Spatial Characteristics of Claypan Soil Properties in an Agricultural Field

W. K. Jung, N. R. Kitchen,* K. A. Sudduth, and S. H. Anderson

ABSTRACT

Spatial variability in soil properties has long been observed within uniformly managed fields. Understanding the spatial characteristics of soil properties would be helpful in understanding soil–landscape relationships and in the development of site-specific management. The primary objective of this research was to quantify the spatial characteristics of claypan soil properties for a 4-ha agricultural field located in north-central Missouri. Soil samples were collected in 2002 at three depths (0–7.5, 7.5–15, and 15–30 cm) on a 30-m grid. Samples were analyzed for physical, chemical, and microbiological properties. Handheld and mobile apparent soil-profile electrical conductivity (EC$_a$) values were also obtained. Spatial dependence was not identified for many properties. Yet, at a separation distance of ~40 m, clay and silt content, cation exchange capacity, and Bray-1 P were spatially autocorrelated for the 15- to 30-cm depth. Soil EC$_a$ showed a similar spatial autocorrelation. Spatial variations in most soil properties were better estimated by cross-semivariance analysis with EC$_a$ as a secondary variable than by simple semivariance analysis. Clay content was lowest and mostly homogeneous at the 0- to 7.5-cm depth (mean = 170 g kg^{-1}, SD = 2.0), and highest and most variable at the 15- to 30-cm depth (mean = 410 g kg^{-1}, SD = 15.8). Thus, the spatial characteristics of soil texture and related soil properties varied greatly by depth and landscape position, probably the result of an uneven distribution of topsoil caused by tillage-accelerated water erosion. We conclude that characterizing the variation in the depth of the claypan horizon is a helpful step in describing other properties for these soils.

I N UNIFORMLY managed crop production fields, soil characteristics are commonly observed to have significant within-field variability (Cline, 1944). The predominant variability of a soil is determined by the cumulative effect of natural factors involved in its formation, including climate, topography, parent material, biological activity, and time (Jenny, 1941). Crop management practices also contribute to the spatial heterogeneity of some soil properties, beyond that attributable to natural processes (Cambardella and Karlen, 1999). Thus, soils under agricultural management are highly variable in chemical and physical characteristics. Due to within-field variation, uniform management of fields often results in overapplication of inputs in low-yielding areas and underapplica-

tion of inputs in high-yielding areas (Davis et al., 1996; and Ferguson et al., 2002). This is a reason for considering spatial variability of soil properties in management decisions, with the potential result being more productive and efficient crop management systems. Site-specific management of soils and crops based on varying conditions within a field provides optimal management (Larson and Robert, 1991). Numerous research efforts have been aimed at comparing spatially variable soil characteristics to spatially variable crop yields to develop site-specific management practices (Cahn et al., 1994; Lund et al., 1999; Drummond et al., 2003; Eghball et al., 2003; Kitchen et al., 2003; Chang et al., 2004).

Quantifying spatial characteristics of soil properties, particularly when these properties are related to specific soil functions (e.g., crop production or water quality), can help improve understanding of soil–landscape processes and formulation of site-specific management; however, intensive grid soil sampling and subsequent laboratory analysis and interpolation for mapping such properties is most often impractical because of time and expense. These issues are less of a concern when sensors are employed to gather spatial information about soil and field characteristics. For example, a sensor technology commonly used for assessing soil variation is EC$_a$. Soil EC$_a$ can depend on various soil properties, including soil water content, soil salinity, cation exchange capacity (Rhoades et al., 1999; Corwin and Lesch, 2005), soil particle-size distribution (Sudduth et al., 2003; Jung et al., 2005), topsoil depth (Doolittle et al., 1994), and management practices (Johnson et al., 2001, 2003).

Whether soil properties are assessed through soil sampling or sensors, geostatistical techniques play an important role in the quantitative evaluation of spatial variability within a field. Classical experimental design statistics assumes that the data are independent from each other. If sampled data severely violate this assumption, incorrect conclusions may be made. Because results from field sampling are often spatially dependent, sampled data often violate the independence assumption. The correlation structure of a measurement in space (autocorrelation) provides insight into its spatial structure and describes how it changes in space in relation to the sampling frequency (Kravchenko, 2003). Spatial autocorrelation can also significantly influence interpretation. Descriptions of how spatial relationships change with distance of separation between measurement points are accomplished with tools such as the semivariogram and correlogram.

Interpolation techniques widely used to estimate variability patterns of soil properties are kriging and cokriging. Kriging is a geostatistical interpolation tech-

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Abbreviations: CEC, cation exchange capacity; EC$_a$, apparent profile electrical conductivity; SOM, soil organic matter; TN, total nitrogen.

nique that uses statistical properties of measured points (Isaacks and Srivastava, 1989). Cokriging uses one or more secondary variables to interpolate and accounts for spatial cross-correlation between the primary and secondary variable (Goovaerts, 1998). Cokriging can produce much more accurate and reliable estimation results than can the semivariance analysis technique (Kravchenko et al., 2002). A major disadvantage of geostatistical interpolation of soil properties is the need for a large number of soil samples that must be collected and analyzed for valid representation of the unsampled area. The economic impracticality of intensive soil sampling is one reason the idea of measuring spatial variability with sensors is appealing to producers (Kitchen et al., 2002), as it meets the need of having spatially dense measurements at a low cost.

Claypan soils, common in northeast Missouri and southern Illinois, have a restrictive high-clay subsoil layer usually occurring 20 to 40 cm below the soil surface. Claypans create a unique hydrology, characterized by slow water flow in the soil matrix of the restrictive clay layer. A better understanding of the spatial characteristics of claypan soil properties would be desirable when managing these soils, which are sensitive to soil degradation (e.g., runoff and erosion; Nikiforoff and Drosdoff, 1943; Kitchen et al., 1998), have high variability in crop productivity (Kitchen et al., 2005), and which frequently contribute to water quality impairment (Lerch et al., 2005). The claypan also has a large effect on plant root development (Wang et al., 2002). Clay content in the argillic horizon is generally >40% and is comprised of smectitic (high shrink–swell) clay minerals. Depth to the argillic horizon (or topsoil depth) of claypan soils has been proposed as an important soil quality indicator (Kitchen et al., 1999). Lerch et al. (2005) estimated topsoil losses using GIS (geographic information system) models and found spatial variance of topsoil

losses within a field as a result of long-term management practices. In a previous study, claypan soil properties were related to soil EC_a, but the spatial characteristics of these properties were not evaluated (Jung et al., 2005).

We hypothesized that similar spatial relationships exist among claypan soil properties, and that descriptions of the spatial characteristics of these properties would be helpful in understanding soil–landscape relationships and in considering site-specific soil management options. The objectives of this study were to: (i) quantify the spatial characteristics of soil properties for an agricultural claypan soil field, and (ii) evaluate if the description of spatial variation in soil properties could be improved by cokriging with soil EC_a.

