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Agronomic consequences of potential management zones delineated on the basis of EM38DD measurements

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ABSTRACT

This study was conducted to investigate the feasibility of dual dipole apparent electrical conductivity (ECa) measurements obtained with an EM38DD sensor as an explicit information source to delineate potential management classes in an agricultural field in the Polder area of Belgium. The success of class delineation was evaluated in relation to soil physical-chemical properties and sugar beet yield. The average apparent electrical conductivity (ECa-A) derived from vertical and horizontal dipole measurements was capable of delineating 3 relatively large management classes. The analysis of variance of soil properties indicated that topsoil sand and lime and subsoil clay, sand and lime were largely different across these classes (all having a proportion of the variance accounted for by a classification of >0.5). During the growing season of 2005, we monitored topsoil NO_3^--N and moisture content and found strong differences among classes. As a result, the crop biomass at harvest (roots plus leaves) was strongly variable between classes (ranging from 105 Mg ha^{-1} to 153 g ha^{-1}), as well as the sugar content (ranging from 15.4% to 17.2%). However, due to a compensation effect between the crop biomass and sugar accumulation, differences in sugar yield and financial income between classes were relatively small (the income ranged from 3950 € ha^{-1} to 4230 € ha^{-1}). However, these income values resulted from strongly different growing conditions, calling for a class-specific management. The image of the average ECa was found to be a reliable basis for delineating agronomically relevant management zones.

INTRODUCTION

Traditional agricultural practices use parcel delineations as the identification of homogeneously managed units (Mulla and Schepers 1997). However, these parcel delineations are based on cadastral units, which do not necessarily reflect differences in natural land resources like soil and relief. This results in an inefficient use of agricultural inputs such as lime and fertilizer due to a non-optimal application rate in some parts of the field. Accounting for within-field differences in soil and other crop growth influencing properties, has led to the development of precision agriculture or site-specific management. This agricultural system has a large potential to overcome negative environmental and economical impacts associated with traditional agriculture. Recent technological advances enabled the mapping of yield variability within fields with relative ease. These yield maps often act as an eye-opener to farmers and agronomists, realizing the magnitude of within-field variability of crop productivity. One of the most important crop yield determining properties is soil texture, due to its strong influence on fertility and water-holding capacity. However, soil maps are mostly too general, both in attribute and in resolution, to be used as an information sources for within-field variability. Therefore, ancillary information sources, like digital elevation models, proximally sensed data or remotely sensed images are increasingly being used to investigate agricultural fields and create sub-units called management zones, which are the basis for varying application rates in site-specific management (Sylvester-Bradley *et al*. 1999).

The EM38 sensor (Geonics Ltd, Ontario) measures the apparent electrical conductivity (ECa) of the top 1.2–1.5 m on the basis of electromagnetic induction. This coincides with the active root zone of most agricultural crops. It is therefore especially suited for agricultural purposes. Under humid climates, soil ECa was found to be related to several key soil properties like texture (mainly the clay fraction), organic matter content, compaction and soil moisture content (Williams and Hoey 1987;

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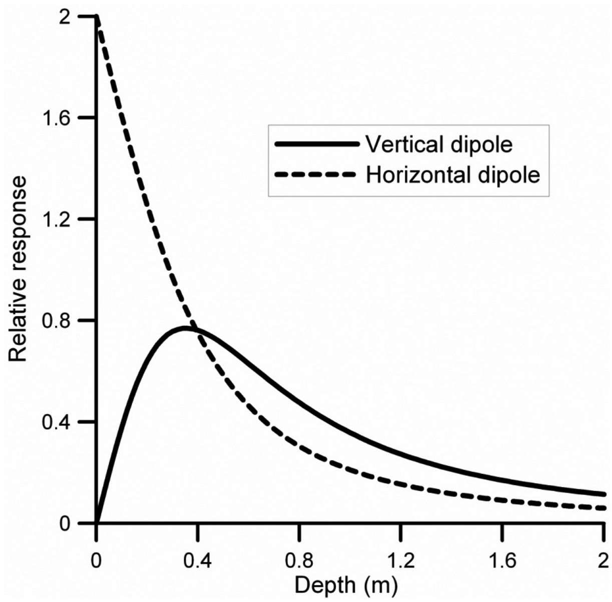

FIGURE 1
The variation of relative response with depth for vertical and horizontal dipole configurations of EM38DD sensor over homogeneous ground.

