Spatial Variability of Apparent Electrical Conductivity and Cone Index as Measured with Sensing Technologies: Assessment and Comparison

J.D. Jabro, R.G. Evans, Y. Kim, W.B. Stevens, and W. Iversen*

Introduction

Assessment and interpretation of spatial variability of soil physical and chemical characteristics are very important for precision farming. 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 sensors have been developed and are available that can take measurements continuously and provide detailed soil maps while traveling across a field (Sudduth and Kitchen, 2004).

Surveying agricultural fields for soil electrical conductivity (ECa) and cone index (CI) using Veris 3100 (coulter) and Veris 3000 (penetrometer) sensors (Veris Technologies, 2002) is considered one of the most accurate and powerful methods of characterizing soil variability for a variety of important soil properties such as bulk density, particle size distribution, water content, and salinity.

The objectives of this study were to evaluate ECa and CI for identifying and quantifying soil variability, and to compare the two Veris sensors for their ability to estimate soil properties in the field. (*For study methodology, see orange panel.*)

Results and Discussion

Classical Statistics

Descriptive statistics of log transformed of ECa and CI parameters measured using Veris 3100 and Veris 3000 sensors are given in Table 1. The CV values for the ECa and CI were slightly higher than 10%, suggesting low to medium variability for the soil at this site. Further, the range values were small, reflecting low soil variability within the study area.

Table 1. Statistical Summary

Statistical Parameters	ECa-Coulter (mS/m)	ECa-Penetrometer (mS/m)	CI (MPa)
	logarithmically transformed data		
Mean	4.92	3.21	2.14
Variance	0.31	0.37	0.152
Coefficient of variation, CV (%)	11.3	18.9	18.2
Number of observations, n	410	134	134

Statistics are based on log transformed ECa data.

The mean values of ECa from both sensors were compared (SAS Institute, 2003). ECa means of Veris 3100 and Veris 3000 differed significantly at the 0.01% probability level.

The Md in ECa measurements between Veris 3100 and Veris 3000 devices was significantly different from zero (Md=0.44 mS/m; t=31.5, n=134; pr<0.01). Further, Probit functions and probability frequency distributions (not shown) exhibited log-normal distributions for the ECa property from both sensors while the CI resembles a normal distribution.

Spatial Statistics

Figs 2, 3 and 4 show the distribution of ECa and CI in the field at depth of 0-30 cm.

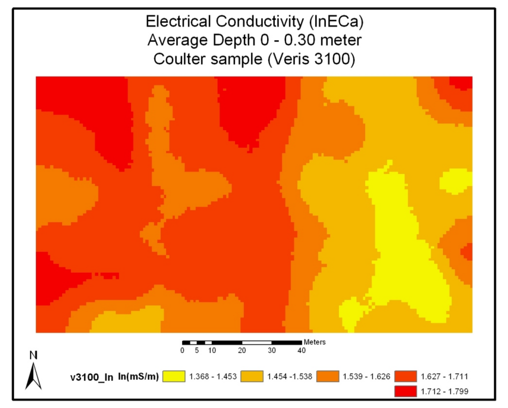

Fig 2. Ordinary kriging spatial mapping for soil ECa measured using the Veris 3100 sensor.

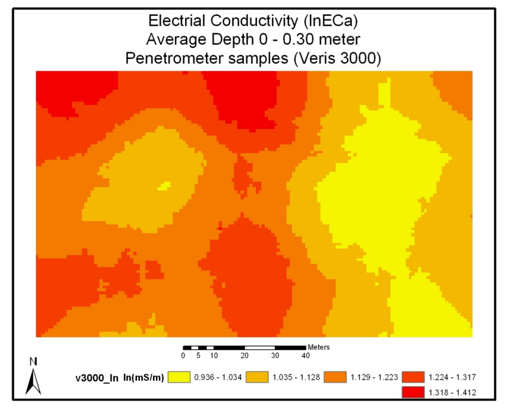

Fig 3. Ordinary kriging spatial mapping for soil ECa measured using the Veris 3000 sensor.