MATERIALS AND METHODS

Study Site

A 4-ha study site (Fig. 1), located 3 km north of Centralia in central Missouri (39°13′48″ N, 92°07′00″ W) was selected from a 35-ha research field. Mean annual temperature is ~12°C, and mean annual precipitation is 1004 mm. An Order 1 soil survey (1:5000 scale) conducted in 1993 described the soil series of the study site as Adco (fine, smectitic, mesic Vertic Albaqualf) and Mexico (fine, smectitic, mesic Aeric Vertic Epiaqualf), as documented previously (Fraisse et al., 2001). These soils are formed in loess or a combination of loess and pedisediment and are poorly drained. They usually occur in upland areas with slopes varying from 0 to 5%. Surface soil texture ranges from silt loam to silty clay loam. The subsoil claypan horizons consist of silty clay loam, silty clay, or clay (NRCS, 1995). Within the study site, the topsoil thickness above the claypan (B_t horizon) ranges from 10 cm to >100 cm. This site has been managed in a corn (*Zea mays* L.)–soybean [*Glycine max* (L.) Merr.] crop rotation under mulch tillage (i.e., crop residues are generally left on the surface after tillage operations) since 1991 and has experienced significant topsoil loss from water erosion as a result of ~150 yr of agricultural practices (Lerch et al., 2005).
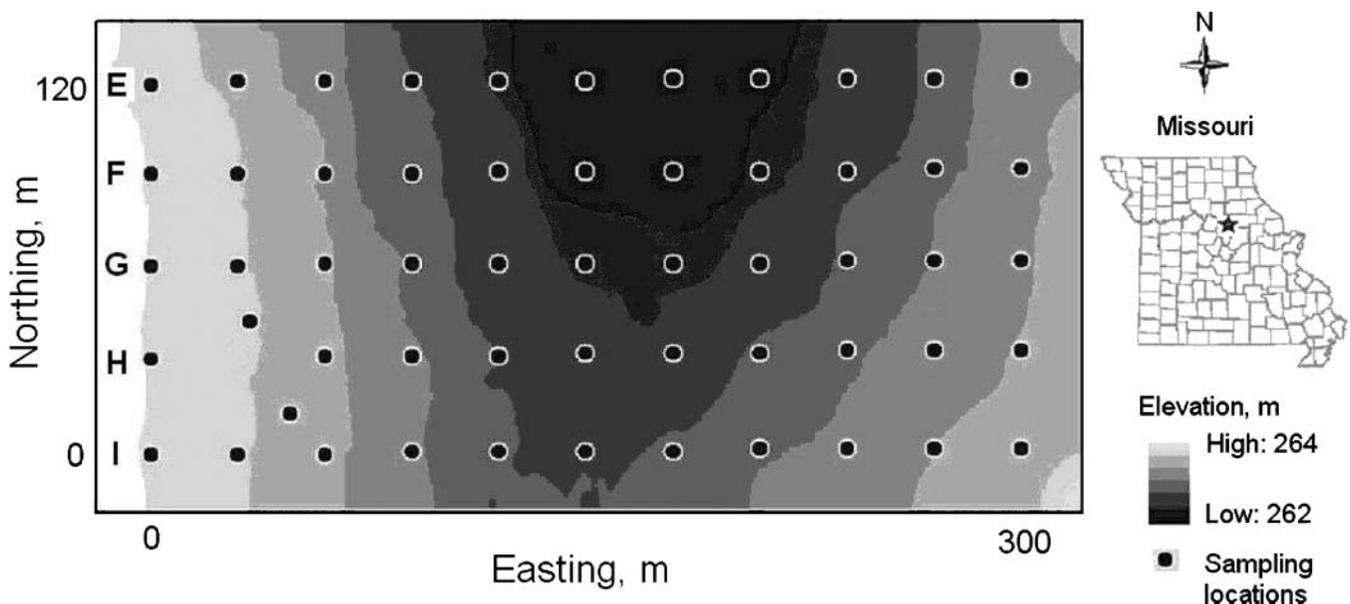

Fig. 1. Research site and sampling design (dotted lines represent sampling transects E and H, which were selected to illustrate topsoil variation in Fig. 9).

Measurements and Analysis

Soil samples were collected in June 2002 at three soil depths, 0 to 7.5, 7.5 to 15, and 15 to 30 cm, using a 30-m grid sampling design (n = 55; Fig. 1). A real-time kinematic GPS (global positioning system) survey (accuracy 2–5 cm) was used to identify sampling locations. Three soil cores (5.5-cm diameter) were taken by a hydraulic soil core sampler at each sampling site and were appropriately prepared for physical, chemical, and microbiological analysis. One extra soil core from each site was taken to a depth of 100 cm for visually identifying the claypan (B_t horizon) depth. Physical properties measured included soil particle size fraction (pipette method) and soil bulk density (D_b) following accepted methods (National Soil Survey Center Staff, 1996). Measured chemical properties consisted of CEC (cation exchange capacity) by the sum of cations (1 M NH_4OAc extractable at pH 7.0), SOC (soil organic carbon, pretreated to remove carbonates when necessary; dry combustion, LECO, St. Joseph, MI), TN (total nitrogen, dry combustion, LECO, St. Joseph, MI) and P by the Bray-1 extraction method (Olsen and Sommers, 1982). Samples from the shallowest soil depth (0–7.5 cm) were used to determine aggregate stability, soil enzyme activity using the dehydrogenase method (Casida et al., 1964), and microbial biomass C as respired CO_2–C using a 3-wk soil fumigation–incubation method (Johnson et al., 1994).

Soil EC_a data (n = 55) were obtained at each location concurrent with soil sampling using a Geonics EM38 (Geonics Ltd., Mississauga, ON, Canada) instrument. The EM38 was operated in horizontal dipole mode at the soil surface, which provided an effective measurement depth of ~0.75 m. In this mode, sensitivity of the sensor is greatest nearest the sensor (i.e., at the soil surface) and declines exponentially with increasing soil depth (McNeill, 1992). Given this, the sensor will be, on average, twice as responsive to soil properties in the surface 30 cm of soil (i.e., the sampling depth of this study) than soil below 30 cm. Soil EC_a data were also obtained from a mobile EC_a survey (EM38 operated in vertical mode with ~1.5-m effective depth) conducted on this field in 1999. Mobile EC_a data on an approximate 10-m grid (error <2 m) were extracted and used for this analysis (n = 399). Procedures for mobile EM38 operations and measurement depths, along with a detailed description of the 1999 data collection, are given in Sudduth et al. (2003).