Kitchen *et al*. 1999). Its non-invasive nature allows the collection of a large number of observations in a short time. Consequently, it has become common to include ECa mapping in precision agriculture, especially as a basis to identify within-field soil variability and subsequent delineation of management zones (Kitchen *et al*. 2005; Hedley *et al*. 2004). Since the soil depth sensitivity of the EM38 sensor depends on its orientation, a double dipole version, EM38DD, was introduced by its manufacturer. The EM38DD was developed to measure the apparent electrical conductivity in a horizontal coplanar coil and a vertical coplanar coil configuration, i.e., in vertical magnetic dipole and horizontal magnetic dipole mode, respectively. This device operates at a frequency of 14.6 kHz as a low-induction-number frequency domain electromagnetic instrument (Callegary *et al*. 2007). The dual dipole construction provides simultaneous measurements of ECa in vertical (ECa-V) and horizontal (ECa-H) dipole configurations with depths of investigation, roughly 0.75 m and 1.50 m, respectively (Hendrickx and Kachanoski 2002). The EM38DD response as a function of the depth of a homogeneous soil profile is shown in Fig. 1, adapted from McNeill (1980). This illustrates that these two orientations are complementary, since the horizontal dipole orientation measurements are sensitive from the topsoil with steadily decreasing influence in depth, whereas the vertical orientation measurements receive a larger contribution of the subsoil. The cumulative response curves of two orientations (McNeill 1980) indicated that in the horizontal configuration 50% of the response results from the top 0.40 m of the soil profile while a similar response is achieved by the vertical orientation from 0.85 m depth. This differential response pattern for the two coil configurations enhanced the suitability of this sensor to explore the spatial variability of soils with a layered build up. So far, not many applications of the EM38DD have been reported, one exception is Cockx *et al*. (2006).

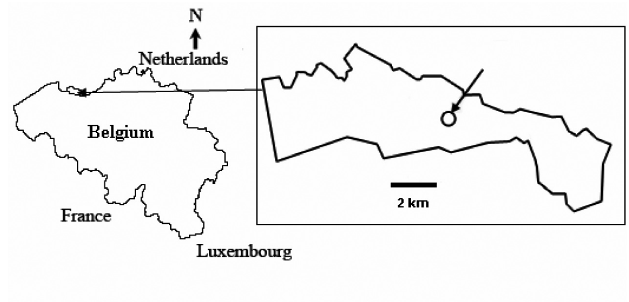

FIGURE 2
The polder area of northwest East Flanders in Belgium (left) and the location of the study field inside this area (right).

This study aims to investigate the usefulness of the EM38DD device for delineating potential management zones in an agricultural field in the Polder area of Belgium. This area is of agricultural importance due to its very fertile soils. However, from our pedological experience, these soils are known to be heterogeneous, both horizontally and vertically. Van Meirvenne and Hofman (1989) found a lithological discontinuity between 40 cm and 50 cm depth and greater spatial variation in the subsoil texture (50–80 cm) than in the topsoil (0–40 cm). Consequently there is the potential to adopt precision agriculture. Our objective was to evaluate the relevance of the potential management zones delineated through a classification of EM38DD measurements, in relation to the soil physical-chemical properties and sugar beet (*Beta vulgaris* L.) yield.

STUDY AREA AND METHODS

Study area

The study site was an 11.3 ha field in the Polder area of northwest East-Flanders, Belgium, with central coordinates: 51° 16' 17" N and 3° 40' 35" E (Fig. 2). The topsoil consists of Holocene alluvial loam to clay sediments deposited over Pleistocene aeolian material with a predominantly sandy texture. The study site is nearly flat with elevation ranging from 3.2 m to 3.8 m above mean sea level. The national soil map (scale 1:20 000) shows mainly one soil series with the letters sEdp. This indicates a light clayey topsoil texture (E) with a shallow sandy substrate (s) and moderately wet conditions (d) without a profile development (p). Both relief and mapped soil types suggest a very homogeneous field and provide no basis for the identification or delineation of within-field sub-units. The field has been in a potato (*Solanum tuberosum* L.), sugar beet and winter wheat (*Triticum aestivum* L.) rotation for many years under conventional rain-fed management practices.

The growing season of 2005 was monitored. It started in early October 2004, after the harvest of potatoes, when the farmer ploughed the field incorporating uniformly composted chicken manure at a rate of 11 Mg ha^{-1}. This corresponded to an equivalent total nitrogen fertilization of 320 kg N ha^{-1} (both in organic and mineral form). In April 2005, sugar beets were sown and managed without any additional N-fertilization during the entire growing season. These beets were harvested in mid-October 2005.

Apparent electrical conductivity mapping, soil sampling and crop yield

The ECa of the field was measured on 17th November 2003 with the EM38DD sensor. Before the ECa survey, the vertical and horizontal dipole measurements were set to zero by installing the sensor 2 m above the ground. The sensor was connected to a GPS receiver and a field computer and was pulled by an all-terrain vehicle at about 15 km h^{-1} along 5 m spaced transects. The measurements were taken at ground level at a frequency of 1 Hz, resulting in a spatial resolution of approximately 5 m by 4 m. This yielded 3938 simultaneous ECa-V and ECa-H measurements. Possible systematic measurement drifts caused by instrument electronics were checked by comparing repeated ECa-V and ECa-H measurements at a reference point of the field in approximately one and a half-hour intervals during the survey. We found that the measurement drifts were negligible during the entire survey. The data set was subjected to exploratory analysis to remove numerical and spatial outliers. McNeill (1980) mentioned the nonlinear behaviour of electromagnetic induction sensor measurements beyond approximately 100 mS m^{-1}, requiring shift corrections. However, neither dipole measurements required this correction since observed maximums were well below this threshold. Finally, ECa data were interpolated to a grid with a resolution of 2.5 m by 2.5 m, using ordinary punctual kriging (Goovaerts 1997).

