0038-075X/06/17108-627–637
Soil Science

August 2006
Vol. 171, No. 8
Printed in U.S.A.

CHARACTERIZATION OF SPATIAL VARIABILITY OF SOIL ELECTRICAL CONDUCTIVITY AND CONE INDEX USING COULTER AND PENETROMETER-TYPE SENSORS

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Assessment and management of spatial variability of soil chemical and physical properties (e.g., soil texture, organic matter, salinity, compaction, and nutrient content) are very important for precision farming. With current advances in sensing technology, soil electrical conductivity (EC) mapping is considered the most efficient and inexpensive method that can provide useful information about soil variability within agricultural fields. The objectives of this research study were to determine if coulter and penetrometer-type EC sensors produce similar descriptions of soil variability, and if EC and cone index (CI) measured using a penetrometer-type sensor are correlated. The spatial variability of apparent EC (ECa) and penetration resistance expressed as CI for soil compaction were investigated with coulter and penetrometer sensing technologies. The study was conducted in April 2005 at the research farm located near Williston, North Dakota, on a Lihen sandy loam (sandy, mixed, frigid Entic Haplustoll). The ECa and CI values generated by the penetrometer sensor were averaged over a 0- to 30-cm depth for comparison with values measured using the coulter sensor over the same 0- to 30-cm depth. Classical and spatial statistics were used to evaluate spatial dependency and assess the overall soil variability within the experimental site. The statistical results indicated that the ECa data from both coulter and penetrometer sensors exhibited similar spatial trends across the field that may be used to characterize the variability of soil for a variety of important physical and chemical properties. The coefficients of variation (CVs) of log-transformed ECa data from coulter and penetrometer sensors were 11.3% and 18.9%, respectively. The mean difference, M_d, of log-transformed ECa measurements between these two devices was also significantly different from zero (M_d = 0.44 mS/m; t = 31.5, n = 134; $P < 0.01$). Soil ECa and CI parameters were spatially distributed and presented strong to medium spatial dependency within the mapped field area. Results from this study indicate the effectiveness of the ECa and CI sensors for identifying spatial variability of soil properties, and thus, the sensors may be useful tools for managing spatial variability in agricultural fields. (Soil Science 2006;171:627–637)

Key words: Precision farming, cone index, electrical conductivity, geostatistics.

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Received Oct. 13, 2005; accepted March 20, 2006.
DOI: 10.1097/01.ss.0000228037.80270.1d

CHARACTERIZATION of spatial variability of soil physical and chemical characteristics (e.g., soil texture, organic matter, salinity, water content, compaction, and nutrient content) is very important for precision farming and managing agricultural practices. Because of this, farmers need new, quick, reliable, and inexpensive sensing technology to measure soil properties such as soil compaction and apparent electrical conductivity (ECa) that characterize soil variability in their fields. To meet this need, on-the-go and stationary sensors (electrical and electromagnetic sensors) have been developed and are available commercially that can take measurements continuously and provide detailed soil maps while traveling across a field (Mueller et al., 2003; Sudduth et al., 2003; Farahani and Buchleiter, 2004; Sudduth and Kitchen, 2004; Sudduth et al., 2004; Adamchuck, 2005; Akbar et al., 2005; Farahani et al., 2005; and Kravchenko et al., 2005). The aforementioned authors concluded that these sensors were efficient and effective tools for soil mapping and interpreting soil variability for precision farming. They also concluded that spatial data collected by this advanced sensor technology can be used as a baseline for precision farming and future planning management practices.

With recent advancements in computer and sensing technology, spatial measurements of ECa and compaction have become quick, easy, and reliable for mapping and monitoring variations in these soil properties in both space and time. Therefore, surveying and mapping agricultural fields for soil ECa and cone index (CI) using coulter and penetrometer sensors (Veris Technologies, 2002) are among the most efficient and useful methods of characterizing soil variability for a variety of soil properties such as bulk density, particle size distribution, water content, clay pan, and salinity that may have relationship to yield variations and therefore affect crop productivity (Corwin and Lesch, 2003; Sudduth et al., 2003; Farahani and Buchleiter, 2004; and Sudduth et al., 2004).

Traditionally, the spatial variability of soil properties has been evaluated through classical statistics and through geostatistical techniques that verify relationships among several soil samples of a specific area or field, using the study of regionalized variables (Davis, 1986).