Geostatistical Data Analysis

Measurements were assessed for spatial autocorrelation among neighboring observations of a variable, X, using Moran's I (Moran, 1948; Boots and Getis, 1988). Moran's I was computed by dividing the spatial covariance by the total variance according to

$$I = \frac{n \sum \sum Z_i Z_j}{\sum Z_i^2} \qquad [1]$$

where n = number of localities in an interval class, $Z_i = X_i -$ mean X, and $Z_j = X_j -$ mean X. Spatial autocorrelation is the relationship among values of a single variable that comes from the geographic arrangement of the areas in which these values occur. It measures the similarity of objects within an area or the degree to which a spatial phenomenon is correlated to itself in space (Cliff and Ord, 1973, 1981). Moran's I was determined using a 150-m active lag distance (which is half of the research site length), a 30-m first lag distance, and a 15-m lag interval (GS+ software, Version 5.1, Plainwell, MI). The average number of sample pairs per distance class was 102 and ranged from 52 to 184, above the minimum standard of 30

pairs recommended by Legendre and Fortin (1989). Moran's I values range from −1 to 1. A positive value represents positive spatial autocorrelation and a negative value represents negative spatial autocorrelation. Following Snedecor and Cochran (1989) and Lauzon et al. (2005), we concluded significant spatial autocorrelation when the absolute value of Moran's I was >0.3.

Geostatistics provided a tool for interpolation of unsampled locations, taking into account the spatial correlation of paired samples based on semivariance (Cliff and Ord, 1973). The sample semivariogram, $\gamma(h)$ is commonly used to estimate the structure of the spatial variation of a variable V. Semivariance is defined as

$$\gamma(h) = \frac{1}{2n(h)} \sum [V(s) - V(s + h)]^2 \qquad [2]$$

where $V(s)$ and $V(s + h)$ are the observed values of V at location s and $s + h$, respectively, h is the separation distance, and $n(h)$ is the number of paired comparisons at the distance h. The range is the separation distance beyond which two observations are independent of each other. The sill is the semivariogram value corresponding to the range. The discontinuity at the origin is called the *nugget effect* and arises from a combination of random errors and sources of variation at distances smaller than the shortest sampling interval (Goovaerts, 1998).

Isotropic semivariogram models were fitted to the soil properties. Lag-specific isotropic semivariogram models (i.e., maximum lag distance = 150 m, first lag distance = 30 m, and lag distance interval = 15 m) were calculated and compared on the basis of range, sill, and nugget among spherical, exponential, linear, and Gaussian models. Only the best model based on R^2 was reported. We assumed a property to have significant spatial dependency when the spatial range was less than the maximum lag distance, the model R^2 was >0.5, and the proportion of the non-nugget spatially dependent variability was >0.5. Maps of soil properties were created by the block kriging interpolation method for each sampling depth.

To investigate the possibility of using sensor data to improve estimates of soil properties, isotropic cross-semivariogram models were also fit to the measured soil properties, using soil EC_a from either handheld or mobile readings as the secondary variable. Model parameters and significance were as defined above for ordinary semivariogram models.

RESULTS AND DISCUSSION
Frequency Distribution of Soil Properties

Frequency distributions of the soil properties were different by soil depth (Fig. 2). Soil bulk density values were lower at the 0- to 7.5-cm depth due to tillage operations and consequent mixing of crop residue with topsoil. Clay and silt contents and CEC for the upper two soil depths (0–7.5 and 7.5–15 cm) were notably different than the 15- to 30-cm soil depth. Distribution of clay content and CEC were very similar and unimodal at the two shallow soil depths and multimodal at the third soil depth. High clay content and CEC at this depth were clearly the result of sampling in the claypan (B_t horizon). Low clay content and CEC at this depth indicated that sampling excluded the claypan, and that the claypan was apparently deeper within the profile.

Soil organic C and TN were highest near the surface and intermediate in the deepest sampling depth. Several explanations are possible for this observation. Previous studies have shown that plant residues (e.g., quantity

and quality of sources) affect C sequestration rates in soil (Allison, 1973). Soil organic matter decomposition is relatively dynamic at the shallow soil depth because of soil disturbance from annual tillage practices, plant residue inputs, and chemical fertilization. While not measured, the SOM (soil organic matter) turnover in the 15- to 30-cm depth may be slow because it is more stable from decomposition. Also, the slightly higher SOC and TN at the 15- to 30-cm depth than at the 7.5- to 15-cm depth may be attributed to an increase in crop root growth at the deeper depth in response to the morphological characteristics of the claypan (argillic horizon). Others have documented that the claypan can stimulate root growth (Wang et al., 2002; Myers, 2005). Bray-1 P was higher and more variable for the shallowest soil depth (i.e., 0–7.5 cm), presumably an effect of fertilization and plant residues. We conclude that significant vertical spatial variation of many soil properties (i.e., variability among sampling depths) exists on this site. Further, we assert that variation in clay content is the primary driving factor causing vertical spatial variation for many of the other soil properties measured like EC_a or CEC (discussed below).

Soil aggregate stability (Fig. 2) and microbial properties (not shown) were also highly variable and generally exhibited multimodal distributions. Soil EC_a was normally distributed for both the 2002 handheld and the 1999 mobile EC_a readings (Fig. 2). Handheld EC_a was positively correlated to coincident (within ~2 m) mobile EC_a measurements (Fig. 3). The mean handheld EC_a reading (47 mS m^{-1}) was slightly higher than the mean mobile EC_a reading (41 mS m^{-1}). Factors potentially contributing to this difference included the handheld EC_a reading being closer to the soil surface than the mobile EC_a reading, soil moisture differences at the time the measurements were taken, and the differences in weighting factors and effective measurement depths between horizontal mode (handheld) measurements and vertical mode (mobile) measurements (Sudduth et al., 2001).
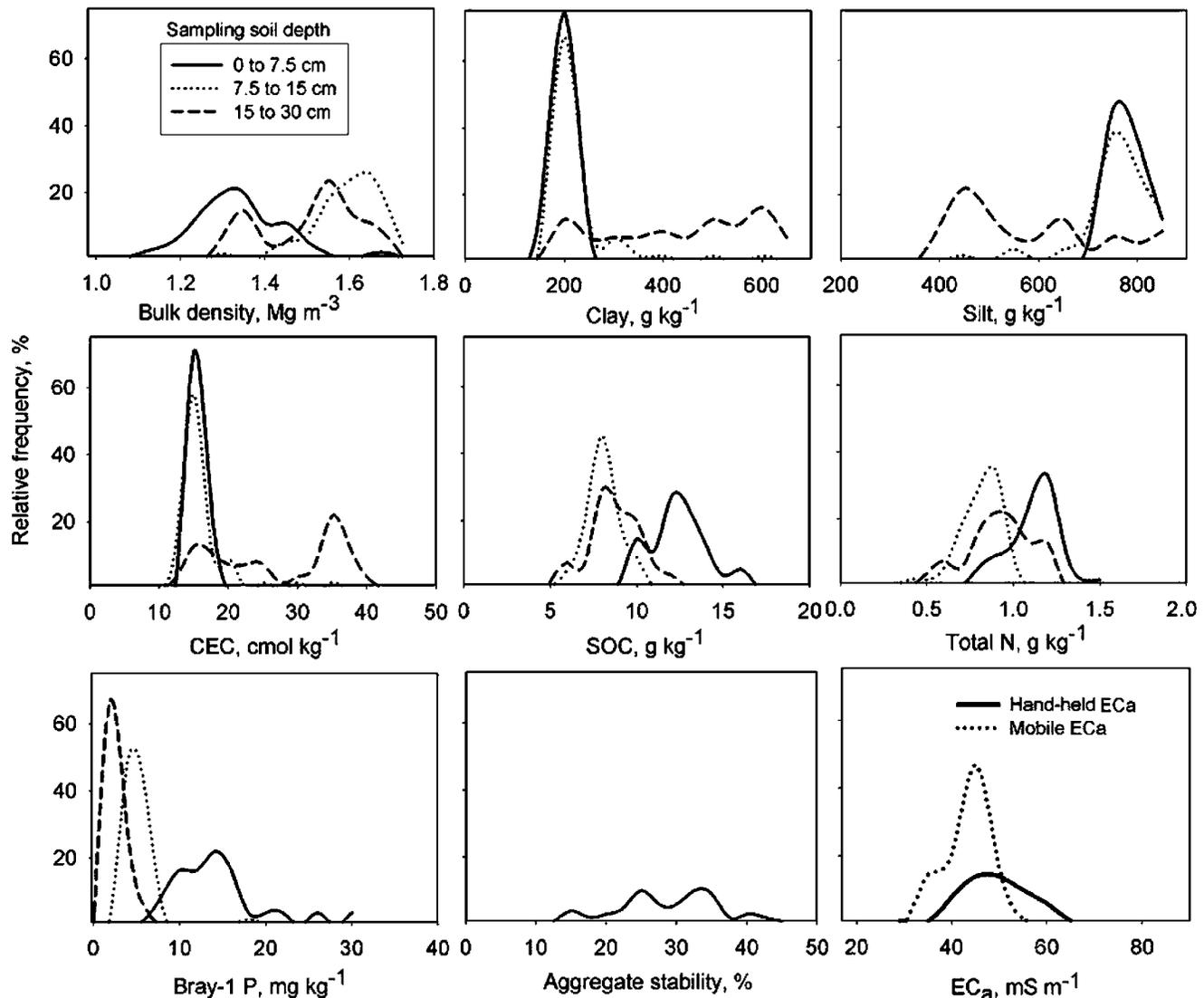