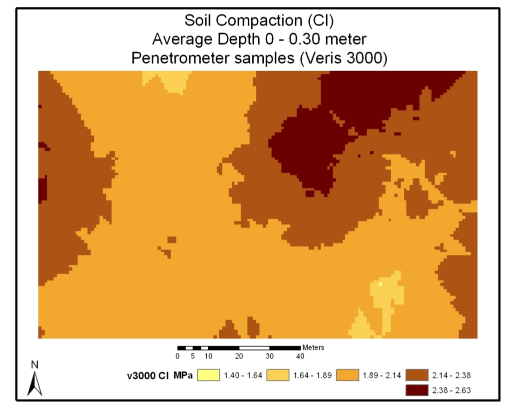

Fig 4. Ordinary Kriging spatial mapping for soil cone index (CI) using the Veris 3000 sensor.

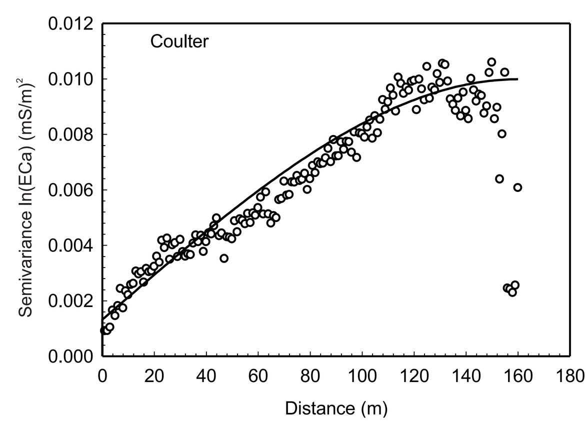

Fig. 5. Experimental and fitted semivariograms of soil ECa measured by the Veris 3100 sensor.

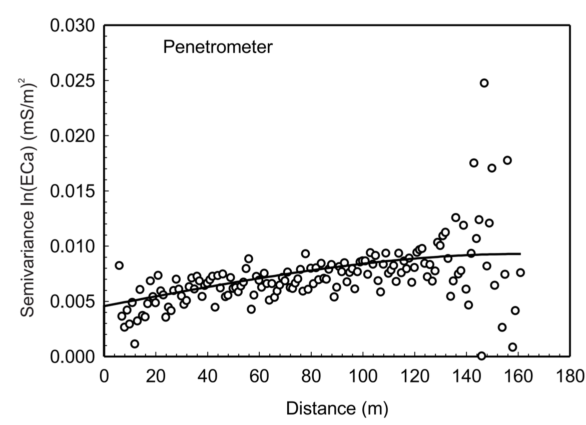

Fig. 6. Experimental and fitted semivariograms of soil ECa measured by the Veris 3000 sensor.

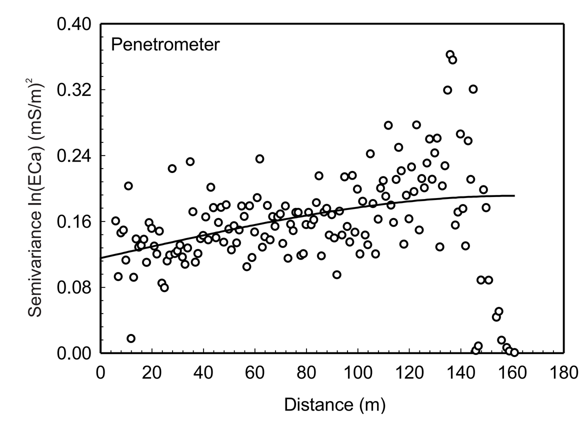

Fig. 7. Experimental and fitted semivariograms of soil CI measured by the Veris 3000 sensor.

> ***"The findings from this study indicate the potential for using the Veris sensing technology for precision farming to understand and manage spatial variability of soil properties and also to identify contrasting areas within agricultural fields."***

Regarding the spatial dependence aspect, the spherical model [Eq. 4] most closely fit the actual semivariograms, presenting nugget effect, sill and range values to the ECa and CI soil parameters (Figs. 5, 6, and 7).

