Comparison of Electromagnetic Induction and Direct Sensing of Soil Electrical Conductivity

K. A. Sudduth,* N. R. Kitchen, G. A. Bollero, D. G. Bullock, and W. J. Wiebold

ABSTRACT

Apparent profile soil electrical conductivity (EC_a) can be an indirect indicator of a number of soil physical and chemical properties. Commercially available EC_a sensors can be used to efficiently and inexpensively develop the spatially dense data sets desirable for describing within-field spatial soil variability in precision agriculture. The objective of this research was to compare EC_a measurements from a noncontact, electromagnetic induction–based sensor (Geonics EM38)[1] to those obtained with a coulter-based sensor (Veris 3100) and to relate EC_a data to soil physical properties. Data were collected on two fields in Illinois (Argiudoll and Endoaquoll soils) and two in Missouri (Aqualfs). At 12 to 21 sampling sites in each field, 120-cm-deep soil cores were obtained for soil property determination. Depth response curves for each EC_a sensor were derived or obtained from the literature. Within a single field and measurement date, EM38 data and Veris deep (0–100 cm depth) data were most highly correlated (r = 0.74–0.88). Differences between EC_a sensors were more pronounced on the more layered Missouri soils due to differences in depth-weighted response curves. Correlations of EC_a with response curve–weighted clay content and cation exchange capacity were generally highest and most persistent across all fields and EC_a data types. Significant correlations were also seen with organic C on the Missouri fields and with silt content. Significant correlations of EC_a with soil moisture, sand content, or paste EC were observed only about 10% of the time. Data obtained with both types of EC_a sensors were similar and exhibited similar relationships to soil physical and chemical properties.

Efficient and accurate methods of measuring within-field variations in soil properties are important for precision agriculture (Bullock and Bullock, 2000). Apparent profile soil electrical conductivity is one sensor-based measurement that can provide an indirect indicator of important soil physical and chemical properties. Soil salinity, clay content, cation exchange capacity (CEC), clay mineralogy, soil pore size and distribution, soil moisture content, and temperature all affect EC_a (McNeill, 1992; Rhoades et al., 1999). In saline soils, most of the variation in EC_a can be related to salt concentration (Williams and Baker, 1982). In nonsaline soils, conductivity variations are primarily a function of soil texture, moisture content, and CEC (Rhoades et al., 1976; Kachanoski et al., 1988). Rhoades et al. (1989) modeled EC_a as a function of soil water content (both the mobile and immobile fractions), the electrical conductivity (EC) of the soil water, soil bulk density, and the EC of the soil solid phase.

Measurements of EC_a can be used to provide indirect measures of the soil properties listed above if the contributions of the other soil properties affecting the EC_a measurement are known or can be estimated. If the EC_a changes due to one soil property are much larger than those attributable to other factors, then EC_a can be calibrated as a direct measurement of that dominant factor. Lesch et al. (1995a, 1995b) used this direct-calibration approach to quantify variations in soil salinity within a field where water content, bulk density, and other soil properties were "reasonably homogeneous." Research in Missouri has established direct, within-field calibrations between EC_a and the depth of topsoil above a subsoil claypan horizon (Doolittle et al., 1994; Sudduth et al., 1995, 2001; Kitchen et al., 1999).

Mapped EC_a measurements have been found to be related to a number of soil properties of interest in precision agriculture, including soil water content (Sheets and Hendrickx, 1995), clay content (Williams and Hoey, 1987), CEC, and exchangeable Ca and Mg (McBride et al., 1990). Because EC_a integrates texture and moisture availability, two soil characteristics that affect productivity, it can help to interpret spatial grain yield variations, at least in certain soils (e.g., Sudduth et al., 1995; Jaynes et al., 1993; Kitchen et al., 1999). Other uses of EC_a in precision agriculture have included refining the boundaries of soil map units (Fenton and Lauterbach, 1999), interpreting within-field corn rootworm (*Diabrotica barberi* Smith and Lawrence) distributions (Ellsbury et al., 1999), and creating subfield management zones (Fraisse et al., 2001).

