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SPATIAL RELATIONSHIPS AMONG SOIL PHYSICAL PROPERTIES IN A GRASS-ALFALFA HAY FIELD

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Knowledge of the spatial variability of soil physical properties is important for site-specific soil management. The objectives of this study were to characterize the field-scale spatial variability of cone index (CI), soil bulk density (ρ_b), moisture content (θ_v), and sand and clay contents in the A horizon of a Lihen sandy loamy soil (sandy, mixed, frigid Entic Haplustoll), and to describe the relationship among these soil physical properties. This study was conducted on a grassland site of approximately 4.75 ha that has been in rain-fed crested wheatgrass-alfalfa hay production for over 20 years. Soil bulk density was determined from samples collected using a core sampler, whereas CI was measured by inserting a digital penetrometer into the soil at three different locations within a 300-mm radius from where the ρ_b samples were extracted. The measurements were made on a 16 × 36-m grid sampling system, which created 72 individual grid cells. Soil properties were measured at the center of each grid cell at depths of 50 to 100 mm and 200 to 250 mm. Soil parameters were modeled as normally distributed random variables.

Cone index at 50 to 100 mm and 200 to 250 mm depths, ρ_b, θ_v, and sand and clay contents exhibited medium to strong spatial dependence that was well described using either spherical or exponential models. The semivariogram for clay content shows a small range of spatial dependence and nearly zero nugget effect. Positive correlations indicated that direct relationships existed between ρ_b and CI (r = 0.57, $P < 0.01$) at 50 to 100 mm depth and between θ_v and content of clay (r = 0.58, $P < 0.01$) in the soil. Spatial variability of soil physical properties was attributed to a combination of previous farming practices, vegetation history, erosion, and weather conditions. The degree of variability in soil physical properties was concluded to be of sufficient magnitude to influence the spatial distribution of crop yield, thus having considerable implications regarding the implementation of site-specific management practices. (Soil Science 2006;171:719–727)

Key words: Spatial variability, precision farming, physical properties, cone index, bulk density, moisture content, geostatistics.

BOTH inherent (e.g., texture) and dynamic (e.g., water content and compaction) soil properties vary across agricultural fields, causing variability in crop yields. Knowledge of the spatial variability and relationships among soil properties is critical to the success of precision agriculture or site-specific management. Spatial variability of soil physical properties across the landscape has been characterized and well documented (Cambardella et al., 1994; Fulton et al., 1996; Gaston et al., 2001; Huang et al., 2001; Iqbal et al., 2005; Mzuku et al., 2005). These researchers showed that soil bulk density (ρ_b), compaction, moisture content (θ_v), and texture can vary significantly within a single field. Furthermore, spatial variability in soil physical parameters can have a major impact on the spatial distribution of crop productivity potential.

Inmna et al. (2005) reported that fields that have a high degree of spatial variability in soil

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properties could be better managed using site-specific zones. The above studies also concluded that spatial variability of various physical properties are scale dependent.

The spatial variability of soil properties has been evaluated through classical statistics and also through geostatistical techniques that verify relationships among several soil samples of a specific area or field using the study of regionalized variables (Davis, 1986). Geostatistics is based on the theory of regionalized variables and developed primarily by Matheron (1963). Regionalized variables have an average spatial continuity from point to point plus a random component which is not spatially continuous (Journel and Huijbregts, 1978).

Furthermore, geostatistical analysis methods have proven to be useful for mapping spatial variability of soil properties and have increasingly been used by soil scientists and agricultural engineers in recent years (Webster and Oliver, 2001; Iqbal et al., 2005). Geostatistics often consists of variography and kriging. The variography uses semivariograms to characterize and model the spatial variance of the data, whereas kriging uses the modeled variance to estimate values between samples (Journel and Huijbregts, 1978). In this paper, geostatistical methods were used to characterize spatial variability for cone index (CI), ρ_b, θ_v, and contents of sand and clay before designing site-specific application rates of irrigation, fertilizer, soil sampling, and planning for other future land management practices. Therefore, the specific objectives of this study were (i) to characterize the field-scale spatial variability of CI, ρ_b, θ_v, and sand and clay contents in the A horizon; and (ii) to describe the relationship among these soil physical properties.