Soil samples were taken at 87 locations after the ECa survey. Sampling locations were located on the basis of the ECa maps in order to target the observed patterns and at the same time ensuring a more or less uniform density over the field (Fig. 3a). Both topsoil (0–30 cm) and subsoil (50–80 cm) samples were taken by pooling three augurings taken within 1 m^2. Air dried samples were crushed and sieved through a 2 mm sieve for textural analysis by the pipette method after pre-treatment for organic residues and $CaCO_3$. The soil organic carbon content (OC) was determined by the conventional Walkley & Black method.

Soil samples were taken repeatedly at 10 sampling points to monitor the NO_3^--N (nitrate-nitrogen) and moisture dynamics during the growing season of 2005 (sampling dates were: 18/5, 20/6, 11/7, 14/8 and 13/10). These locations were selected to represent the delineated management zones (Fig. 4b), so they cannot be considered as pure random samples. This limits the possibilities for statistical processing, as discussed further. The main reason for limiting this number of locations to 10 was the limited field accessibility granted by the farmer during the growing season. Samples were obtained from two layers (0–30 cm and 30–60 cm) by pooling 3 augurings within 1 m^2. The NO_3^--N content was determined using a continuous flow auto analyzer. The samples were oven dried to obtain the gravimetric soil moisture content.

At the same 10 locations, crop samples were taken the day before the farmer harvested the sugar beets (on 13/10). Therefore, at each sampling location sugar beet plants were collected within an area of 2.25 m by 3.5 m and the weight of fresh beets (including soil attached to the beets) and of the leaves were determined on the field. A subsample of the beets was taken to the Iscal sugar beet processing factory of Moerbeke, Belgium, to determine the amount of soil attached to the beets and the sugar content. Total biomass was obtained by adding the weight of the fresh leaves to the weight of the fresh roots without attached soil.

Classification and analysis of variance

A fuzzy *k*-means classification was performed on interpolated ECa data using the FuzME program of Minasny and McBratney (2002). This classification provides a continuous grouping of objects by assigning partial class membership values on the basis of minimizing an objective function $J(\mathbf{M},\mathbf{C})$. Consider a set of n

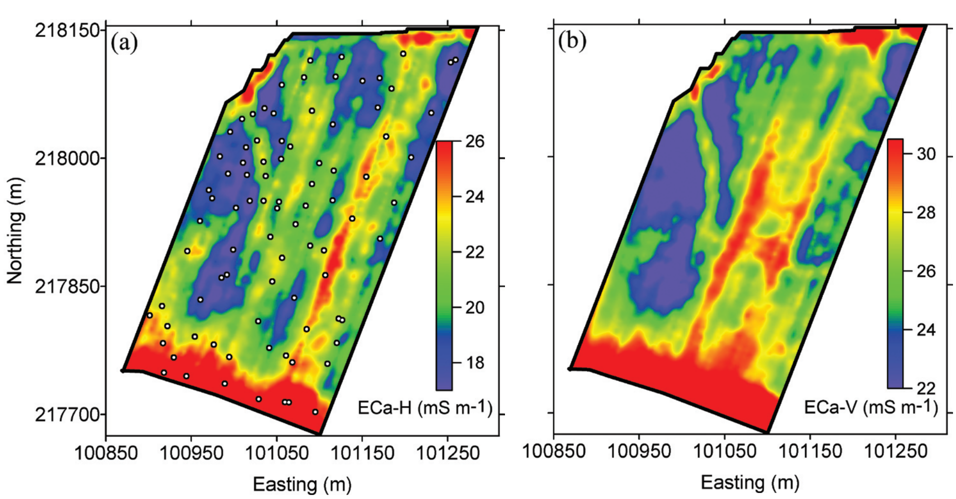

FIGURE 3
(a) Interpolated ECa-H and (b) ECa-V in mS m^{-1}, with the 87 soil sampling locations on the ECa-H map (dots).

