
	3	V	Dowd	14	21
	3	H	Cressie-Hawkins	7	17
Field 3	1	V	Dowd	< 5 (20)	12
	1	V	Dowd	< 5 (24)	11
Field 4	1	V	Dowd	< 5 (17)	11
	1	H	Cressie-Hawkins	> 60	> 60
	2	V	Dowd	< 5 (24)	13

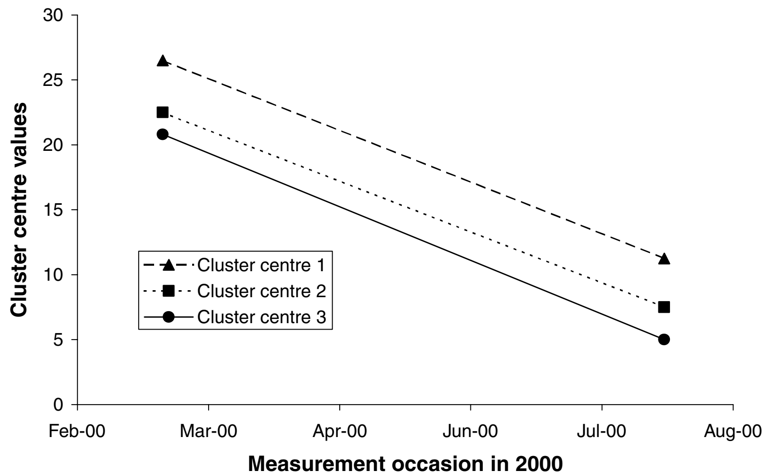

Figure 6. NCE cluster centres for EC_a readings taken on both dates (March and August 2000) at Field 1.

occasions indicate that the fields tended to be uniform. Although the absolute values of soil EC_a changed significantly according to the prevailing soil moisture levels at the time of measurement, kriged estimates of the change in EC_a showed that the spatial patterns of EC_a were generally stable for all fields studied irrespective of whether measurements were undertaken under moist or dry soil conditions (King *et al.,* 2003). Furthermore, a cluster analysis of the EC_a data from each field showed that there was virtually no change in the order of NCE cluster centres between "wet" and "dry" dates of EC_a measurement (King *et al.,* 2003). The three cluster centres identified for field 1 are shown as an example in Figure 6. On other fields, the order was also usually the same, though centres may come closer together in drier conditions.

Discussion

The cost of precision farming techniques can only be justified if the variability of a site and differences in yield potential warrant it. We have demonstrated here that by using the information from an investment already made in yield mapping equipment, a judgement may be made on the basis of the maps obtained as to whether discrete zones of differential yield actually exist within a field and persist over several years. Other methods of identifying zones from yield maps have simply obtained mean yields over several years and related site locations in a field to this overall mean (Grenzedörffer and Gebbers, 2001; Godwin *et al.*, 2002). This method is only useful when yield variations are very consistent between seasons. In particular they will not pick out zones where variable site conditions (e.g. hydrology) may produce above or below average yields depending on weather conditions. The cluster analysis techniques employed here produce zones which are coherent in themselves and behave in a predictable manner compared with other zones.

In addition, the analysis of soil properties measured across the fields (reported in Table 2) showed that in all fields at least some measured soil variables were significantly associated with the zonation of the field based on yield data. This provides a firm indication that the zones identified were determined by site variation and could therefore be managed differentially. The measurement of soil physical variables, however, remains an expensive procedure if samples have to be taken from many locations across fields to identify or confirm differentially manageable zones. EMI equipment can be operated quickly and relatively cheaply.

Geostatistical analysis of EC_a data from 9 separate passes (Table 5) showed that, to obtain point predictions of EC_a with an error of less than 10%, a pass spacing of < 5 m was usually needed. However, spacing of around 20–25 m commonly gave point predictions with errors of less than 25%, and to obtain an estimation error of $< 10\%$ for a 10 m square block commonly required a pass spacing of only 10–20 m. Travel at speeds of 10–20 km h^{-1} is practically realistic, and with a pass spacing of around 24 m (a common tractor tramline spacing) which King *et al.* (2001) considered to be an acceptable compromise for practical purposes, large fields can be surveyed within a day.

Soil clay content has often been correlated with EC_a readings, either directly (Dalgaard *et al.,* 2001) or with other textural components (Schmidhalter *et al.,* 2001), but usually within single sites or soil types. Here we have demonstrated the importance of texture, both clay and sand contents, in determining EC_a values across several soil types at three sites on more than one occasion. At the fourth site, clay content was also highly correlated with the most influential principal components of EC_a, even though the dataset was statistically distinct from the other three. Clay will have a direct effect on EC_a readings (McNeill, 1980) but sand contents will primarily act through their modification of site hydrology. Where sand contents are high (and clay contents commensurately lower), soils will usually be more permeable with lower moisture contents and hence lower EC_a readings. Soil moisture content was not itself directly related to EC_a readings in this study but its influence has been demonstrated many times previously (e.g. Bobert *et al.,* 2001) and was observed to determine the overall values of EC_a readings on both wet and dry occasions in this study. However, the differential in moisture contents across the sites in the two contrasting seasons proved insufficient to alter the basic pattern of EC_a maps produced and hence the technique's value as a site surveying tool is sustained.

Although some work has shown a general relationship between yield and EC_a (Nuedecker *et al.,* 2001), this only indicates that the factors which contribute to fertile soils (such as high clay, organic matter and moisture contents) are also those that give high conductivity readings. We do not propose that EC_a maps could be used directly to determine management zones. Rather, their use is in determining the spatial distribution and variability of soil texture within a site which has been shown here to be mutually influential on both EC_a and crop yield zonation. Expert knowledge of soils on a site will always be important in determining the optimum management of that site. However, it is becoming clear that EMI and yield maps can be cheap and easily obtainable methods for not only deciding whether site variation warrants precision farming techniques but also to identify management zones over which to apply those techniques. We have shown that both variables are related to soil variation, though neither is consistently better than the other, and both are very useful.

Conclusions

It can be seen from these results that both yield and EC_a data contain information that relates directly to the spatial distribution of some soil properties, though neither were consistently better at predicting the soil properties over all fields. Whilst EC_a measurements may be more directly dependant upon certain soil physical properties, the yield data is more likely to be an integrated response to those properties which are most important for crop growth.

Although not widespread yet, yield mapping provides a way of using already collected data to determine whether discrete zones of differential yield actually exist across a field. We have shown that at least some soil physical properties in each field correlate to such zones identified in yield data. These properties were invariably texture or available water holding capacity, and varied across the site in a manner that determined the yield zonation. Thus such discrete zones could be open to differential management.

EMI sensing proves itself to be a relatively inexpensive way of collecting spatial data on the relevant soil physical properties (such as AWC and clay content), that may tell us something about discrete zones of differential yield within a field.

Both yield and EC_a maps, however, are only tools to aid the determination of potential management zones within a field and should be allied to expert site assessment and knowledge. Neither can they determine what the optimum management for zones should be however, but they can help to indicate whether differential management of such zones would be a profitable course of action.

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