Table 2 presents a summary of the geostatistical parameters nugget, variance, sill, proportion of structural variance and the range for the ECa and CI.

In order 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 were calculated based on the ratio of nugget (C_0) to the sill ($C_0 + C$) value . 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 . 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, while 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).

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

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Both descriptive and spatial statistics indicated that the ECa and CI Maps produced using the Veris 3100 and the Veris 3000 clearly showed uniformity representing a small scale trend of variability in the field. The ECa from both sensors exhibited higher values at the western parts of the field and presented 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.

Correlation between Two Sensors' Measurements

A significant positive correlation (r = 0.51, p<0.01) was found between the ECa measurements from both sensors. A simple linear regression model was proposed for predicting ECa-Veris-3000 measurements from those of ECa-Veries-3100 (Fig 8 and Eq.5).

$$ECa_{Veris\text{-}3000} = -0.074 + 0.832\ \ln ECa_{Veris\text{-}3100} \quad R^2=0.26 \quad [5]$$

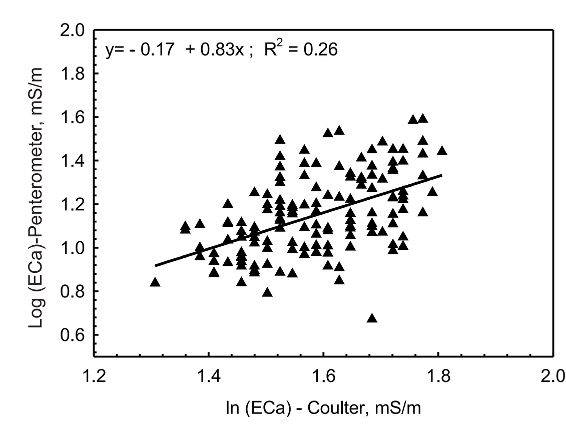
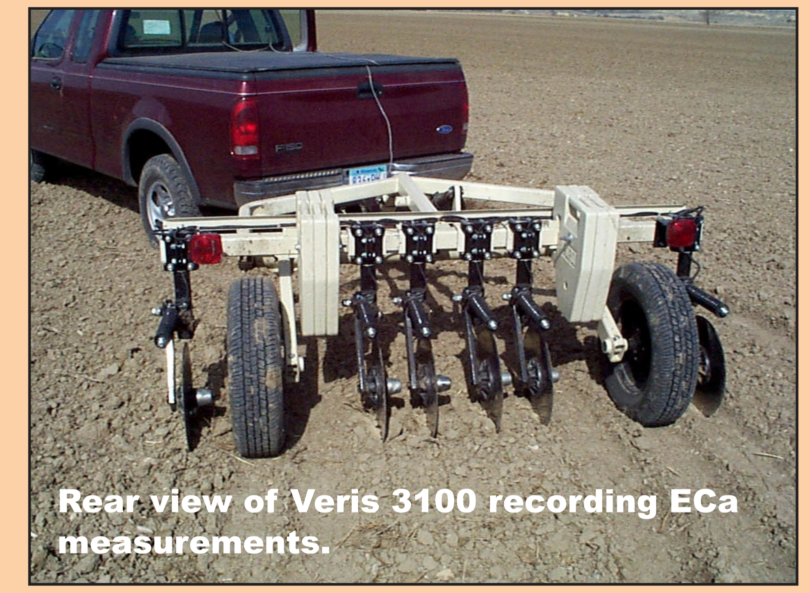


Fig. 8. Correlation between Veris 3100 and Veris 3000 for ECa on sandy loam soil at the test site.

Conclusions

- New sensors' based measurements of soil ECa and CI can provide important information to assess and examine spatial variability for precision farming.
- Interpolated spatial maps for ECa and CI using a 1 m² grid pixel may be used as a baseline for precision farming and future management decisions.
- Under both descriptive and spatial statistics, the ECa and CI maps clearly showed uniformity representing a small scale trend of variability in the field.
- The soil ECa and CI variability was spatially structured and spatial maps had the potential of explaining the variability within the field.