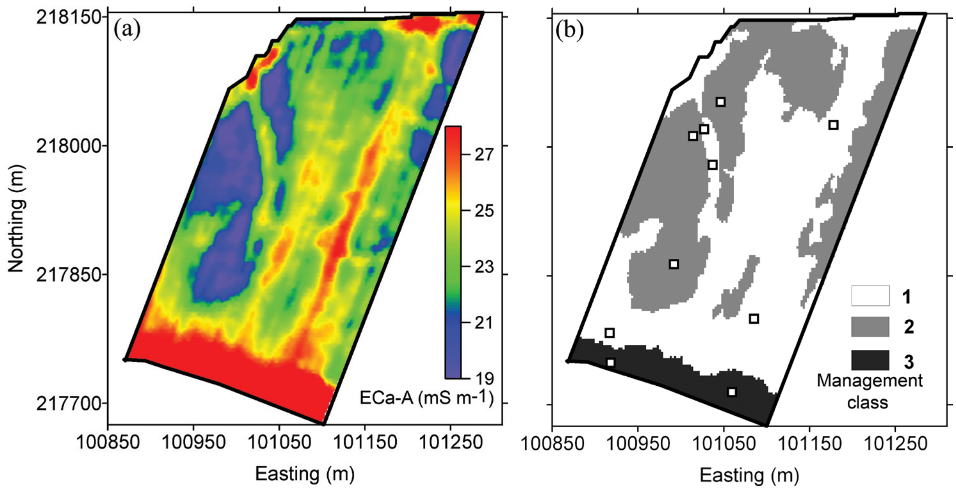

FIGURE 4
(a) ECa-A (in mS m-1), integrating both ECa-H and ECa-V and (b) generalized potential management zones obtained from a fuzzy *k*-means classification of ECa-A. The 10 monitoring points for NO_3^--N and crop yield are shown by squares.

objects (i = 1,....., n) each having p attributes (v = 1,....., p) grouped into k classes (c = 1....., k), then $J(\mathbf{M,C})$ can be expressed as:

$$J(\mathbf{M,C}) = \sum_{i=1}^{n} \sum_{c=1}^{k} m_{ic}^{\varphi} d^2(\mathbf{x}_i, \mathbf{c}_c) \tag{1}$$

where $\mathbf{M} = m_{ic}$ is a n x k matrix of membership values, $\mathbf{C} = c_{cv}$ is a k x p matrix of class centroids, c_{cv} denotes the centroid of class c for variable v, $\mathbf{c}_c = (c_{c1},....., c_{cp})^T$ is the vector representing the centroid of class c, $\mathbf{x}_i = (x_{i1},....., x_{ip})^T$ is the vector representing object i, $d^2_{ic}(\mathbf{x}_i,\mathbf{c}_c)$ is the square distance between $\mathbf{x}_i$ and $\mathbf{c}_c$ according to a chosen distance metric and φ is the fuzziness exponent that determines the degree of fuzziness. A fuzzy *k*-means classification was found to be very suitable to classify soil sensor data by several authors (e.g., Triantafilis and Lesch 2005; James *et al*. 2003)

To evaluate ECa classification in relation to soil physical-chemical properties and yield, we focused on the class mean m_i (i being the class number, i = 1,..,k), and its standard error, $s_{e,i}$, obtained as:

$$s_{e,i} = \sqrt{\frac{s_i^2}{n_i}} \tag{2}$$

with s_i^2 the sample variance of class i, and n_i the number of observations in class i. Further, differences between classes were evaluated using an analysis of variance (ANOVA) as described by Webster and Oliver (1990) and Burrough and McDonnell (1998). It consists in identifying three types of variance: the total variance σ_T^2, the within class variance σ_W^2 and the between class variance σ_B^2. These are estimated on the basis of a sample which results in the following, theoretical, relationship: $s_T^2 = s_W^2 + s_B^2$. The total variance is obtained by the well-known formula:

$$s_T^2 = \frac{1}{N-1} \sum_{i=1}^{k} \sum_{j=1}^{n_i} (z_{ij} - m)^2 \tag{3}$$

with N the total sample size, z_{ij} the j-th (j = 1,….., n_i) observation of variable Z within class i and m the mean of the whole sample. The within class variance is calculated by pooling the variances of the classes according to:

$$s_W^2 = \frac{1}{N-k} \sum_{i=1}^{k} \sum_{j=1}^{n_i} (z_{ij} - m_i)^2 \tag{4}$$

It is obvious that a successful classification aims at reducing s_W^2 in respect to s_T^2. Therefore, the smaller the ratio the better the classification, but conventionally, its complement is used:

$$R_i^2 = 1 - \frac{s_W^2}{s_T^2} \tag{5}$$

This can be regarded as the proportion of the variance accounted for by the classification, so the larger its value the more successful the classification. Its interpretation is similar to the coefficient of determination R^2 in a regression analysis, hence the symbol R_i^2. Dent and Young (1981) mention R_i^2 values of about 0.5 for physical properties and 0.3 for chemical properties as being successful for soil maps, whereas Webster and Beckett (1968) found maximum values of 0.7 for a classification of soil mechanical properties.