Fig. 2. Frequency distributions of soil properties by soil depth. Soil EC_a (apparent profile electrical conductivity) was measured using two methods and aggregate stability was only measured for the surface depth at each location. CEC = cation exchange capacity; SOC = soil organic carbon.
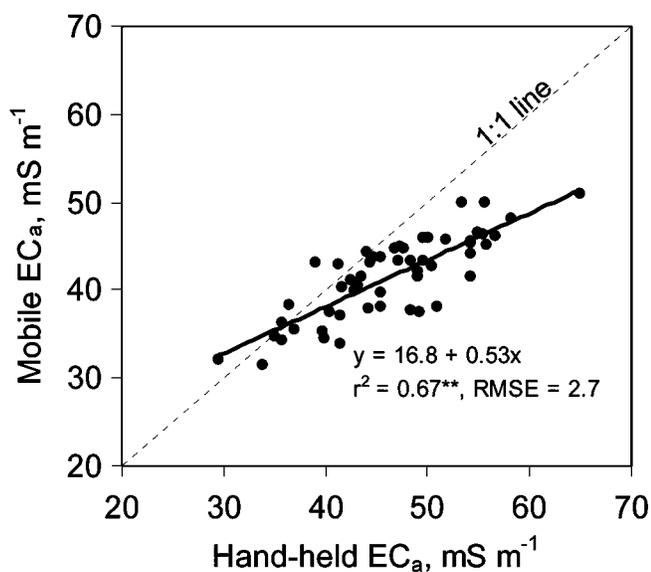
Fig. 3. Relationship between handheld and mobile EC_a (apparent profile electrical conductivity) readings.

Autocorrelation of Soil Properties

Spatial autocorrelations of soil properties were calculated from grid points at 15-m lag intervals (Fig. 4 and 5). For many properties and soil sampling depths, spatial autocorrelations were positive at a separation distance <50 m; however, significant spatial autocor-

relation ($|I| > 0.3$) was generally only found at the lower end of separation distances for which calculations could be made. This implies that we would have lost our ability to determine spatial structure for these soil properties had sampling spacing been >50 m. As examples, spatial correlations of soil texture at the shallowest sampling depth were highest and >0.3 at ~40-m separation distance. Spatial autocorrelation at the 15- to 30-cm sampling depth for clay content, silt content, CEC, and Bray-1 P were also highest (>0.3) at ~40-m separation distance. We assume that, at the 15-to 30-cm depth, intact undisturbed soil expressed inherent spatial characteristics. In contrast, surface soil has been disturbed from tillage-accelerated water erosion or deposition processes (Jamison et al., 1968), and thus exhibited less spatial structure. For a separation distance >60 m, spatial autocorrelation of most soil properties was generally neutral to slightly negative. Spatial autocorrelation of soil microbial properties and soil aggregate stability was consistently close to zero for all separation distances (Fig. 5). For these, our sampling strategy failed to identify spatial structure.

Spatial autocorrelation of EC_a for both handheld and mobile readings was positive and >0.3 at the <40-m separation distance. At separation distances >60 m, spatial correlation of EC_a generally remained close to zero.

Thus, the trend observed was positive spatial autocorrelation at short-range distances (<50 m) and little or no autocorrelation at greater distances. Overall, the
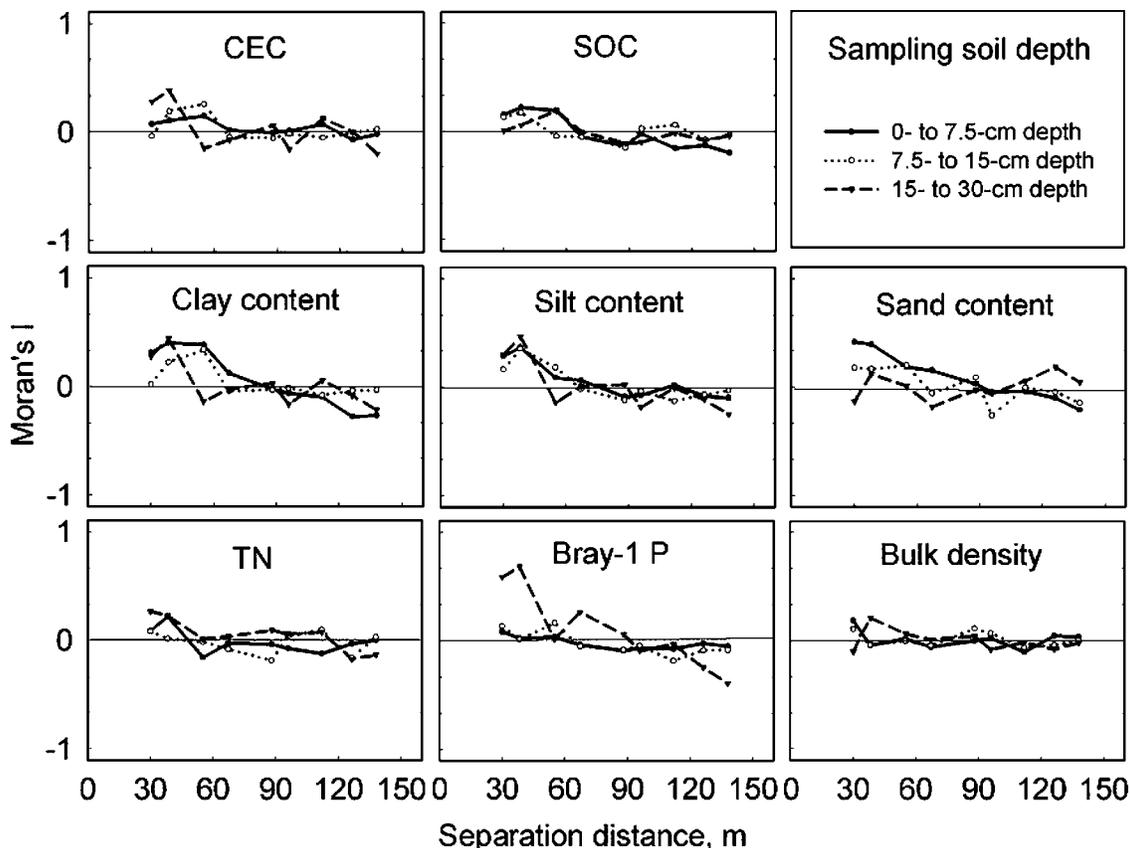