MATERIALS AND METHODS

Soil Description, Data Collection, and Site Characterization

This study was conducted from April 6–7, 2005, on a grassland site of 4.75 ha at the USDA-ARS Nesson Valley Research farm located approximately 23 miles east of Williston, North Dakota (48.1640 N, 103.0986 W). The topography of land gently slopes (2%) from NW to SW (Fig. 1). The soil is classified as Lihen sandy loam (sandy, mixed, frigid Entic Haplustoll) consisting of very deep, somewhat excessively or well-drained soils that formed in sandy alluvium, glaciofluvial, and eolian deposits. Particle size distribution analysis indicated that the textural class of the surface horizon (0–250 mm) fell consistently within the sandy loam classification (Table 1). The site is a new research area that has been in rain-fed crested wheatgrass-alfalfa (*Agropyron cristatum* (L.) Gaertn. and *Medicago sativa* L., respectively) hay production for more than 20 years and will be converted into a long-term, irrigated cropping systems study. Thus, the site was selected because it presents an opportunity to study the effects of various agricultural management systems on the spatial relationships among selected soil properties.

A georeferenced sampling scheme using Differential Global Positioning System was used for acquiring soil samples and making soil compaction measurements. Soil physical properties measured at the site include CI as an indicator of soil strength or compaction, ρ_b, θ_v, and particle size distribution. Soil bulk density and θ_v were measured by collecting undisturbed soil cores from 50 to 100 mm and 200 to 250 mm depths using a standard 50-mm-diameter probe. Particle size distribution for each core was determined by the hydrometer method. Cone index was measured by inserting a handheld digital penetrometer (Field Scout, SC 900 Soil Compaction Meter; Spectrum Technologies, Inc., Plainfield, IL) into the soil at three different locations within a 300-mm radius where soil cores for ρ_b were extracted. Measurements were made based on a 16×36-m grid sampling pattern, which created 72 individual grid cells. Soil properties were measured at the center of each grid cell at depths of 50 to 100 mm and 200 to 250 mm.

Statistical Methods

Descriptive statistics, including mean, variance, coefficient of variation (CV), range, maximum, and minimum were obtained for each measured soil property using SAS software (SAS Institute, 2003). Linear regression analysis was performed between variables that were strongly correlated. All data were checked for normality using SAS probit procedure, which indicated no need to transform the data before using geostatistical analysis. A student *t* test showed that there were no significant differences between the two depths for all measured soil variables, except for CI parameter, thus allowing the two depths to be averaged for the assessment of spatial variability of soil properties using geostatistical methods.