Geostatistical analysis methods have been proven to be useful for characterization and mapping spatial variation of soil properties and have also received increasing interest by soil scientists and agricultural engineers in recent years (Webster and Oliver, 2001; Corwin et al., 2003; Mueller et al., 2003; Corwin and Lesch, 2005). Geostatistics often consists of variography and kriging. Variography uses semivariograms to characterize and model the spatial variance of the data, whereas kriging uses the modeled variance to estimate values between samples (Journal and Huijbregts, 1978).

The overall objective of this study is to characterize the spatial variability of soil ECa and CI measured by coulter and penetrometer sensors within a newly established research farm using classical and spatial statistical methods. Specifically, the goals of this research study are to determine (i) if coulter and penetrometer-type EC sensors produce similar descriptions of soil variability, and (ii) if ECa and CI measured using a penetrometer-type sensor are correlated.

MATERIALS AND METHODS

Site Description and Data Acquisition

This study was conducted on a 1.4-ha, nearly level (2% slope) grassland field at the USDA-ARS Nesson Valley Research farm located approximately 23 miles east of Williston, North Dakota (48.1640° N, 103.0986° W). The soil is classified as Lihen sandy loam (sandy, mixed, frigid Entic Haplustoll). The Lihen soil series consists of very deep, somewhat excessively or well-drained soils that formed in sandy alluvium, glaciofluvial, and Eolian deposits that are in places over till or sedimentary bedrock (Sucik, 2002). The site is a new research area that has been in rain-fed hay production for more than 5 years.

Spatial ECa and CI data were collected in the early spring of 2005, before spring tillage, using both coulter and penetrometer sensors, both operated in the same serpentine pattern within the study area (Fig. 1). On April 12, the coulter sensor was used to map the ECa at two depths (0−30 and 0−90 cm) monitored with the GPS unit providing spatial coordinates for each ECa measurement. A total of 410 sampling points were created and spaced at approximately 2.8 m, and only shallow measurements (0−30 cm) were used in this study. On April 14, the penetrometer sensor equipped with the GPS unit was used to collect measurements of both ECa and CI that were recorded in 2-cm intervals to a depth of 90 cm. When measurements were collected, soil-moisture content was 15.2%, using the gravimetric method which was near field capacity (16.1%). A total of 134 points were created approximately 7.6 m apart with a few points that were spaced at larger distances (10−14 m). Sampling point locations (Fig. 1) were georeferenced using the Trimble Ag132 Global Positioning System with differential correction (Omni STAR Inc., Houston, TX). The EC and CI values generated by the penetrometer sensor were averaged over a 0- to 30-cm depth for comparison with values measured using the

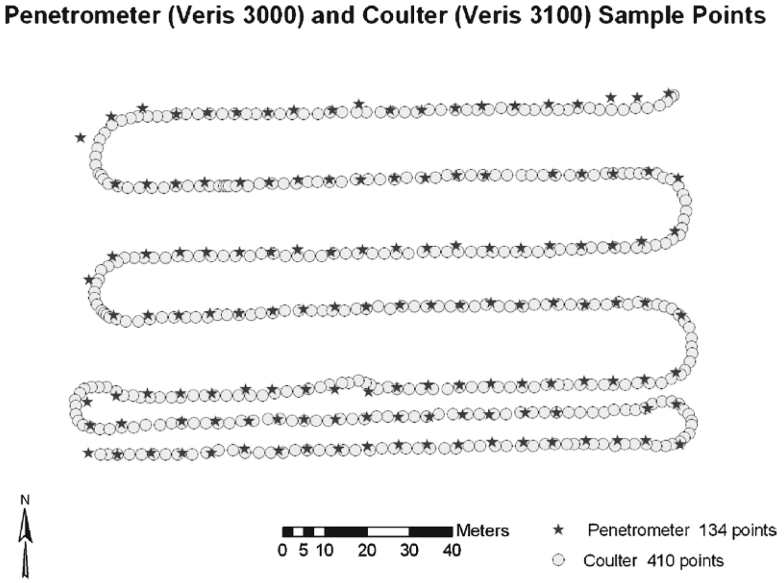

Fig. 1. Sampling points generated by both coulter and penetrometer sensors for the experimental plot.

coulter sensor over the same 0- to 30-cm (shallow) depth.