Two types of portable, within-field EC_a sensors have been used in agriculture—an electrode-based sensor requiring direct contact with the soil and a noncontact electromagnetic induction (EM) sensor. The earliest sensors were of the contact type and included four electrodes inserted into the soil, coupled with an electric current source and resistance meter. Hand-carried four-electrode sensors were initially used in salinity surveys (Rhoades, 1993), and later versions were tractor-mounted for mobile, georeferenced measurement of EC_a. The electrode-based sensing concept formed the

[1]Mention of trade names or commercial products is solely for the purpose of providing specific information and does not imply recommendation or endorsement by the USDA or the Univ. of Illinois.

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Abbreviations: CV, coefficient of variation; DGPS, differential global positioning system; EC, electrical conductivity; EC_a, apparent soil electrical conductivity; $EC_{a\text{-sh}}$, shallow (0–30 cm) apparent soil electrical conductivity measured by Veris 3100; $EC_{a\text{-dp}}$, deep (0–100 cm) apparent soil electrical conductivity measured by Veris 3100; $EC_{a\text{-em}}$, vertical-mode apparent soil electrical conductivity measured by Geonics EM38; EM, electromagnetic induction; GPS, global positioning system; TD, topsoil depth.

Fig. 1. Veris 3100 coulter-based apparent soil electrical conductivity sensor.

basis of a commercial product, the Veris 3100 (Veris Technol., Salina, KS). This mobile system (Fig. 1) uses six rolling coulters for electrodes and simultaneously generates *shallow* ($EC_{a\text{-}sh}$; nominally 0–30 cm) and *deep* ($EC_{a\text{-}dp}$; 0–100 cm) measurements of EC_a (Lund et al., 1999). It includes all necessary components except for the tow vehicle and global positioning system (GPS) receiver and requires no user calibration.

The EM-based EC_a sensor most often used in agriculture is the EM38 (Geonics Limited, Mississauga, ON, Canada). Details of the EM-sensing approach are given by McNeill (1980, 1992). The EM38 is a lightweight bar and was initially designed to be carried by hand and provide stationary EC_a readings. To implement mobile data acquisition with this unit, it is necessary to assemble a data collection system (Fig. 2), including a cart or sled to transport the sensor, a tow vehicle, a data collector or computer, an analog-to-digital converter, and a GPS receiver (e.g., Jaynes et al., 1993; Cannon et al., 1994; Sudduth et al., 2001).

Each of the commercial EC_a sensors has operational advantages and disadvantages. The EM38 requires the user to complete a daily calibration procedure before use. Changes in ambient conditions such as air temperature, humidity, and atmospheric electricity (spherics) can affect the stability of EM38 measurements. Sudduth et al. (2001) reported that EM38 output could drift by as much as 3 mS m^{-1} h^{-1} and that this drift was not consistently related to ambient conditions. They suggested that drift compensation be accomplished by use of a calibration transect or through frequent recalibration of the EM38. In contrast, the Veris 3100 system includes all necessary components and requires no user calibration. Thus, the Veris requires less user setup and

Fig. 2. Mobile apparent soil electrical conductivity data collection system, including Geonics EM38 sensor attached to rear-wheeled cart.

Table 1. Study fields.

State	Field	Field size	Location	Dominant soils	Sampling date	Calibration sites
		ha				
Missouri	F1	35	39°13′48″ N, 92°7′0″ W	Mexico, Adco	24 Nov. 1997	21
					16 Nov. 1999	19
Missouri	GV	13	39°14′5″ N, 92°8′49″ W	Mexico, Adco	25 Nov. 1997	15
					17 Nov. 1999	15
Illinois	WN	16	40°18′18″ N, 88°32′38″ W	Varna, Drummer, Chenoa	14 Oct. 1999	12
Illinois	WS	16	40°18′5″ N, 88°32′38″ W	Varna, Drummer, Chenoa	14 Oct. 1999	17

configuration before use and has the advantages of a single-vendor system when it comes to troubleshooting.