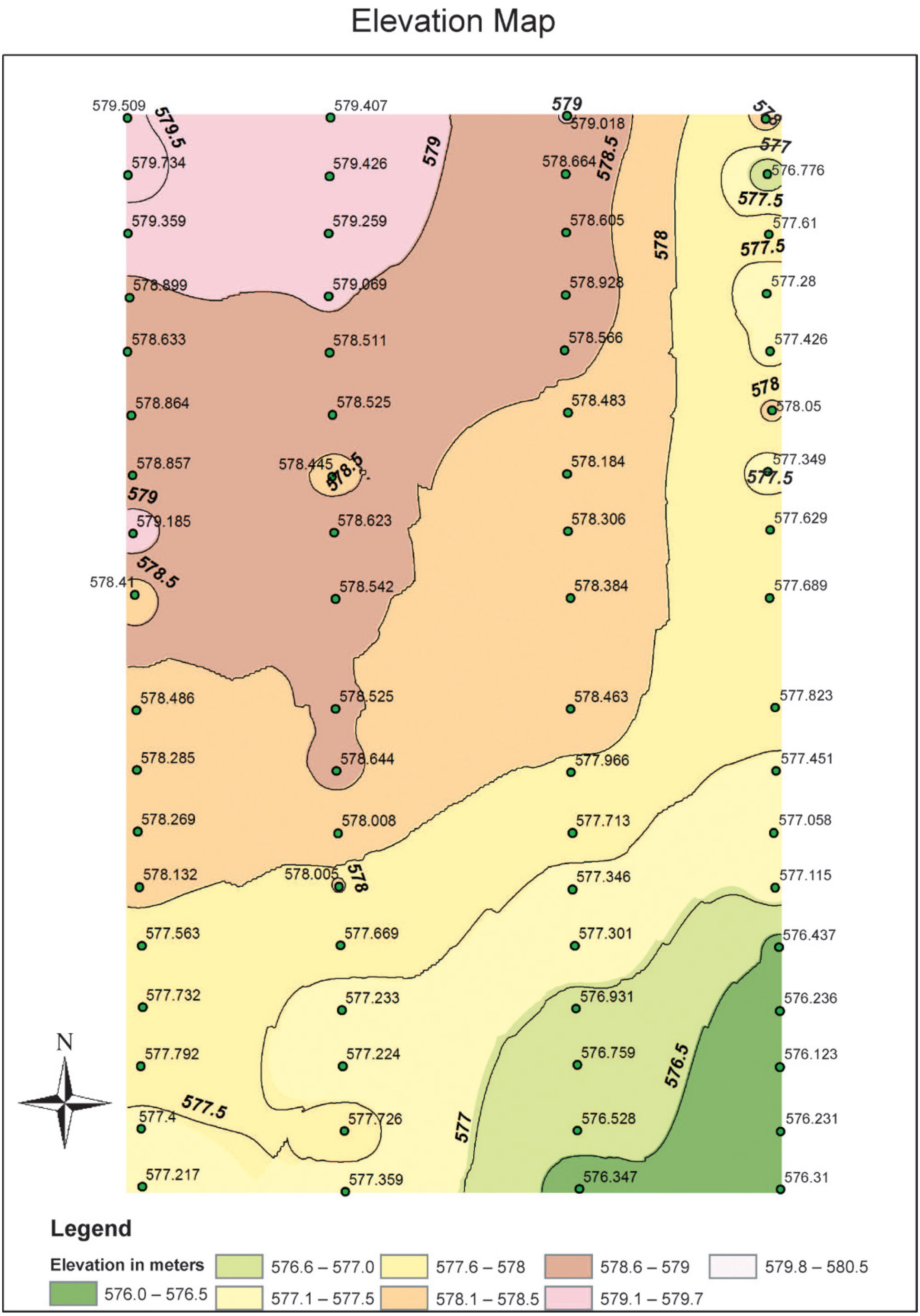

Fig. 1. Site elevation contour map.

TABLE 1
Statistical summary of soil physical properties

Statistics[†]	CI (MPa)		ρ_b (Mg m^{-3})	θ_v (m^3 m^{-3})	Sand content (g kg^{-1})	Clay content (g kg^{-1})
	50–100 mm	200–250 mm				
Mean	1.499	2.259	1.54	0.152	667	171
Variance	0.212	0.196	0.0032	0.00026	3440	591
CV (%)	30.7	19.6	3.7	10.5	8.8	14.2
Range	1.898	1.858	0.27	0.064	240	146
Minimum	0.557	1.241	1.38	0.127	535	86
Maximum	2.455	3.099	1.65	0.191	775	232

[†]Statistics are based on 72 measurements.