Description of Penetrometer Sensor

The penetrometer sensor (Veris 3000 Profiler) was manufactured by Veris Technologies in Salina, Kansas. The penetrometer consists of a movable probe that measures both ECa and soil compaction (CI). The probe is pulled through the field by a pickup truck (Veris Technologies, 2002). The power and hydraulic units in the probe are used to insert the penetrometer into the ground to a maximum depth of approximately 90 cm. The maximum penetration force is approximately 5.6 MPa that can be used to prevent overload force to other mechanical parts of the sensing unit. The soil penetration force is measured by the pressure transducer, and soil ECa is measured by a sensor that is placed directly above the tip of the penetrometer (Veris Technologies, 2002). The sensing unit interfaces with the GPS and records readings of spatial coordinates, CI, penetration speed, penetration depth, and ECa for each penetrating cycle using a data logger. Soil ECa is measured in millisiemens per meter (mS/m), whereas the CI as an indicator of soil compaction is measured in megapascal (MPa) (Veris Technologies, 2002).

Description of Coulter Sensor

The coulter sensor mapping system (Veris 3100) consists of six spaced rotating coulter electrodes mounted on a metal beam that can be pulled by a pickup truck (Veris Technologies, 2002). The coulter Electrodes 2 and 5 transmit an electrical current in the soil as arrays. The remaining four coulters (1, 3, 4, and 6) are spaced to measure voltage drop caused by electrical resistance of the soil and, hence, ECa over two depths, 0 to 30 cm (shallow) and 0 to 90 cm (deep). The sensor unit interfaces with a differential GPS that provide georeferenced readings of soil ECa. The ECa measured by this unit is in millisiemens per meter (Veris Technologies, 2002).

One distinct difference between the two sensors is that penetrometer measurements are stationary, whereas the coulter measurements are logged on-the-go with a vehicle-type sensor. Further information regarding coulter and penetrometer sensors, their description, features, and operational mechanism is given by Drummond et al. (2000), Veris Technologies (2002), and Mueller et al. (2003).

Classical Statistics

The ECa and CI measured data were checked for normality of distribution using histograms and SAS probit procedures. Soil ECa measurements from coulter and penetrometer sensors were found to be well described by a log normal distribution, whereas CI measurements were normally distributed (SAS Institute, 2003).

The descriptive statistics (mean, variance, and CV) and probability frequency distributions of logarithmic ECa and CI were carried out with SAS software (SAS Institute, 2003). The CV has also been used for expressing variability on a relative basis allowing the variability of different parameters to be compared.

In addition, the significance of the difference, M_d, between logarithmically transformed ECa measurements from both sensors [Eq. (1)] was evaluated with a Student's *t* test (SAS Institute, 2003). The *t* test was performed only on those pairs located on same or a close point coordinates (n = 134) using spatial join procedure.

$$M_d = \frac{\sum_{i=1}^{n} (\text{In } \textit{coulter } \text{ECa}_i - \ln \textit{ penetrometer } \text{ECa}_i)}{n} \quad (1)$$

The M_d in Eq. (1) measures the average difference between logarithmic ECa measurements by coulter and penetrometer sensors. An M_d value equal to zero indicates no difference between the ECa measurements sensed by both devices. A Student's *t* test was used to determine whether M_d was significantly different from zero (SAS Institute, 2003).

Spatial Statistics

Geostatistical analyses (semivariance and kriged maps) were performed with Arc-Info (ESRI, 2005). The logarithmically transformed ECa and CI measured values were point-ordinary kriged to produce interpolated spatial maps using a 1-m^2 grid pixel. Isotropy semivariograms were computed for each of soil parameters from both sensors using Arc-Info methods (ESRI, 2005). Spherical models were best fitted to the experimental semivariance data that were used interpolated using the kriging method. Semivariance is expressed in Eq. (2) as described by Journal and Huijbregts (1978).

$$\gamma^*(h) = \frac{1}{2N(h)} \sum_{i=1}^{N} (z_i - z_{i+h})^2 \quad (2)$$

where $\gamma^*(h)$ is semivariance for the interval distance class, h is the lag distance, z_i is the measured sample value at point i, z_{I+1} is the measured value at point i + h, and $N(h)$ is the total number of pairs for lag interval h. The semivariogram represents the mean square of the increment between two points separated by the distance h.