Using a wheeled cart pulled by an all-terrain vehicle (Fig. 2), an EM38 system is adaptable to a wide variety of data collection conditions. This lightweight system requires little power and makes it possible to collect data under wet or soft soil conditions. Also, it is possible to collect data after a crop has been planted in 76-cm rows, up until the time that the crop is 15 to 20 cm tall. The Veris 3100 is much heavier and requires a tractor or truck to pull it through the field, limiting its use to firmer soil conditions and unplanted fields. The newer Veris 2000XA, which only has four coulters and one measurement depth, can be pulled by a large all-terrain vehicle and can collect data between planted 76-cm crop rows.

Commercial operators are using EC_a sensing systems to provide soil variability information to producers. Although many or most of these are coulter-based sensors, the vast majority of research information has been obtained with EM-based sensors. As more use is made of EC_a sensing in precision agriculture, it will be important to compare the data obtained with each type of system and to understand how these data are related to soil properties. This study was undertaken to compare EC_a data collected on Missouri and Illinois fields with the noncontact Geonics EM38 and the coulter-based Veris 3100 and to relate those data to measured soil properties. Objectives were to (i) interpret differences in EC_a sensor data in relation to response curves of the sensors, (ii) document the relationship of EC_a data to soil properties, and (iii) investigate the improvement, if any, obtained by combining multiple EC_a variables for estimating soil properties.

MATERIALS AND METHODS

Study Fields

Data were collected on two Missouri fields and two Illinois fields. The Missouri fields (F1, 35 ha and GV, 13 ha) were located within 3 km of each other near Centralia, in central Missouri. The two Illinois fields (WS and WN, 16 ha each) were adjacent to each other near Bellflower, in east-central Illinois. Geographic coordinates of the fields are given in Table 1.

The soils found at the Missouri sites include the claypan soils of the Mexico series (fine, smectitic, mesic aeric Vertic Epiaqualfs) and the Adco series (fine, smectitic, mesic aeric Vertic Albaqualfs). These soils were formed in moderately fine-textured loess over a fine-textured pedisediment and are classified as somewhat poorly drained. Surface textures range from silt loam to silty clay loam. The subsoil claypan horizon(s) are silty clay loam, silty clay, or clay and commonly contain as much as 50 to 60% smectitic clay. Within each study field, topsoil depth (TD) above the claypan (depth to the first B horizon) ranged from <10 cm to >100 cm.

Soils of the Illinois fields include the Varna series (fine, illitic, mesic Oxyaquic Argiudolls), Drummer series (fine silty, mixed, superactive, mesic Typic Endoaquolls), and Chenoa series (fine, illitic, mesic Aquic Argiudolls). Surface textures include silt loam and silty clay loam. Drainage classes represented at the Illinois fields range from poorly drained to well drained (Kravchenko et al., 2001).

Apparent Soil Electrical Conductivity Sensors and Response Curves

The EM sensor used in this research (Geonics EM38) has a spacing of 1 m between the transmitting coil located at one end of the instrument and the receiver coil at the other end. Calibration controls and a digital readout of EC_a in millisiemens per meter (mS m^{-1}) are included, and an analog data output allows data to be recorded on a data logger or computer. The EM38 was operated in the vertical dipole mode, providing an effective measurement depth of approximately 1.5 m. The vertical-mode EC_a measurement from the EM38 by Geonics EM38 (designated by $EC_{a\text{-em}}$ in this study) is averaged over a lateral area approximately equal to the measurement depth. The instrument response to soil conductivity varies as a nonlinear function of depth (McNeill, 1992). Sensitivity in the vertical mode is highest at about 0.4 m below the instrument (Fig. 3). The EC_a measurement is determined by the soil conductivity with depth, as weighted by this instrument