Geostatistical analyses, including semivariance model fitting and kriged mapping, were performed using GS$^+$ (Gamma Design Software, 2004; Geostatistics for the Environmental Sciences, St. Plainwell, MI) to assess the degree of spatial variability of each soil property. Measurements of CI, ρ_b, θ_v, and sand and clay contents were point-ordinary kriged to produce interpolated spatial maps. Before applying geostatistical procedures, each soil variable used in this study was checked for presence of trends in the data and for anisotropy at various directions (0, 45, 90, and 135 degrees). Isotropic semivariogram models were best fitted to the experimental data. Residual sums of squares (RSS) in combination with R^2 were used to select the exact form of the semivariance model. The RSS provides a sensitive, robust measure of how well the model fits the semivariogram data: the lower the RSS, the better the model fits the data (Geostatistics for the Environmental Sciences). A trial and error procedure based on optimization of both RSS and R^2 was used to select the model, providing the best fit between actual and fitted semivariance values for each soil property. Spherical or exponential models provided the best fit for the semivariograms of all soil physical properties used in this study (Journel and Huijbregts, 1978).

Kriged contour maps were created of each soil variable using ordinary point kriging (Journel and Huijbregts, 1978) using GS$^+$ geostatistical software.

RESULTS AND DISCUSSION

Descriptive statistics, including mean, variance, CV, range, maximum, and minimum for each measured soil property is given in Table 1. The CV values of measured physical properties ranged between 3.7 for ρ_b and 30.7 for CI at 50 to 100 mm depth. The variability of soil physical properties within the study site was classified as low (0%–15%) to medium (15%–75%) based on the CV values according to the groupings described by Dahiya et al. (1984).

Semivariance Analysis

Isotropic models were fitted to the semivariograms, and spherical or exponential models were obtained as the best fit to the experimental results. Table 2 presents the semivariogram parameters for CI at two depths along with ρ_b, θ_v, and sand and clay contents averaged across the two depths. The R^2 values in Table 2 show that the model fit the actual semivariance data very well for CI 50–100 mm, ρ_b, and sand and clay contents, whereas the fit was somewhat poorer for CI 200–250 mm and θ_v. The nugget-to-sill ratio expressed as the structural variance was calculated for each soil physical property and used to evaluate the degree of spatial dependence associated with each soil property (Table 2). Structural variance values were then categorized into one of three classes of spatial dependence as proposed by Cambardella et al. (1994). A structural variance value close to zero indicates continuity in the spatial dependence.

Structural variance was categorized to define distinctive spatial dependence. If the structural variance was less than 0.25, the variable was considered strongly spatially dependent; if the structural variance was greater than 0.25 and less than 0.75, the variable was considered moderately spatially dependent; and if the structural variance was greater than 0.75, the variable was considered weakly spatially dependent (Cambardella et al., 1994; Iqbal et al., 2005).

Figures 2A–F show the isotropic semivariograms of CI at 50 to 100 mm, CI at 200 to 250 mm, ρ_b, θ_v, sand content, and clay content, respectively. The parameters for the models corresponding to the semivariograms are also listed in Table 2. The ranges of spatial dependencies vary between 9 m for CI at 200 to 250 mm depth and 120 m for θ_v, indicating that the optimum sampling interval varies greatly among the different soil properties.

Furthermore, the resulting semivariograms (Figs. 2A–F) indicate strong spatial dependencies for CI in the 50 to 100 mm depth (0.16), CI in the 200 to 250 mm depth (0.09), and sand content (0.17). The structural variance also showed moderate spatial dependencies of 0.50 and 0.33 for ρ_b and θ_v, respectively. However, the semivariogram for clay content shows a nugget value close to zero and a small range of spatial dependence (Table 2, Fig. 2F). The zero or pure nugget effect value indicates a very smooth spatial continuity between neighboring sample points. This small range of spatial dependence of clay content (14 m) indicates that this continuity diminishes rapidly over a short distance. The other soil variables have larger ranges of spatial dependence, except for CI at 200 to 250 mm depth (Table 2).