The spherical model that was best fitted to the experimental semivariance values for ECa and CI was defined in Eq. (3) as:

$$\gamma(h) = C_0 + C\left(\frac{3h}{2a} - \frac{1}{2}\left(\frac{h}{a}\right)^3\right) \quad \textit{for } h \leq a \quad (3)$$

and

$$\gamma(h) = C_0 + C \quad \textit{for } h > a \quad (4)$$

where C_0 is nugget effect value, C is the spatial variance, a is the range, and h is the distance.

The sum C_0 + C is the total variance (sill) for the semivariogram. The distance at which the sill value is reached, denoted as its range that gives information about the zone of the dependency influence. The range divides the sample into two groups. Observations that are located within the range are correlated or spatially dependent. This information can be used to estimate values at other points within that range. Observations beyond the range are independent observations (Journal and Huijbregts, 1978). The slope of the semivariogram is an expression of the rate at which observations become increasingly independent with increasing distance until they approach or fluctuate around the sill. The range is often larger for a larger study area. The shape of the semivariograms reflects the nature of the overall distribution of the regionalized variables (Journal and Huijbregts, 1978; Davis, 1986).

RESULTS AND DISCUSSION

The spatial variability of ECa and CI measurements from the coulter and penetrometer sensors were evaluated through both classical statistics and geostatistical techniques for 0- to 30-cm soil depth.

Analysis Using Classical Statistics

Fractile diagrams (probit function), histograms, and probability frequency distributions (not shown) exhibited log normal distribution (not bell shaped and skewed to the left) for the soil ECa data from both coulter and penetrometer sensors, whereas the CI resembles a normal distribution. Therefore, statistical analyses were performed on logarithm transformation of the ECa data. Corwin and Lesch (2003) also used logarithm-transformed ECa measured with the electromagnetic induction soil conductivity meter (EM-38) and other techniques in their statistical analyses and for comparison of various EC measuring techniques.

TABLE 1

Statistical summary of soil ECa and CI measured with coulter and penetrometer sensors

Statistical parameters	Logarithmically transformed data		
	$ECa_{coulter}$ (mS/m)	$ECa_{penetrometer}$ (mS/m)	CI (MPa)
Mean	4.92*	3.21*	2.14
Variance	0.31†	0.37†	0.152
CV (%)	11.3‡	18.9‡	18.2
No. of observations, n	410	134	134

The following statistical calculations are used when the observations are log normally distributed (Warrick and Nelson 1980):

*Geometric mean = exp $(\mu + \sigma^2/2)$

†Variance = exp $(\mu + \sigma^2/2)^2[\exp(\sigma^2) - 1]$

‡CV = $[\exp(\sigma^2) - 1]^{1/2}$, where $\sigma = \frac{1}{n-1}\sum_{i=1}^{n}(\ln(ECa_i) - \mu^2)$, and $\mu = \frac{1}{n}\sum_{i=1}^{n}\ln(ECa_i)$.

Descriptive statistics of log-transformed ECa and CI parameters measured using coulter and penetrometer sensors are given in Table 1. The CVs of the ECa measurements from coulter and penetrometer sensors were 11.3 and 18.9%, respectively, and the CV for the CI parameter for the penetrometer was 18.2%. The variability of ECa and CI measurements 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). The penetrometer sensor (n = 134) exhibited higher variation in ECa measurements compared with those of the coulter sensor (n = 410) because of their different sample sizes. Furthermore, the CV values of both ECa and CI measurements resulting from coulter and penetrometer sensors (Table 1) were small, reflecting low soil variability within the study area.

Furthermore, the M_d [Eq. (2)] was used to measure the average variation in ECa results between two sensors. The M_d in logarithmic ECa measurements between coulter and penetrometer devices was significantly different from zero (M_d = 0.44 mS/m; t = 31.5, n = 134; $P < 0.01$).