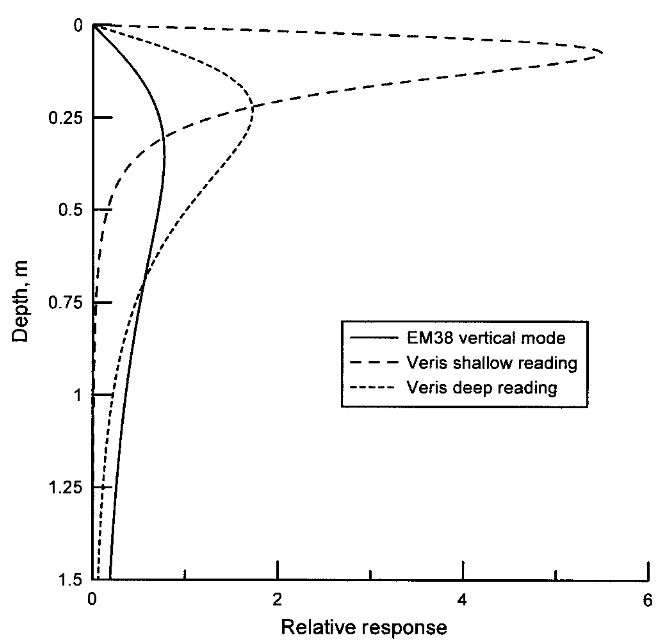

Fig. 3. Relative response of apparent soil electrical conductivity sensors as a function of depth. Responses are normalized to yield a unit area under each curve.

response function (McNeill, 1992). The EM38 was combined with a data acquisition computer and differential GPS (DGPS) system for mobile data collection (Fig. 2), as described by Sudduth et al. (2001).

The Veris Model 3100 sensor cart (Fig. 1; Lund et al., 1999) identifies soil variability by directly sensing soil EC. As the cart is pulled through the field, a pair of coulter electrodes transmit an electrical current into the soil while two other pairs of coulter electrodes measure the voltage drop. The system georeferences the conductivity measurements using an external DGPS receiver and stores the resulting data in digital form. The measurement electrodes are configured to provide both $EC_{a\text{-sh}}$ and $EC_{a\text{-dp}}$ readings of EC_a. As with the EM38, the Veris 3100 response to soil conductivity varies as a nonlinear function of depth. The coulter electrodes of the Veris 3100 are configured as a Wenner array, an arrangement commonly used for geophysical resistivity surveys. The theoretical response function of the Wenner array (Roy and Apparao, 1971) is somewhat similar to that of the EM38 although it decreases more rapidly with depth (Fig. 3).

If the response curves of Fig. 3 are integrated with respect to depth, differences in the soil volumes measured by the different sensors are readily apparent (Fig. 4). With $EC_{a\text{-sh}}$, 90% of the response is obtained from the soil above the 30 cm depth. With $EC_{a\text{-dp}}$, 90% of the response is obtained from the soil above the 100 cm depth. With $EC_{a\text{-em}}$, 90% of the response is obtained above 5 m depth while 70% of the response is obtained above about 1.5 m. The curves of Fig. 4 are based on equations that assume a homogeneously conductive soil volume. Actual responses will vary somewhat due to EC_a differences between soil layers, with a high-conductivity surface layer reducing the depth of response (Barker, 1989).

Data Collection

For each field, EC_a data were collected with both sensors on the same date in the fall of 1999. Additional EC_a data were collected for the Missouri fields in the fall of 1997 (Table 1). Soil moisture conditions were relatively dry at the time of data collection for all sites and dates because there had been little profile recharge due to fall rains. Although reliable operation of the Veris 3100 can be a problem in dry, low-conductivity soils due to poor electrical contact between the coulters and the soil, such a problem was not observed in these data. Examination of the Veris data showed it varied smoothly from point to point except for one small field area where stony ground presented coulter contact problems. In this area, a small number of data points with extreme Veris EC_a values were excluded from the data set.

The Veris 3100 and Geonics EM38 were operated in tandem, taking measurements on transects spaced approximately 10 m apart. Data were recorded on a 1-s interval, corresponding to a 4- to 6-m data spacing. Between 4400 and 11 000 individual EC_a measurements were obtained for each field. Data obtained by DGPS were associated with each sensor reading to provide positional information with an accuracy of 1.5 m or better.