In general, results from both classical and spatial statistics indicated small to moderate spatial variability across the field for all parameters.

Kriged Contour Maps

Continuous maps of the individual soil attributes were also generated by point kriging (Figs. 3A–F). The spatial distribution of θ_v and clay content follows the topographic feature of the field (Fig. 3D), where the land gradually slopes from northwest to southeast at approximately 2%. Consequently, comparison of areas relatively high in θ_v to areas high in clay content generally shows the expected direct relationship with the highest values of both properties occurring at the lowest topographic position.

Kriged contour maps indicated that soils with high ρ_b were found in the northwestern part of the field, extending mainly from northwest to southeast (Fig. 3C). The CI at 50 to 100 mm depth map shows a similar scenario with higher CI values (2–2.5 MPa) are on the western half of the field, and low values (1–1.5 MPa) are located on the eastern half. This relationship is discussed in greater detail in the following section.

Spatial statistics indicated that CI, ρ_b, θ_v, and sand and clay contents were spatially structured explaining some trends in soil variability within the field. The surface soil variations may also be affected by other factors, such as vegetation, previous farming practices, and weather conditions. For example, soil erosion by both wind and water may have caused finer soil particles to be transported from higher to lower landscape positions, causing differences in soil moisture holding capacity. There is also strong evidence at the site that previous tillage management has accelerated wind erosion. This soil particle transport, along with inherent topographic variation, would be expected to influence the amount and type of biomass produced by both native and cultivated forage species, leading to spatial variability in soil organic matter content, which influenced moisture holding capacity, soil structure, and ρ_b. Regardless of what factors caused the spatial variability observed, its magnitude may be expected to influence the spatial distribution of crop yield, thus having considerable implications regarding

TABLE 2

Geostatistical parameters of soil physical properties

Soil variable	Nugget C_0	Sill $C_0 + C$	Structural variance	Range A_0 (m)	RSS	R^2	Model
CI at 50–100 mm (MPa)	0.0385	0.235	0.16	117	2.9×10^{-4}	0.99	Spherical
CI at 200–250 mm (MPa)	0.0166	0.1922	0.09	9	5.1×10^{-4}	0.50	Exponential
ρ_b (Mg m^{-3})	0.0018	0.0036	0.50	39	1.89×10^{-7}	0.82	Exponential
θ_v (m^3 m^{-3})	0.00011	0.00033	0.33	120	1.6×10^{-8}	0.59	Exponential
Sand content (g kg^{-1})	527	3020	0.18	54	52,513	0.97	Exponential
Clay content (g kg^{-1})	1	448	0.002	14	2389	0.87	Exponential