An ANOVA is subject to three assumptions: (i) observations should be independent (i.e. random variation), (ii) classes have similar variances, and (iii) distributions are normal. None of these can be assumed to be fulfilled automatically, especially not the first, since we did not randomize the sampling selection. Therefore, the results of the ANOVA analysis should be interpreted with care; for this reason we did not include statements about the statistical significance of the results. They should be considered as indications rather than statistical proof.

RESULTS AND DISCUSSION

ECa maps

Figure 3 shows the interpolated maps of ECa-H and ECa-V. It can be observed that both measurements were quite similar in spatial distribution and the Pearson correlation coefficient between both variables was 0.81. However, spatial patterns were more clear in the ECa-V map. On average, ECa-V values were larger in comparison to the ECa-H because the influence of the shallow ground water table (0.70–0.80 m) persisted in this area during the winter. The southern part showed a band of large ECa-V values (larger than 28 mS m^{-1}), reflecting an increased wetness caused by a drop in micro-relief (of about 0.5 m). Distinct patterns with low (fewer than 24 mS m^{-1}) and intermediate (24-28 mS m^{-1}) ECa-V values can be observed in the rest of the field. These reflected the fluviatile processes of sedimentation of parent material. More details about this interpretation can be found elsewhere (Vitharana *et al*. 2006). Because of the similarity of both measurements, they were combined into an average value, ECa-A, by a simple pixel-by-pixel averaging of the interpolated ECa-H and ECa-V maps (Fig. 4a).

Potential management classes and soil properties

The ECa-A map was subjected to a fuzzy *k*-means classification. Based on a previous study conducted on the same field (Vitharana *et al*. 2006), a fuzziness exponent value of 1.35 was selected and *k* was set to 3. Since the classification was based on only one variable (ECa-A), the Euclidean distance metric was used. Relatively small, isolated spots within these classes were removed, since they were not relevant for site-specific management. Figure 4(a) shows the generalized potential management classes. Classes 1 and 2 occupied a large part of the field with areas of 6.0 ha and 4.4 ha, respectively. Class 3 was comparatively smaller (0.9 ha) and occupied the southern part of the field.

The 87 soil samples (topsoil and subsoil) were attributed to the three management classes. Classes 1, 2 and 3 contained 41, 39 and 7 samples, respectively. Table 1 provides the class centroid ECa-A and mean values for each soil variable per class with associated standard errors. It shows that the topsoil of the study field was quite homogeneous, with rather small differences between the classes. But the texture of class 2 was more sandy than the other two classes, which was also reflected in a lower lime ($CaCO_3$) content (clay tends to reduce the rate of natural decalcification). On the other hand, the subsoil was markedly variable: class 2 was dominated by very sandy soil, whereas class 3 remained rich in clay and class 1 had an intermediate composition. This tendency was also clearly reflected by OC and lime: the more clay the higher the values of OC and lime. All standard errors were much smaller than the differences between the class means, except for OC in the topsoil. The response of the EM38DD sensor for soil textural variation is clearly reflected by class centroid ECa-A values: higher ECa-A in subsoil clay rich class 3, intermediate values in class 1 with moderate subsoil clay content and lowest in class 2 with sandy top and subsoil. It is likely that the less variable topsoil has caused less distinctive patterns of ECa-H in comparison to ECa-V measurements that influenced by strong subsoil variability. Although the topsoil is not heterogeneous as the subsoil, the spatial patterns of textural variation, especially the sand content retained similar order as in subsoil possibly due to mixing topsoil and the upper part of the subsoil by deep ploughing. This might have caused the similarities in the ECa-H and ECa-V maps. Therefore, averaging horizontal and vertical dipole ECa can be considered as appropriate for comprehensive classification of spatial variability in this field.

Table 2 gives the results of the ANOVA of these soil properties. It shows that for all properties, except OC, the s_T^2 was much smaller in the topsoil than in the subsoil, confirming the conclu-

TABLE 1

Centroid ECa-A and mean values of the soil properties per management class with associated standard error of the mean (in brackets)

Class	ECa-A	Topsoil (%, 0-30 cm)				Subsoil (%, 50-80 cm)			
	(mS m^{-1})	Clay	Sand	OC	$CaCO_3$	Clay	Sand	OC	$CaCO_3$
1	24.9	20.6	38.8	0.86	7.5	12.1	64.2	0.26	8.2
		(0.27)	(1.1)	(0.02)	(0.2)	(0.7)	(2.3)	(0.02)	(0.6)
2	21.3	17.6	52.4	0.81	4.8	6.4	82.8	0.16	4.4
		(0.35)	(0.9)	(0.02)	(0.2)	(0.4)	(1.2)	(0.01)	(0.4)
3	33.3	18.5	34.3	0.87	9.3	22.7	21.4	0.45	14.1
		(0.34)	(1.8)	(0.04)	(0.3)	(0.8)	(1.7)	(0.03)	(0.3)

TABLE 2

Results of the ANOVA of the soil properties based on the 3 management classes s_T^2 = total variance, s_W^2 = within-class variance, R_i^2 = proportion of the variance accounted for by the classification