Using our previously reported approach (Sudduth et al., 2001), a calibration transect was established in each field to monitor instrument drift during the survey. Data were collected on this transect at least every hour, and raw EC_a readings were adjusted based on any change in calibration transect data. As expected, the direct EC_a–sensing approach of the Veris system was much less (<50%) prone to instrument drift than the EM38. We believe that drift compensation would not be a necessary component of Veris EC_a surveys although it should be done for EM38 surveys.

Within each field, between 12 and 21 sampling sites were selected to cover the range of EC_a values present. These sites were chosen by a soil scientist familiar with the soils in the particular field with the additional goal of including samples from all of the landscape positions and soil map units present. One 4.0-cm-diam. core that was 120 cm long was obtained at each site using a hydraulic soil-coring machine. Cores were examined within the field by a skilled soil scientist and pedogenic horizons identified. Cores were segmented by horizon for laboratory analysis. Soil moisture was determined gravimetrically.

Additionally, samples for each horizon were analyzed at the University of Missouri Soil Characterization Laboratory using methods described by the National Soil Survey Center Staff (1996). Data were obtained for the following properties: sand, silt, and clay fractions (pipette method); CEC (base + Al method); organic C; and saturated paste EC.

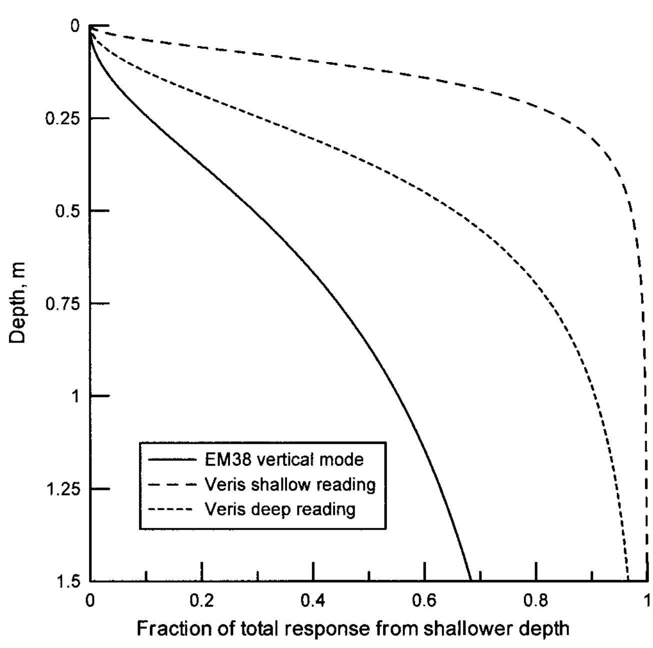

Fig. 4. Cumulative response of apparent soil electrical conductivity sensors as a function of depth.

Data Analysis

To allow comparison between EC_a sensors, a combined data set was created for each field. Each Veris data point was combined with the nearest EM38 data point based on GPS coordinates. If a match was not found within a 2-m radius, that point was removed from the data set. Additional data sets were created to compare across sampling dates on the Missouri fields. Because measurement transect locations were not identical between 1997 and 1999, it was necessary to increase the search radius for these data sets to 3 m. Pearson correlation coefficients (r) were calculated between the various EC_a sensors and measurement dates.

In this study, soil property data were obtained by horizon, rather than on an even depth increment. To facilitate comparison across calibration points, a depth-weighted mean was calculated for each soil property at each calibration point. To provide a measure of the variability in each soil property with depth, a depth-weighted coefficient of variation (CV) was also calculated. To account for the fact that the response of each EC_a sensor is not constant with depth, three additional sets of data were created by weighting each soil property profile by the sensor response curve (Fig. 3).