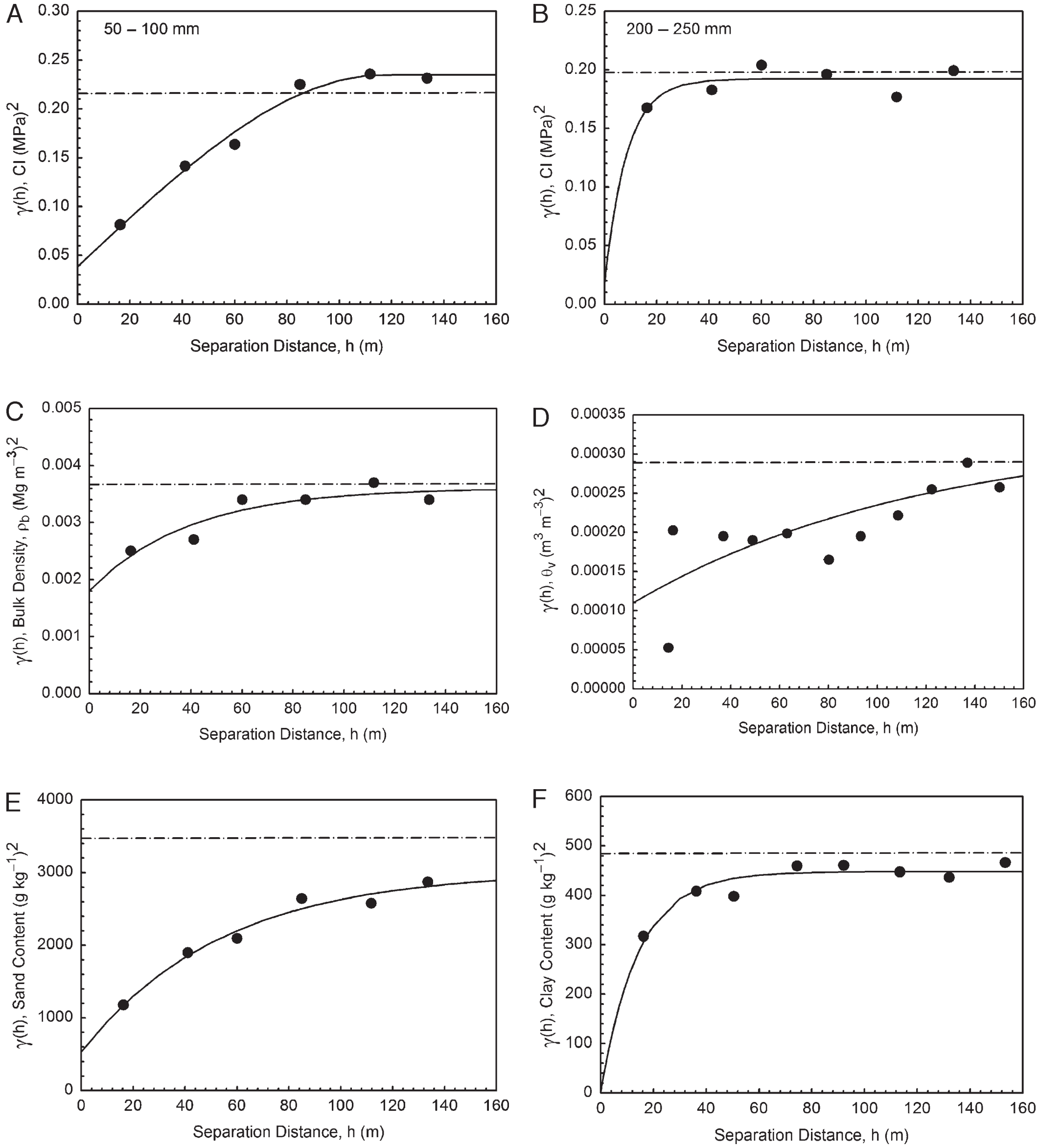

Fig. 2. Isotropic semivariograms for (A) CI at 50 to 100 mm depth, (B) CI at 200 to 250 mm, (C) ρ_b, (D) θ_v, (E) sand content, and (F) clay content. The dashed line represents sample variance.

the implementation of site-specific management practices.

Relationship Among Soil Properties

Soil properties with strong and moderate spatially dependence were regressed against each other. Linear correlation coefficients (r) among soil physical parameters were computed using SAS software (SAS Institute, 2003). The θ_v was positively associated with clay content ($r = 0.58$, $P < 0.01$) and negatively correlated with sand content ($r = -0.68$, $P < 0.01$) in the soil samples. The relationship between θ_v and clay content at the depth of 200 to 250 mm is described by the linear regression equation shown in Fig. 4. The basis of the positive relationship between soil θ_v and clay content is direct; that is, higher θ_v values are associated with finer rather that coarser textured soil. In addition, a positive correlation ($r = 0.57$, $P < 0.01$) described the relationship between ρ_b and CI at the depth of 50 to 100 mm (Fig. 5). It would be