Fig. 4. Spatial autocorrelation (Moran's *I*) of soil physical and chemical properties by soil sampling depth. CEC = cation exchange capacity; SOC = soil organic carbon; TN = total nitrogen.
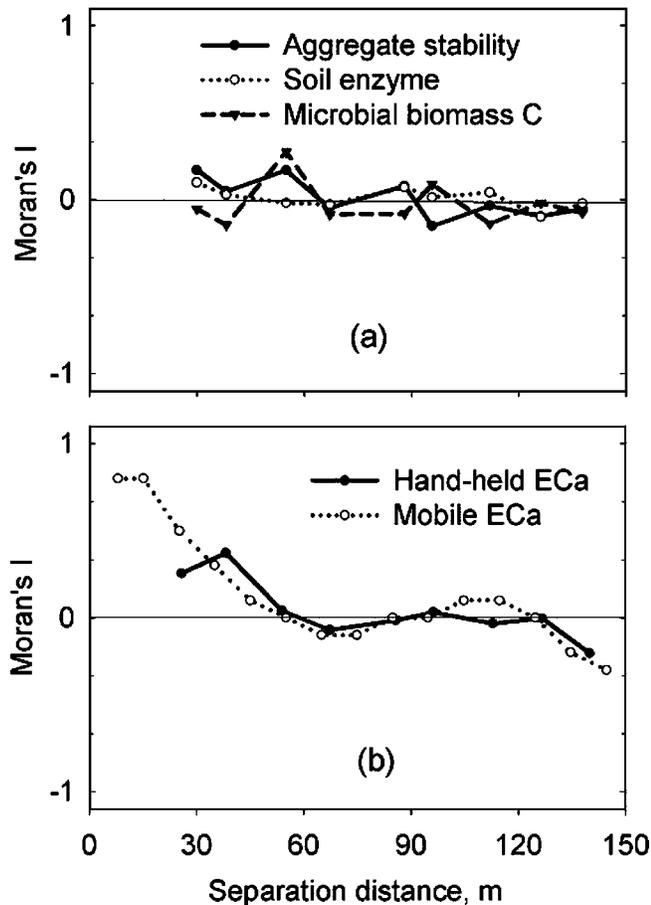
Fig. 5. Spatial autocorrelation (Moran's *I*) of (a) microbiological soil properties and aggregate stability for the 0- to 7.5-cm depth, and (b) soil EC$_a$ (apparent profile electrical conductivity).

similar patterns of spatial dependence indicate that soil formation and degradation processes affect these claypan soil properties in a similar manner.

Semivariance Analysis of Soil Properties

Several soil properties showed strong spatial dependence at the three sampling depths (Table 1). Ranges of spatial dependence from the semivariogram models were highly variable among properties, varying from 71 to >150 m. Clay and silt content showed a range of spatial dependence between 77 and 147 m at the shallowest and deepest soil sampling depths, but the range could not be determined at the intermediate sampling depth. Semivariance of CEC at the deep sampling depth was similar to silt and clay content. Soil EC$_a$ showed spatial dependency at a range similar to that of soil texture. The EC$_a$ was correlated with clay content at the subsurface soil depth. This result is reasonable because, on claypan soils, EC$_a$ is largely affected by depth to the argillic horizon (Sudduth et al., 2003). Soil organic C (0–7.5 cm) and Bray-1 P (15–30 cm) also showed spatial dependence. In other claypan soil investigations, soil P at the 15- to 30-cm soil depth was found to be significantly correlated with soil EC$_a$ (Jung et al., 2005).

Semivariogram models for TN, aggregate stability, and microbiological properties generally did not show evidence of spatial dependence. Thus, if spatial dependence occurred with these properties, it must have occurred at either shorter (<30-m) or longer (>150-m) distances. Closer sampling locations (i.e., higher sampling density) would be needed to determine if spatial dependence occurred at shorter distances.

Cross-Semivariance Analysis of Soil Properties

To evaluate if soil EC$_a$ could be used to improve the understanding of spatial characteristics of soil properties, cross-semivariance analyses were performed using the handheld EC$_a$ readings (Table 2). Given the criteria we used to identify significant spatial structure, cross-semivariance with soil EC$_a$ enhanced detection of spatial structure. For example, at the shallowest soil depth,

Table 1. Parameters† of the semivariogram models‡ for soil properties by soil sampling depth. Results are shown when range ≤ active lag distance and R^2 > 0.5. Aggregate stability, soil enzyme, and microbial biomass data were only obtained for the 0- to 7.5-cm soil depth. Soil EC$_a$ (apparent profile electrical conductivity) is a soil profile measurement and is not associated with a specific soil depth.