Analysis Using Spatial Statistics

Spatial statistical methods (semivariograms and kriging) were used for characterizing and mapping spatial variation of ECa and CI soil properties. Interpolative spatial maps of soil ECa

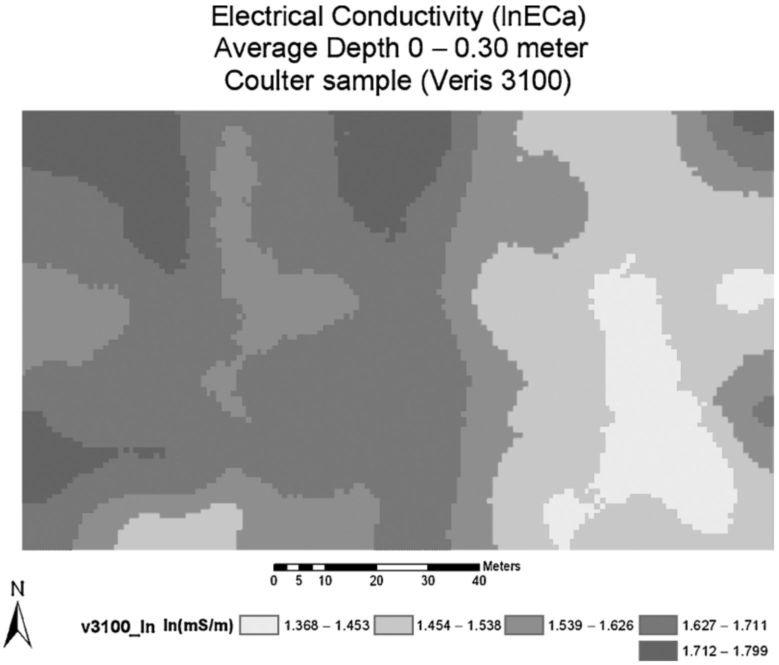

Fig. 2. Ordinary kriging spatial mapping for logarithmic ECa measured using the coulter sensor.

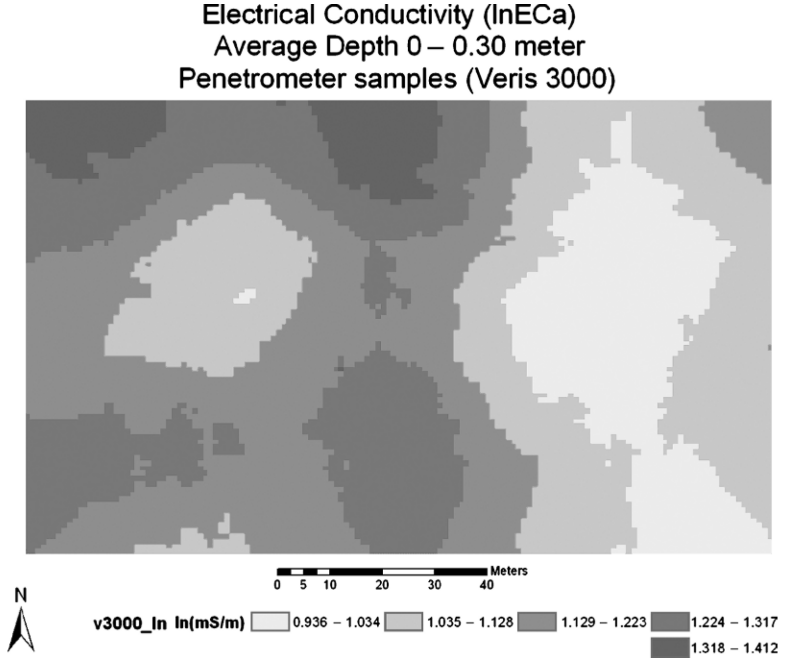

Fig. 3. Ordinary kriging spatial mapping for logarithmic ECa measured using the penetrometer sensor.

and CI measurements were created by point-ordinary kriging procedure. Figures 2, 3, and 4 show the distribution of ECa and CI in the field at depth of 0 to 30 cm (ESRI, 2005).

Regarding the spatial dependence aspect, the spherical model [Eq. (4)] most closely fits the semivariance of the ECa and CI soil parameters measured by coulter and penetrometer sensors