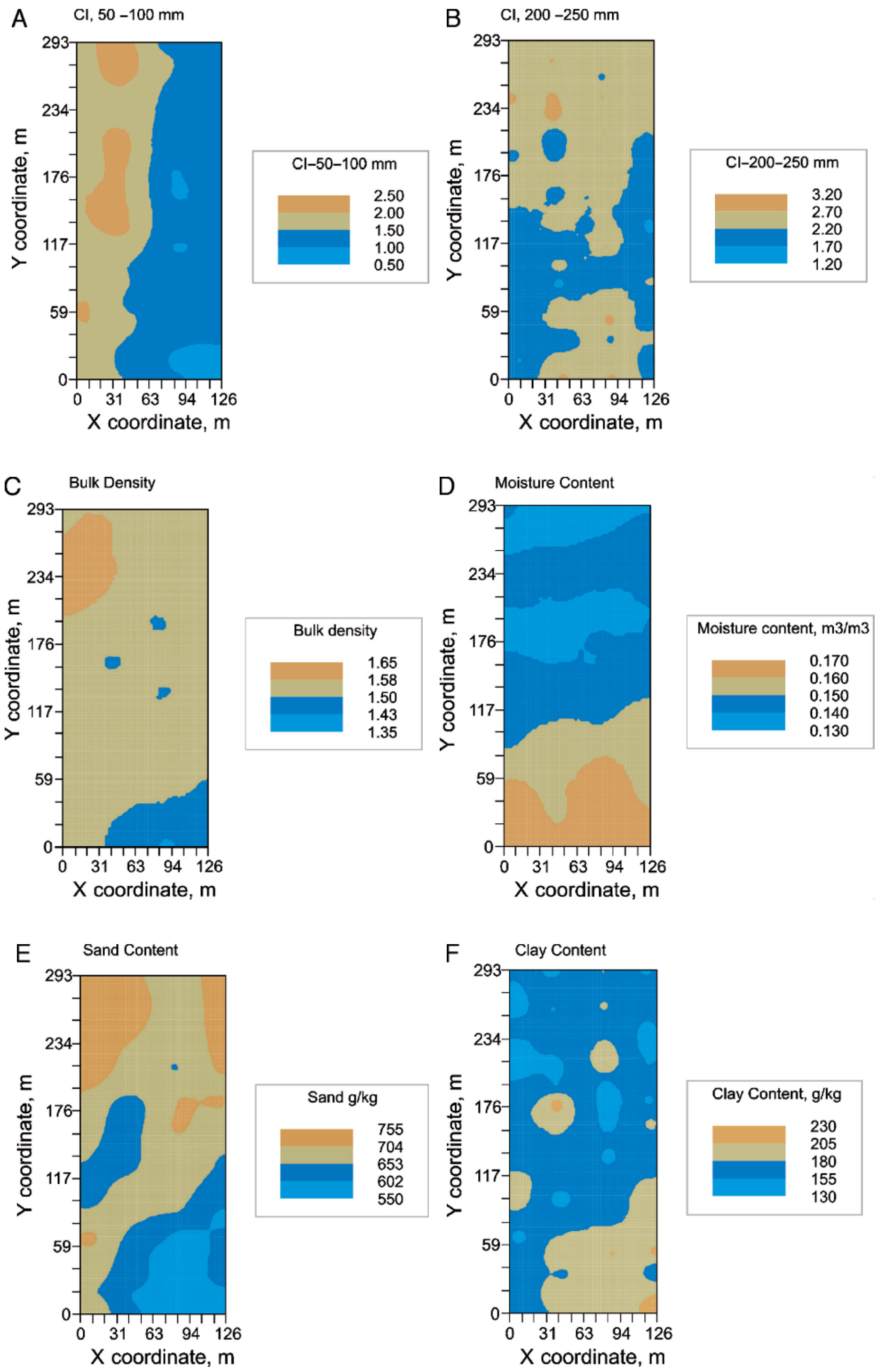

Fig. 3. Kriged contour maps for (A) CI at 50 to 100 mm depth, (B) CI at 200 to 250 mm, (C) ρ_b, (D) θ_v, (E) sand content, and (F) clay content.