*The authors are: Research Soil Scientist, Research Leader/Agricultural Engineer, Research Associate, Research Agronomist and Physical Scientist. Northern Plains Agricultural Research Laboratory, USDA-ARS, 1500 N. Central Avenue, Sidney, MT 59270; phone: 406-433-9442; fax: 406-433-5038; e-mail: jjabro@sidney.ars.usda.gov.



Description of Veris 3000 Profiler Model

The penetrometer (Veris 3000) consists of a movable probe that measure both apparent electrical conductivity (ECa) and soil compaction (CI). The probe is pulled through the field by a pickup truck. 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. The sensing unit interfaces with the GPS and records readings of spatial coordinates, cone index, penetration speed, penetration depth, and ECa for each penetrating cycle using a data logger.

Description of Veris 3100 Model

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 due to electrical resistance of the soil, and hence electrical conductivity over two depths, 030 cm (shallow) and 090 cm (deep). The sensor unit interfaces with a differential GPS that provide geo-referenced readings of soil ECa. The ECa measured by this unit is in milliSiemens per meter (mS/m) .

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 research farm located approximately 23 miles east of Williston, ND (48.1640 N, 103.0986 W). The soil is classified as Lihan sandy loam soil (Sandy, mixed, frigid Entic Haplustoll).

Sampling point locations (Fig. 1) were georeferenced using the Global Positioning System, and ECa and CI data from the Veris 3100 and Veris 3000, respectively, was collected in early spring of 2005 prior to spring tillage.

On April 12, the Veris 3100 sensor was used to map the ECa at two depths using a parallel swathing monitored with the GPS unit providing spatial coordinates for each ECa measurement (Fig. 1). 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 Veris 3000 was used to collect measurements of both ECa and CI that were recorded in 2-cm intervals to a depth of 90 cm. A total of 138 points were created approximately 7.6 m apart.

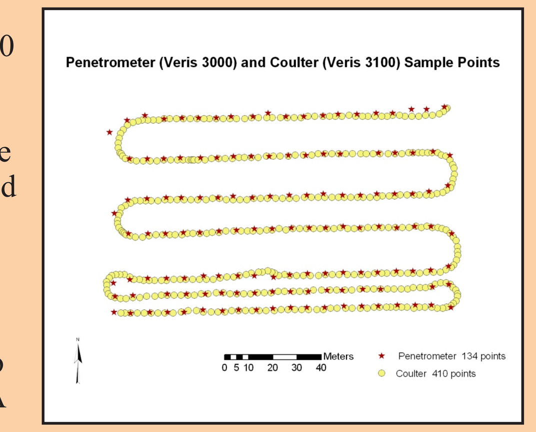


Fig. 1. Sampling points.

Classical Statistics

The descriptive statistics of ECa and CI soil parameters were carried out with SAS software (SAS Institute, 2003). The coefficient of variation, CV, has also been used for expressing variability on a relative basis.

$$CV\% = \frac{\sigma}{\mu} \times 100 \quad \text{Eq. [1]}$$

The significance of the difference, M_d, between the ECa measurements from both sensors (Eq. [2]) was evaluated (SAS Institute, 2003)

$$M_d = \frac{\sum_{i=1}^{n} (\ln CoulterECa_i - \ln PenetrometerECa_i)}{n} \quad \text{Eq. [2]}$$

Spatial Statistics

Geostatistical analysis was performed with Arc-Info (ESRI, 2005). Measurements of ECa and CI were point-ordinary kriged to produce interpolated spatial maps using a 1 m² grid pixel. Spherical models were best fitted to the experimental semivariance data. Semivariance is expressed in Equation [3].

$$\gamma^*(h) = \frac{1}{2N(h)} \sum_{i=1}^{N} (z_i - z_{i+h})^2 \quad \text{Eq. [3]}$$

Where y*(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 spherical model that was best fitted to the experimental semivariance values for ECa and CI was defined in Eq. [4] as:

$$\gamma(h) = Co + C\left(\frac{3h}{2a} - \frac{1}{2}\left(\frac{h}{a}\right)^3\right) \quad \text{for } h \le a \quad \text{Eq. [4]}$$

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, gives us information about the zone of the dependency influence.

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