Property	0- to 7.5-cm soil depth						7.5- to 15-cm soil depth						15- to 30-cm soil depth					
	Model	C_0	$C_0 + C$	A_0	PSV	R^2	Model	C_0	$C_0 + C$	A_0	PSV	R^2	Model	C_0	$C_0 + C$	A_0	PSV	R^2
				m						m						m		
							Soil properties											
Bulk density																		
Soil texture																		
Clay content	G	213	589	147	0.64	0.93							S	1120	26950	77	0.96	0.65
Silt content	S	334	1545	94	0.78	0.83							S	1480	23550	86	0.94	0.70
Sand content	G	469	1075	134	0.56	0.95	S	460	921	117	0.5	0.61						
Cation exchange capacity													S	4.3	83	71	0.95	0.59
Soil organic C	S	1.4	3.1	147	0.56	0.93												
Total N																		
Bray-1 P													G	0.6	2.3	144	0.74	0.85
Aggregate stability							–	–	–	–	–	–	–	–	–	–	–	–
Soil enzyme							–	–	–	–	–	–	–	–	–	–	–	–
Microbial biomass							–	–	–	–	–	–	–	–	–	–	–	–
							Soil EC$_a$											
Handheld EC$_a$	S	20	53	92	0.63	0.76	–	–	–	–	–	–	–	–	–	–	–	–
Mobile EC$_a$	S	0.01	23.1	80	0.99	0.90	–	–	–	–	–	–	–	–	–	–	–	–

† C_0 = nugget; $C_0 + C$ = sill; A_0 = range; PSV = C/($C_0 + C$), which is the proportion of the non-nugget, spatially dependent variability as an indicator of degree of spatial structure: as the value approaches 1, the spatial autocorrelation becomes stronger.
‡ G = gaussian, S = spherical; for the gaussian model, A_0 is the effective spatial range, or the point where the model reaches 95% of the sill value.

Table 2. Parameters† of the cross-semivariogram models‡ for soil properties with handheld EC_a (apparent profile electrical conductivity; $n = 55$) as a covariate by soil sampling depth. Aggregate stability, soil enzyme, and microbial biomass data were only obtained for the 0- to 7.5-cm soil depth. Results are shown when range ≤ active lag distance and $R^2 > 0.5$.

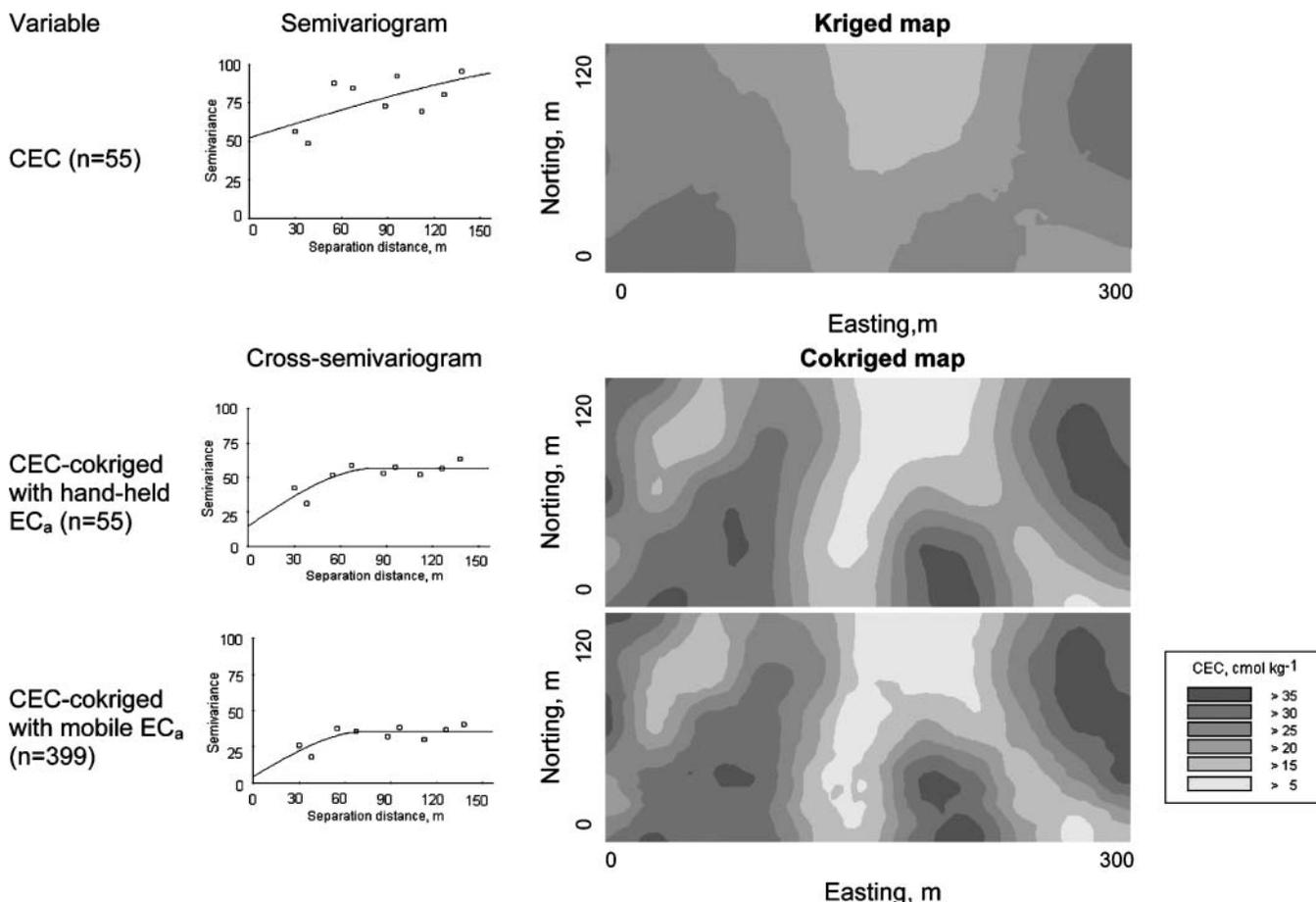| Soil property	0- to 7.5-cm soil depth						7.5- to 15-cm soil depth						15- to 30-cm soil depth					
	Model	C_0	$C_0 + C$	A_0	PSV	R^2	Model	C_0	$C_0 + C$	A_0	PSV	R^2	Model	C_0	$C_0 + C$	A_0	PSV	R^2
				m						m						m		
Bulk density	S	0.04	0.56	65	0.93	0.66							G	0.35	0.71	110	0.50	0.67
Soil texture																		
Clay content	G	53	124	134	0.57	0.91	S	94	339	88	0.72	0.55	S	184	1026	88	0.82	0.74
Silt content	S	81	219	95	0.63	0.77	S	108	412	90	0.74	0.65	S	201	970	95	0.79	0.78
Sand content	G	94	189	145	0.50	0.90	S	68	159	113	0.57	0.78						
Cation exchange capacity	G	3.1	6.2	104	0.50	0.90	S	2.2	4.4	70	0.5	0.51	S	9.7	57	79	0.83	0.68
Soil organic C	S	2.5	9.1	134	0.73	0.93												
Total N	G	0.4	0.8	100	0.52	0.86												
Bray-1 P													G	2.9	8.6	122	0.67	0.85
Aggregate stability	E	0.1	37.1	59	0.99	0.66	–	–	–	–	–	–	–	–	–	–	–	–
Soil enzyme							–	–	–	–	–	–	–	–	–	–	–	–
Microbial biomass							–	–	–	–	–	–	–	–	–	–	–	–

† C_0 = nugget; $C_0 + C$ = sill; A_0 = range; PSV = $C/(C_0 + C)$, which is the proportion of the non-nugget, spatially dependent variability as an indicator of degree of spatial structure: as the value approaches 1, the spatial autocorrelation becomes stronger.