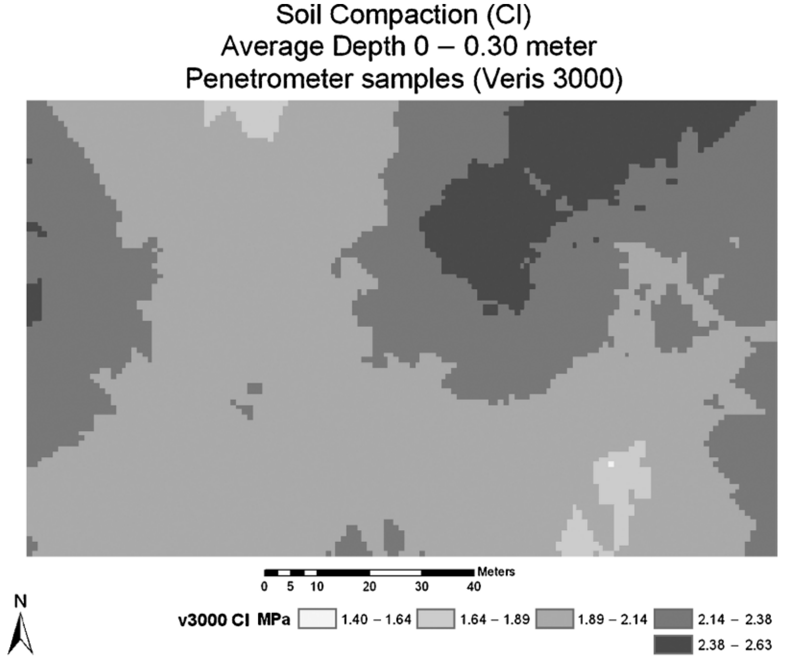

Fig. 4. Ordinary kriging spatial mapping for soil CI measured using the penetrometer sensor.

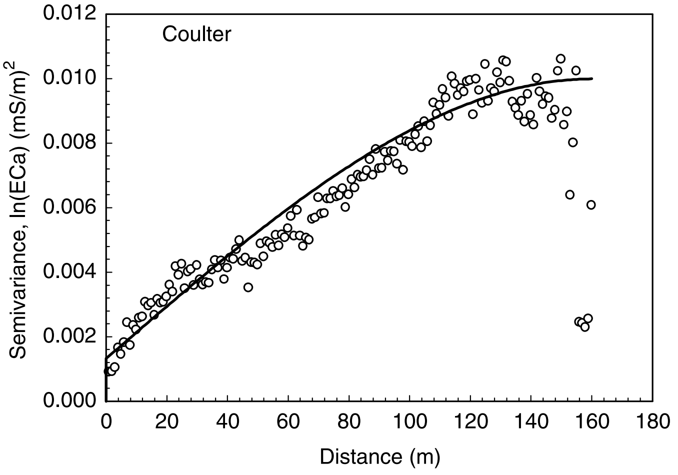

Fig. 5. Experimental and fitted semivariograms of logarithmic ECa measured by the coulter sensor.

(Figs. 5–7). The semivariograms were constructed to find whether the measured data of ECa and CI variables had spatial structure or dependency. These semivariograms represent the sill values which equal the total variance of the process (Table 2). The nugget effect and the range were also observed for all soil parameters, and the fitted semivariance values increased as the distance increased then flatted when they reached the sill values (Figs. 5–7).

To find the distance of dependency of the spatially structured data, the range was evaluated from the semivariogram results. Table 2 presents a summary of the geostatistical parameters nugget, variance, sill, structural variance, and the range for the ECa and CI. The range of the semivariogram indicates the effective distance between samples considered to be independent from each other. The range values for ECa, as measured by the coulter and penetrometer sensors, were 161 and 160 m, respectively. It is interesting to note that the range values for ECa and CI parameters were almost the same. However, the nugget variance and sill values were considerably different (Table 2). This might be attributed to different numbers of observations produced by each sensor (Table 1).

To evaluate the spatial dependency of soil EC and CI parameters, a criterion suggested by Cambardella et al. (1994) was used. Three classes of spatial dependence (structural variance) for the ECa and CI from both sensors

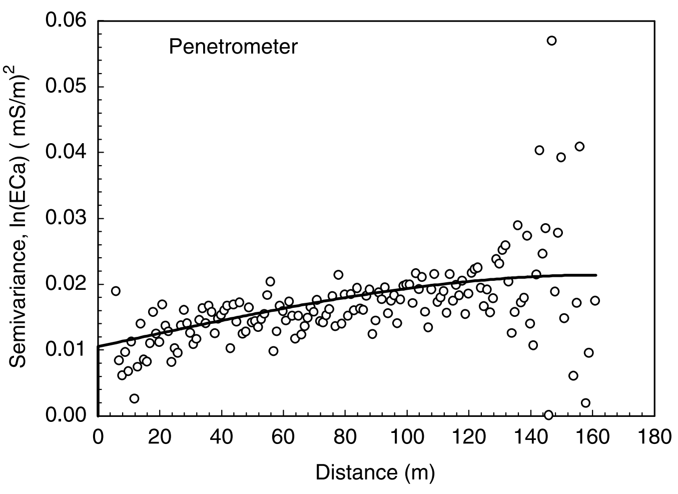

Fig. 6. Experimental and fitted semivariograms of logarithmic ECa measured by the penetrometer sensor.