Analysis of the relationship between EC_a and soil properties was performed for each data source ($EC_{a\text{-em}}$, $EC_{a\text{-sh}}$, and $EC_{a\text{-dp}}$) and profile-weighted soil property, using the 1999 calibration point data. These data were examined for spatial autocorrelation by calculating the Moran coefficient as suggested by Long (1996). No significant autocorrelation was detected in any EC_a data. Only 15% of the soil property data sets showed significant ($P \leq 0.05$) spatial autocorrelation. With this general lack of significant spatial autocorrelation, likely caused by the small number (12–19) and spatial dispersion of the calibration points in each field, we conducted a nonspatial analysis between EC_a and soil properties. Pearson correlation coefficients were calculated between EC_a and soil properties (moisture, clay, silt, sand, organic C, CEC, and saturated paste EC). Regressions were performed to estimate soil properties from (i) each individual EC_a measurement, (ii) both Veris 3100 EC_a measurements, and (iii) all three EC_a measurements. Only parameters statistically significant ($P \leq 0.05$) were retained in the final regression equations.

Our previous work (Doolittle et al., 1994; Kitchen et al., 1999; Sudduth et al., 2001) established the utility of $EC_{a\text{-em}}$ data for estimating TD on claypan soils. In this study, we compared the accuracy of TD estimation by $EC_{a\text{-em}}$ and $EC_{a\text{-dp}}$ for the Missouri claypan soil fields. Estimations based on $EC_{a\text{-sh}}$ were not included because 90% of the theoretical $EC_{a\text{-sh}}$ response is within 30 cm of the surface. Therefore, $EC_{a\text{-sh}}$ data are unable to estimate TDs greater than approximately 30 cm while the TD on these fields exceeded 100 cm in places. Topsoil depth (depth to the first B horizon) data obtained at calibration points in fields F1 and GV were used to develop linear regression equations for estimating TD as a function of the inverse of EC_a (EC_a^{-1}). Only those calibration points where TD was <100 cm were used because 90% of the theoretical $EC_{a\text{-dp}}$ response is within 100 cm of the surface.

RESULTS AND DISCUSSION

Comparison of Apparent Soil Electrical Conductivity Data

Apparent soil electrical conductivity data obtained with each sensor exhibited similar qualitative trends at the field scale (e.g., Fig. 5, showing field F1). A statistical summary of the EC_a data for each field and measurement date is shown in Table 2. In general, the mean $EC_{a\text{-sh}}$ and $EC_{a\text{-dp}}$ measured by the Veris 3100 were somewhat higher on the Illinois fields compared with the Missouri fields; however variation in EC_a as measured by the CV was somewhat less. The mean EM38-measured EC_a was similar for Missouri and Illinois fields while the CV was higher for the Illinois fields. This suggests that the major variability in the soil properties that affect EC_a on the Missouri fields may be in the upper layers that are more heavily weighted in the Veris 3100 EC_a measurements. In contrast, variability affecting EC_a on the Illinois fields may be more pronounced at greater depths.

Correlation coefficients between the various EC_a measurements for each field are shown in Table 3. The highest correlations were observed when comparing the same data ($EC_{a\text{-em}}$, $EC_{a\text{-sh}}$, or $EC_{a\text{-dp}}$) across the 1997 and 1999 measurement dates. Soil conditions were similar