	Topsoil (0-30 cm)				Subsoil (50-80 cm)			
	Clay	Sand	OC	$CaCO_3$	Clay	Sand	OC	$CaCO_3$
s_T^2 ($\%^2$)	5.7	89.9	0.0169	3.65	31.4	382.9	0.0166	15.7
s_W^2 ($\%^2$)	3.6	38.3	0.0165	1.27	12.0	125.4	0.0101	7.92
R_i^2	0.37	0.57	0.02	0.65	0.62	0.67	0.39	0.50

sions made on the basis of Table 1. Based on the R_i^2 parameter (equation (5)), we concluded that the ECa-A classification was very successful in separating mainly subsoil texture (R_i^2: 0.62-0.67), topsoil sand and lime (R_i^2: 0.57-0.65), and to a lesser extent subsoil lime, OC and topsoil clay (R_i^2: 0.37-0.50). The classification was unsuccessful for topsoil OC (R_i^2: 0.02) since this variable was very homogeneous, as the land was tilled conventionally.

Management classes and nitrate-N and moisture content

Although we measured the soil NO_3^--N and gravimetric moisture content at five time sequences over the growing season, we focus here on two moments: after seeding (18/5) and during the ripening stage (14/8). Table 3 contains the mean values per class and associated standard errors and Table 4 summarizes the results of the ANOVA.

At the start of the growing season (18/5) the total soil NO_3^--N in the top 60 cm was very variable. In class 1 we observed a mean NO_3^--N content of 312 kg ha^{-1}, while in class 2 the mean NO_3^--N content (175 kg ha^{-1}) was 44% less than in class 1. The associated smaller standard error values indicated the relevance of these differences. Class 3 had a similar mean NO_3^--N amount as class 1, with a large overlap as indicated by high standard errors. These differences in mean NO_3^--N suggested that a considerable amount of uniformly applied N-fertilizer and residual mineral N of the previous crop was lost during the winter in class 2. This is likely due to the larger leaching capacity of the sandy subsoil in this class compared to the more clayey subsoil of classes 1 and 3. A similar observation was reported by Shaffer and Ma (2001). This implied that particularly class 2 requires careful attention with fertilizer application to avoid losses of NO_3^--N during the winter. Three months later (14/8), most of the NO_3^--N was removed, most likely mainly taken up by the sugar beets. This could be expected, as Armstrong *et al.* (1986) reported that sugar beet plants might need to take up as much as 5 kg N ha^{-1} day^{-1} for rapid leaf expansion. Only a small amount (15–25 kg N ha^{-1}) remained in all classes with overlapping ± 1 intervals. This depletion of NO_3^--N caused a lower total variance. This situation continued for the rest of the growing season. Consequently, the R_i^2, which was 0.39 at 18/5, decreased to almost zero at 14/8 (Table 4). The classification could therefore be linked to differences in NO_3^--N at the start of the growing season, mainly due to a soil texture related N-losses process during winter. However, during the growing season this link weakened and disappeared, as most of the nitrogen was taken up by the crop.

At both observation dates the average soil moisture content showed a strong relationship with the classification ($R_i^2 > 0.7$). The sandy subsoil of class 2 resulted in lower moisture content compared to the other two classes, indicating possible limitations of soil moisture availability. The standard errors were small at 18/5, but increased with overlapping ± 1 $s_{e.i}$ intervals between class 1 and 3 at 14/8.

TABLE 3

Mean values per management class of total soil NO_3^--N and average soil moisture content over 0-60 cm at the sampling dates 18/5/2005 and 14/8/2005 and between brackets the standard errors of these means

Class	Nitrate-N (kg ha^{-1})		Soil moisture content (% w/w)	
	18/5/2005	14/8/2005	18/5/2005	14/8/2005
1	312 (28)	15 (3)	21.8 (0.6)	20.3 (2.0)
2	175 (11)	18 (5)	17.0 (1.1)	15.7 (2.3)
3	301 (95)	25 (9)	23.4 (0.1)	20.9 (3.2)

TABLE 4

Results of the ANOVA on total soil NO_3^--N and average gravimetric soil moisture content over 0-60 cm at the sampling dates 18/5/2005 and 14/8/2005 based on the 3 management classes s_T^2 = total variance, s_W^2 = within-class variance, R_i^2 = proportion of the variance accounted for by the classification

	Nitrate-N (kg ha^{-1})		Soil moisture content (% w/w)	
	18/5/2005	14/8/2005	18/5/2005	14/8/2005
s_T^2	8031	64.8	8.44	6.80
s_W^2	4910	64.5	1.91	1.83
R_i^2	0.39	0.01	0.77	0.73

Management classes and crop yield

The average crop biomass of class 2 was distinctly smaller than that of class 1 and 3: respectively 105 Mg ha^{-1} and about 153 Mg ha^{-1} (Table 5). We observed the largest R_i^2 (0.91) for crop biomass in comparison to all other variables (Table 6). As a consequence, the classification was very successful in differentiating biomass production within this field. It is likely that the less available nitrogen and moisture in class 2 has caused lower biomass yields. Milford (2006) indicated a clear relationship between the nitrogen and moisture availability in the early stages of sugar beet growth and total biomass production.