‡ G = gaussian, S = spherical, E = exponential. For the gaussian and exponential models, A_0 is the effective spatial range, or the point where the model reaches 95% of the sill value.

spatial dependency was found for CEC, TN, and aggregate stability (ranges of 59–104 m) when cross-semivariance was used, but not with ordinary semivariance analysis (Table 1).

A more spatially dense EC_a dataset (mobile survey, $n = 399$) was also used to estimate spatial characteristics of soil properties by cross-semivariance analysis. Similar to results for the handheld EC_a survey, results for the mobile EC_a survey improved spatial structure determination when compared with semivariance analysis (data not shown); however, no appreciable difference was found between cross-semivarigram results of the two different

Fig. 6. Interpolated maps of 15- to 30-cm CEC (cation exchange capacity) obtained by kriging and by cokriging with handheld EC_a (apparent profile electrical conductivity) and mobile EC_a as a covariate. Mapped area is the same as that shown in Fig. 1.

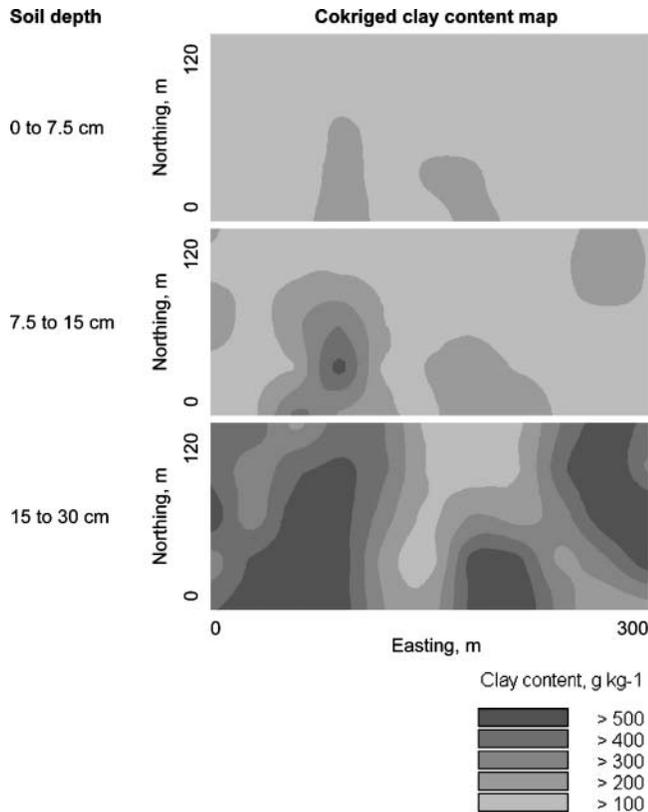**Soil depth** **Cokriged clay content map**

Fig. 7. Interpolated clay content maps for each sampling depth using cokriging with handheld soil EC_a (apparent profile electrical conductivity; n = 55) as a covariate. Mapped area is the same as that shown in Fig. 1.

accuracy when predicting the primary variable, but rather increased mapping resolution. Figure 6 shows an example of three interpolation results for CEC at the 15- to 30-cm soil depth. Spatial detail was increased with cokriging compared with ordinary kriging, but map resolution was most detailed when the higher density mobile EC_a measurements were used as the covariate.

Using the spatial structure from the cross-semivariogram with handheld EC_a as a covariate, clay content was also mapped to show variation by soil depth (Fig. 7). At the 0- to 7.5-cm soil depth, clay content was lowest of the three depths measured (mean = 170 g kg^{-1}, SD = 2.0) and more evenly distributed across the field than clay content at the other depths. At the 7.5- to 15-cm soil depth, clay content increased (mean = 200 g kg^{-1}, SD = 7.4), and at the 15- to 30-cm soil depth, clay content was highest (mean = 410 g kg^{-1}, SD = 15.8), with obvious steep clay content gradients occurring between backslope and footslope areas of the field (Fig. 1). At the 15- to 30-cm soil depth, high-clay-content areas (>400 g kg^{-1}) were often found in summit and backslope positions (i.e., relatively high elevation), while low-clay-content areas (<200 g kg^{-1}) were found in lower elevation footslope positions. Pedisediments in the footslope area from water erosion have effectively buried the higher clay content horizons to a depth below the sampling depth of this study. Semivariograms and kriged maps for both handheld and mobile EC_a are shown in Fig. 8. An area of lower EC_a in the middle part of the field was associated with low clay at the deep soil depth (15–30 cm). Soil EC_a has previously been related to clay content in soil profiles (Sudduth et al., 2003). In this case and for this sampling depth, EC_a could be used as a proxy for estimating spatial characteristics of clay content. Soil at the 15- to 30-cm depth is generally below the soil profile subjected to cultivation, hence this soil has had little disturbance

EC_a datasets, even though the mobile EC_a dataset had more than seven times more readings. The power of secondary measurements in this case was not in improved
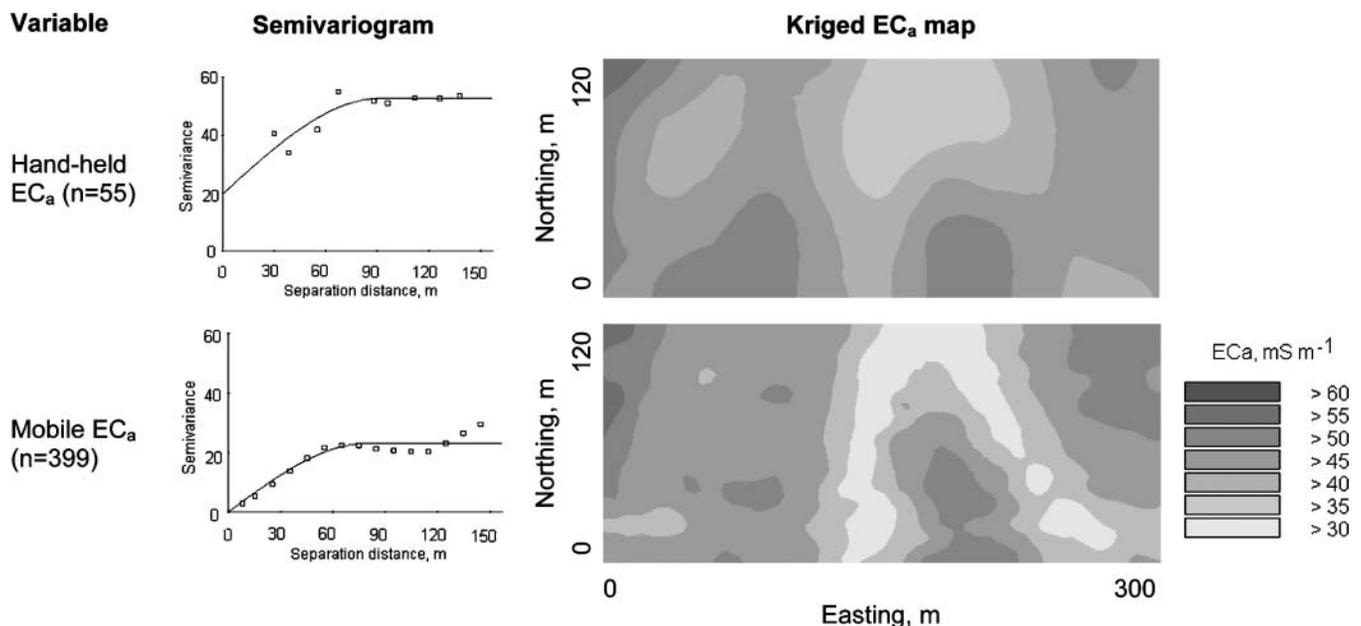