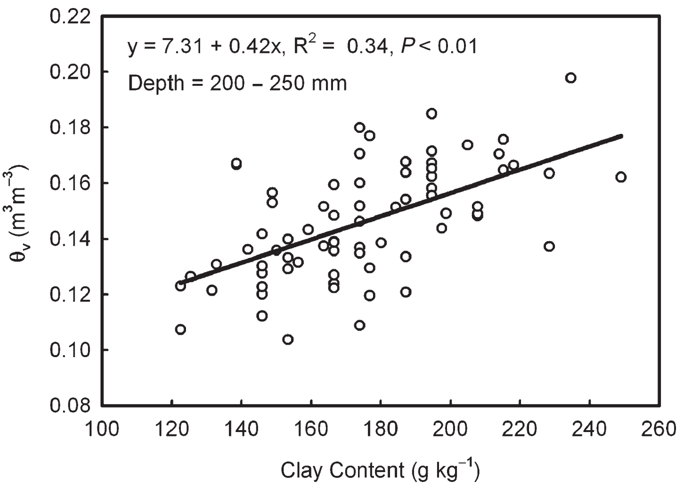

Fig. 4. Relationship between moisture content and clay content at 200 to 250 mm depth.

expected that ρ_b and CI would increase simultaneously; however, weak and nonsignificant ($P > 0.01$) correlations were detected among other soil physical parameters at both levels of soil depth. The results from this study are in agreement with those found by Ayers and Perumpral (1982) who found a significant and direct correlation between ρ_b and CI.

SUMMARY AND CONCLUSIONS

The spatial variation of CI, ρ_b, θ_v, and sand and clay contents in the surface horizon of a sandy loam soil was assessed. The geostatistical methods revealed spatial variability in CI at 50 to 100 mm and 200 to 250 mm depths, ρ_b, θ_v, and sand and clay contents across the field. The variability of these soil physical properties exhibited medium to strong spatial dependence that could be well described using either spherical or exponential models. The semivariogram for clay content shows a small range of spatial dependence and approximately zero nugget effect. Positive correlations indicated that direct relationships existed between ρ_b and CI ($r = 0.57$, $P < 0.01$) at 50 to 100 mm depth and between θ_v and content of clay ($r = 0.58$, $P < 0.01$) in the soil. Furthermore, weaker correlations were found among other soil properties at both depths. Spatial variability of

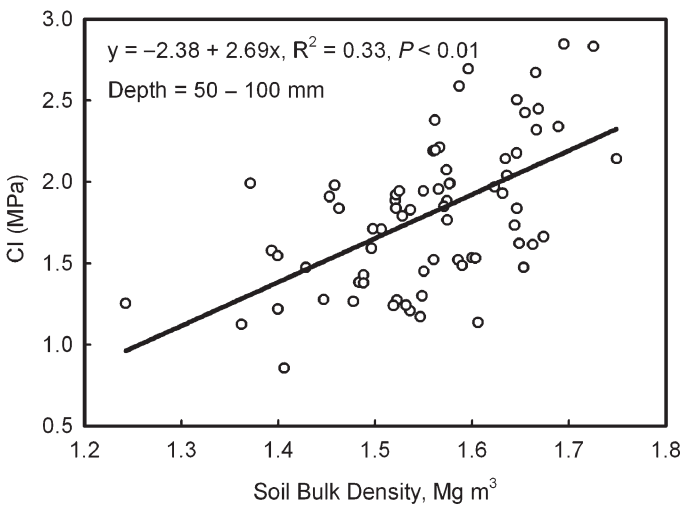

Fig. 5. Relationship between CI and ρ_b at 50 to 100 mm depth.

soil physical properties is caused by a combination of previous farming practices, vegetation history, erosion, and weather conditions.

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