An inverse relationship was found for the sugar content: on average it was 17.2% for class 2, 16.3% for class 1 and 15.4% for class 3, with very small standard errors and a of R_i^2 0.69. There seemed to be a compensation effect for the biomass production (Jaggard and Qi 2006). Class 2 had the smallest root weights, which are generally the richest in sugar content. The opposite was found in classes 1 and 3. As a result, the sugar yield was more homogeneous, it ranged from 13 Mg ha^{-1} for class 2 to 14.2 Mg ha^{-1} for class 1, which was almost the same for class 3. Obviously, R_i^2 dropped to 0.22.

The financial income obtained by the farmer reflected this compensation effect. He receives 45 euros per Mg of fresh beets when the sugar content is 16%. If the sugar content is higher than 16%, he receives 0.09×45 euros extra for each additional 1% of

TABLE 5
Mean values of crop yield (sugar beets) variables per management class and, between brackets, the standard error of the mean

Class	Biomass (Mg ha^{-1})	Sugar content (%)	Sugar yield (Mg ha^{-1})	Income (€ ha^{-1})
1	146.6 (3.2)	16.3 (0.1)	14.2 (0.4)	4228 (118)
2	105.5 (2.5)	17.2 (0.3)	13.0 (0.3)	3958 (72)
3	153.2 (5.7)	15.4 (0.3)	14.1 (0.5)	4095 (172)

TABLE 6
Results of the ANOVA on the crop yield (sugar beets) variables based on the 3 management classes s_T^2 = total variance, s_W^2 = within-class variance, R_i^2 = proportion of the variance accounted for by the classification

	Biomass (Mg ha^{-1})	Sugar content (%)	Sugar yield (Mg ha^{-1})	Income (€ ha^{-1})
s_T^2	472	0.59	0.72	56786
s_W^2	44	0.18	0.56	53220
R_i^2	0.91	0.69	0.22	0.06

sugar content. The inverse applies for a sugar content in the range 15–16%. Currently, the payment does not include a correction for the sugar quality (extractability), but the farmer also receives 2.35 euros per Mg fresh beet as a compensation for the beet pulp. This pulp is a remnant of the sugar extraction process and is sold as organic manure. Although the classification was not able to differentiate the income between the classes (with R_i^2 of 0.06 and relatively large standard errors), there was still a considerable difference in average income of 270 euros ha^{-1} between class 1 and 2. Between class 3 and 2 the difference in average income was 137 euros ha^{-1}.

It should be added that the similarity in income between classes was obtained through a completely different soil-crop interaction, notwithstanding the uniform management. In class 2 both the NO_3^--N and moisture content were the lowest, resulting in small beets with high sugar contents. In class 3 the beets were the largest, but with the lowest sugar content. Class 1 had intermediate values for both variables, resulting in the most financial income. This indicates that if the three management zones had received different N-fertilization, with N-fertilization split into several applications for class 2 and a single but smaller N-application for class 3, both classes could have had an increased sugar production, resulting in an overall increased income. Also, proper water management in class 2 could benefit the crop growth, especially in early growing conditions.

CONCLUSIONS

The dual dipole EM38DD measurements allowed us to obtain an image of the average ECa from vertical and horizontal dipole measurements. This image was then classified using a fuzzy *k*-means algorithm into three management classes. These classes were found to reflect clear differences in soil composition, mainly sand and lime content in the topsoil and clay, sand and lime content in the subsoil. The subsoil variability between the classes explained the different dynamics of NO_3^--N and soil moisture content during the growing season of 2005 and the preceding winter. The soil of class 2 contained less available NO_3^--N at the start of the growing season than the other classes, notwithstanding the more or less uniform application of N-fertilization in the previous autumn.

The differences between management classes had an impact on the sugar beets. The beets grown in class 2 produced clearly less biomass (beet roots and leaves), which was compensated by a larger sugar content. As a consequence, relatively small differences were found between the zones for the sugar yield and the sugar related income by the farmer. However, it should be noted that the relatively small differences in income (of about 270 euros ha^{-1}) are the result of strongly different growing conditions and compensation effects between total biomass and sugar accumulation under uniform input application. Consequently, there is a clear opportunity to optimize the yield while reducing the environmental implications by nitrate losses. Different management for the three classes is recommended. Class 2, with its permeable sandy subsoil, would benefit from a fertilization scheme split into different applications, whereas classes 1 and 3 could suffice with a single, and probably smaller, N-application. Also, differences in water management could be considered.
As a general conclusion it can be stated that ECa measurements are able to provide a stable and relevant basis for delineating agronomically relevant management zones.