Fig. 8. Semivariograms and kriged maps of handheld and mobile EC_a (apparent profile electrical conductivity). Mapped area is the same as that shown in Fig. 1.

by modern tillage practices. Furthermore, soil erosion and deposition processes mostly impact the surface soil. We recognize that our association exists primarily because the claypan has a dominant texture change expressed at the 15- to 30-cm soil depth for most areas of the field.

This investigation illustrates a major challenge with spatial assessment of soil properties that have a distinct vertical spatial component. Further illustrating this, cross-sections showing the soil surface, depth of topsoil over the argillic horizon and soil sampling depths are given in Fig. 9 for two east–west transects (transects identified in Fig. 1). This illustrates how a given sampling depth may either include or exclude a portion of the argillic horizon, depending on position in the landscape. Generally, soils with a deep claypan were found in the middle portion of the transects, in the lower elevation areas of the field. Here, soil sampling to 30 cm did not reach the claypan. In other areas, such as part of Transect H, the claypan boundary was included in the 7.5- to 15-cm soil sampling depth. Through much of the field, the claypan boundary was captured in the 15- to 30-cm soil sampling depth. Previous erosion modeling for this field described topsoil movement from upland landscape positions to lower landscape positions (Lerch et al., 2005). Degraded claypan soils, like those present in this field, offer a special challenge

when the soil morphology that is being sampled varies so dramatically. We propose that understanding the variation in a horizon that has such a pronounced effect on plant growth (Kitchen et al., 1999) and hydrology (Ghidey et al., 2005; Kitchen et al., 1998), i.e., the argillic horizon of claypan soils, is a critical step in characterizing the behavior of that soil. In turn, steps to improve site-specific management of these soils ought to consider how this varying horizon is related to other soil and landscape properties. For example, depth of the argillic horizon for these soils has been shown to be significantly related to subsoil fertility (Spautz, 1998) and potential fertilizer management. Also claypan topsoil depth corresponds with areas of fields vulnerable to sediment, nutrient, and herbicide losses with runoff (Lerch et al., 2005).

While assessing spatial characteristics of soil properties has recognized merit, major obstacles remain, limiting wide adoption of this concept by crop producers. As shown in this study, spatial variation within fields, both between locations and by soil depth, is one of those obstacles. Mapping of soil properties that have spatial structure at short-range spatial dependencies will require high-density sampling. This is generally cost and labor prohibitive for most producers, unless sensors can be employed to accurately and rapidly collect this information. To educate and convince land managers to use soil principles, technologies and procedures for economical detection of variation will need to be developed.

CONCLUSIONS

Understanding spatial characteristics of soil properties may help to understand soil–landscape processes and to optimize strategies for sampling and management. In this study, we assessed spatial characteristics of claypan soil properties obtained by soil sampling and compared them with EC_a readings. Spatial distributions of soil properties (e.g., clay content, silt content, CEC, and Bray-1 P) were significantly different by soil depth. At the 15- to 30-cm depth, clay content, CEC, and Bray-1 P were positively correlated at a separation distance ~40 m and were similar in pattern to both handheld and mobile EC_a readings. For many of the properties measured, semivariance modeling did not indicate strong spatial dependence within the 30- to 150-m range; but when EC_a was used in a cross-semivariance analysis, with both handheld and mobile EC_a as a secondary variable, determination of spatial characteristics of some soil properties improved.

This research showed that spatial characteristics of soil properties varied greatly by field position and by soil depth, and that spatial characteristics of some soil physical properties were similar to spatial characteristics of EC_a readings. Thus spatial dependency was a function of both field location and soil sampling depth. For some soil chemical and microbiological properties, spatial patterns were not observed using our sampling strategy and analytical techniques, and therefore evaluation of their spatial characteristics would require high-density sampling. In conclusion, for properties found to have short-range spatial dependency, traditional soil sampling will be
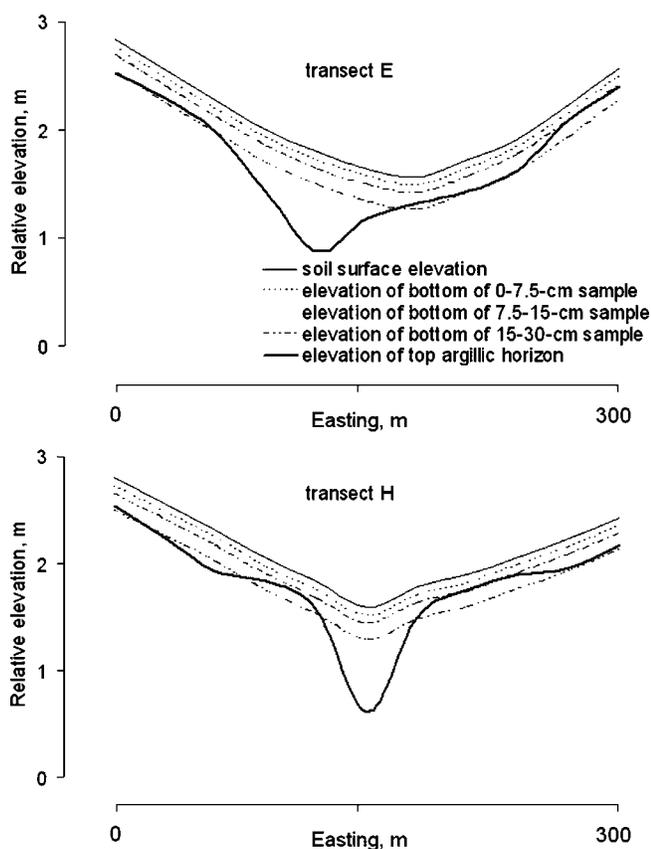
Fig. 9. Elevation of the soil surface, elevation of the bottom of the three sampling depths (dashed lines), and elevation of the top of the argillic horizon for two east–west transects (see transect locations on Fig. 1). This illustrates how a given sampling depth may either include or exclude a portion of the argillic horizon, depending on position in the landscape.

impractical and thus innovative sensor-based strategies will probably be needed to capture spatial structure for characterizing variability and management planning. For this investigation on claypan soils, we conclude that describing the variation in depth of the claypan horizon is a critical step in characterizing these soils.

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