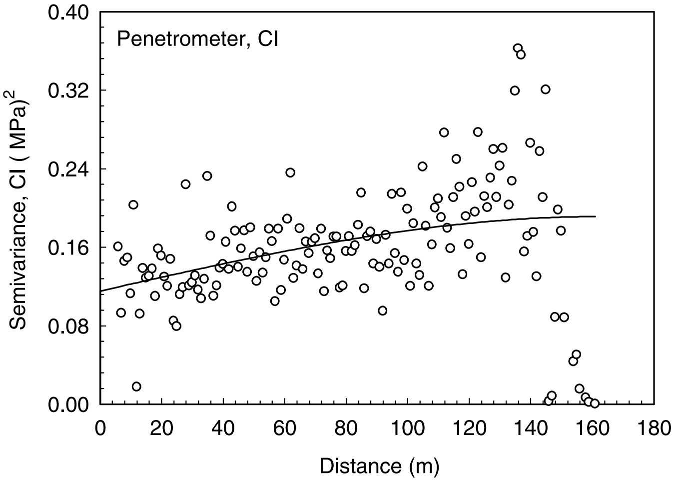

Fig. 7. Experimental and fitted semivariograms of soil CI measured by the penetrometer sensor.

were calculated based on the ratio of nugget (C_0) to the sill (C_0 + C) value (Cambardella et al., 1994). Spatial class ratios were categorized to define distinctive spatial dependency. If the spatial class ratio is <0.25, the variable is considered strongly spatially dependent; if the ratio is >0.25 and <0.75, the variable is considered moderately spatially dependent; and if the ratio is >0.75, the variable is considered weakly spatially dependent (Cambardella et al., 1994). The structural variance of ECa measurements from the coulter sensor was very low (0.20), indicating a strong spatial dependency in the sampling area of the field, whereas the structural variance of soil ECa and CI parameters from the penetrometer sensor were higher than that of coulter sensor (0.53−0.60) which characterized a moderate spatial dependency in the study area (Table 2).

Both descriptive and spatial statistics indicate that ECa and CI maps (Figs. 2–4) represent a fairly narrow range of variability within the field. However, the ECa from both sensors exhibited higher values in the western part of the field and lower values, with tendency of uniformity, in the remaining area. The CI showed a different scenario where the majority of higher values were located at the north western area and parts of eastern area of the field. In general, spatial structure analysis from semivariance results exhibited small to moderate spatial variability across the field for ECa and CI measured by the two sensors.

The findings from this study indicate the effectiveness of the ECa and CI mapping technology for identifying spatial variability within agricultural fields. These maps may prove to be useful tools within precision farming systems as a means to direct soil sample collection for the purpose managing soil properties (e.g., water holding capacity, pH, salinity, and soil fertility) that directly affect plant growth.

Correlation Between Two Sensors' Measurements

Statistical analysis was performed to obtain correlation coefficients and develop regression relationships between the ECa measurements from coulter sensor and ECa measurements from the penetrometer sensor and ECa and CI measurements from the penetrometer sensor (SAS Institute, 2003). A positive correlation (r = 0.51, $P < 0.01$) was found between the ECa measurements from both sensors. A simple

TABLE 2

Semivariogram spherical model kriged parameters

Soil property	Nugget (C_0)	Spatial variance C	Sill $C_0 + C$	Structural variance $\frac{C_0}{(C_0+C)}$	Range a (m)
$ECa_{coulter}$*	0.0016	0.0066	0.0082	0.20	160
$ECa_{penetrometer}$*	0.0095	0.0086	0.0181	0.53	161
CI	0.115	0.076	0.191	0.60	161

*Spatial analyses were performed based on logarithmically transformed data.