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REFERENCES

Armstrong M.J., Milford G.F.J., Pocock T.O., Last P.J. and Day W. 1986. The dynamics of nitrogen uptake and its re-mobilization during the growth of sugar beet. *Journal of Agricultural Science* **107**, 145–154.

Burrough P.A. and McDonnell R.A. 1998. *Principles of Geographical Information Systems*. Oxford University Press.

Callegary J.B., Ferré T.P.A. and Groom R.W. 2007. Vertical spatial sensitivity and exploration depth of low-induction-number electromagnetic-induction instruments. *Vadose Zone Journal* **6**,158–167.

Cockx L., Ghysels G., Van Meirvenne M. and Heyse I. 2006. Prospecting frost-wedge pseudomorphs and their polygonal outline using electromagnetic induction. *Permafrost and Periglacial Processes* **17**, 163–168.

Dent D. and Young A. 1981. *Soil Survey and Land Evaluation*. George Allen & Unwin.

Goovaerts P. 1997. *Geostatistics for Natural Resource Evaluation*. Oxford University Press.

Hedley C.B., Yule I.Y., Eastwood C.R., Shepherd T.G. and Arnold G. 2004. Rapid identification of soil textural and management zones using electromagnetic induction sensing of soils. *Australian Journal of Soil Research* **42**, 389–400.

Hendrickx J.M.H. and Kachanoski R.G. 2002. Indirect measurement of solute concentration: Nonintrusive electromagnetic induction. In: *Methods of Soil Analysis*, *Part 4* (eds J.H. Dane and G.C. Topp), pp. 1297–1306. SSSA Book Ser. 5. SSSA.

Jaggard K.W. and Qi A. 2006. Agronomy. In: *Sugar Beet* (ed. A.P. Draycott), pp. 154–157. Blackwell Publishing.

James I.T., Waine T.W., Bradley R.I., Taylor J.C. and Godwin R.J. 2003. Determination of soil type boundaries using electromagnetic induction scanning techniques. *Biosystems Engineering* **86**, 421–430.

Kitchen N.R., Sudduth K.A., Myers D.B., Drummond S.T. and Hong S. Y. 2005. Delineating productivity zones on claypan soil fields using apparent soil electrical conductivity. *Computers and Electronics in Agriculture* **46**, 285–308.

Kitchen N.R., Sudduth K.A. and Drummond S.T. 1999. Soil electrical conductivity as a crop productivity measure for claypan soils. *Journal of Production Agriculture* **12**, 607–617.

McNeill J. D. 1980, Electromagnetic terrain conductivity measurements at low induction numbers. Geonics Limited, Technical Note TN-6.

Milford G.F.J. 2006. Plant structure and crop physiology. In: *Sugar Beet* (ed. A.P. Draycott), pp. 34–36. Blackwell Publishing.

Minasny B. and McBratney A.B. 2002. *FuzME Version 3*. Australian Centre for Precision Agriculture, The University of Sydney NSW 2006 Australia. Available: http://www.usyd.edu.au/su/agric/acpa/fkme/program.html accessed 17/7/2005.

Mulla D.J. and Schepers J.S. 1997. Key processes and properties for site-specific soil and crop management. In: *The State of Site-Specific Management for Agriculture* (eds F.J. Pierce and E.J. Sadler), pp. 1–18. American Society of Agronomy.

Shaffer M.J. and Ma L. 2001. Carbon and nitrogen dynamics in upland soils. In: *Modelling Carbon and Nitrogen Dynamics for Soil Management* (eds M.J. Shaffer, L. Ma and S. Hansen), pp. 11–26. Lewis Publishers.

Sylvester-Bradley R., Lord E. Sparkes D.L., Scott R.K., Wiltshire J.J.J. and Orson J. 1999. An analysis of the potential of precision farming in Northern Europe. *Soil Use and Management* **15**, 1–8.

Triantafilis J. and Lesch S.M. 2005. Mapping clay content variation using electromagnetic induction techniques. *Computers and Electronics in Agriculture* **46**, 203–237.

Van Meirvenne M. and Hofman G. 1989. Spatial variability of soil texture in a polder area: II. Cokriging. *Pedologie* **39**, 209–226.

Vitharana U.W.A., Van Meirvenne M., Cockx L. and Bourgeois J. 2006. Identifying potential management zones in a layered soil using multiple sources of ancillary information. *Soil Use and Management* **22**, 405–413.

Webster R. and Beckett P.H.T. 1968. Quality and usefulness of soil maps. *Nature* **219**, 680–682.

Webster R. and Oliver M. 1990. *Statistical Methods in Soil and Land Resource Survey*. Oxford University Press.

Williams B.G. and Hoey D. 1987. The use of electromagnetic induction to detect the spatial variability of the salt and clay contents of soils. *Australian Journal of Soil Research* **25**, 21–27.