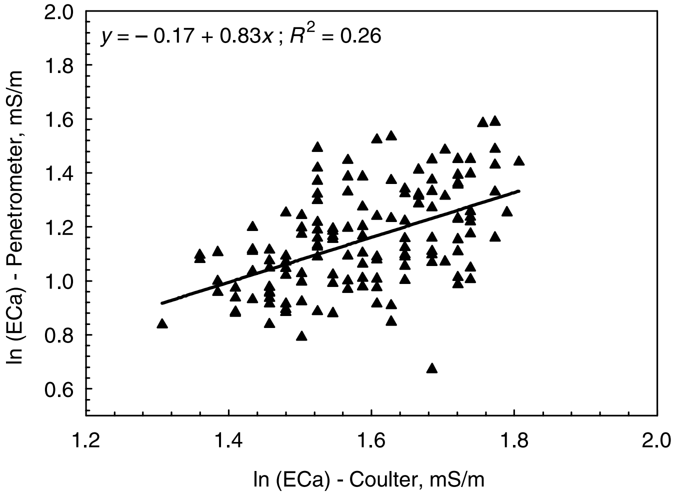

Fig. 8. Relationship between the coulter and penetrometer sensors for logarithmic ECa on sandy loam soil at the Nesson Valley site.

linear regression model was proposed for predicting $ECa_{penetrometer}$ measurements from those of $ECa_{coulter}$ [Fig. 8 and Eq. (5)].

$$\ln(\mathrm{ECa}_{\,\mathrm{penetrometer}}) = -0.17 + \ln(0.832\ \ \mathrm{ECa}_{\,\mathrm{coulter}})$$
$$R^2 = 0.25 \qquad (5)$$

On the other hand, a nonsignificant, weak, and inverse relationship (r = −14, P = 0.09) was found between the CI as an indicator of soil compaction and the log-transformed ECa measurements for the penetrometer sensor (Fig. 9). The results from both sensors are somewhat in agreement with those found by Drummond et al., (2000) and Sudduth et al. (2000) who found a significant and inverse correlation between the ECa results of two sensor devices, a weak inverse relationship between ECa and CI, and a large nugget effect on the CI (Eric Lund, Veris Technologies, personal communication, September 2005). Furthermore, Sudduth et al. (2002) found a weak and inverse relationship between CI and ECa data measured with

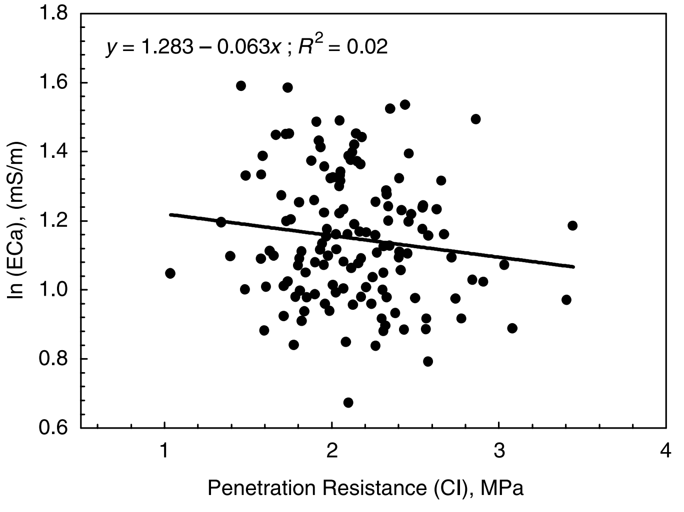

Fig. 9. Correlation between logarithmic ECa and CI from the penetrometer sensor.

the EM-38 and penetrometer sensors, respectively, for both shallow and deep depths.

CONCLUSIONS

The variability of ECa and CI measurements within the study area was classified as low to medium. A positive and significant correlation was found between the logarithmically transformed ECa measurements from both sensors. A nonsignificant, weak, and inverse relationship was found between the CI and the log-transformed ECa measurements for the penetrometer sensor. The soil ECa and CI variability was spatially structured, and these maps have the potential of explaining the soil variability within an agricultural field. The ECa and CI maps may also have the potential to aid farmers with site-specific soil use and define problematic areas within their fields that could affect crop production of their fields.

ACKNOWLEDGMENTS

The authors thank Mr. Dale Spracklin for preparing soil maps using Arc-Info and database software methods. We also thank Mr. Bryan Gebhard for his help during field mapping. The authors also thank Dr. Eric Lund, president of Veris Technologies, Inc., from Salina, KS; and Dr. Robert Grisso, from Virginia Tech, Blacksburg, VA, for their valuable comments and suggestions.

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