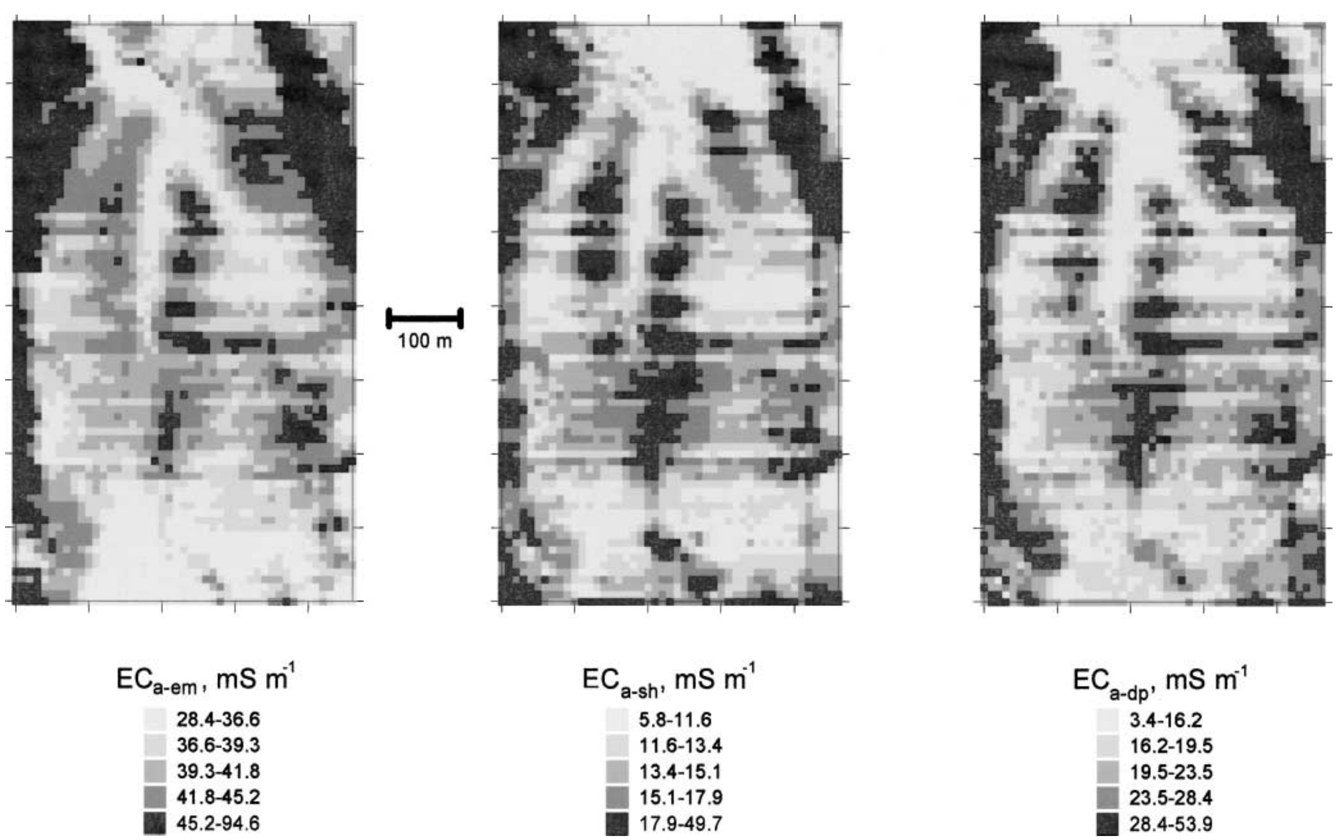

Fig. 5. Comparison of apparent soil electrical conductivity (EC_a) readings obtained with (left) Geonics EM38, (center) Veris 3100 shallow electrodes, and (right) Veris 3100 deep electrodes on Missouri field F1 (39°13′48″ N, 92°7′0″ W, Mexico and Adco soils). Within each map, an equal number of observations is contained in each classification interval.

between these two measurement dates. Each occurred after a water-stressed growing season and little postharvest moisture recharge, so we would expect similar EC_a results. In previous work, we also found high correlations ($0.85 < r < 0.90$) when comparing the 1997 F1 $EC_{a\text{-em}}$ data used here with other EM38 survey data collected on the same field under wetter soil conditions in April 1994 and April 1999 (Sudduth et al., 2001).

Within a single measurement date, the highest correlations were consistently observed between the $EC_{a\text{-em}}$ data and the $EC_{a\text{-dp}}$ data for both Missouri and Illinois fields. Correlations between $EC_{a\text{-em}}$ data and $EC_{a\text{-sh}}$ data were lowest while correlations between $EC_{a\text{-dp}}$ data and $EC_{a\text{-sh}}$ data were intermediate. The reason behind this ranking can be discerned from the differences between the response curves for the various sensors (Fig. 3 and 4) where the $EC_{a\text{-dp}}$ response curve lies between the $EC_{a\text{-sh}}$ curve and the $EC_{a\text{-em}}$ curve. Correlations across years and sensors were similar to correlations observed across sensors for a single measurement date.

When data from both fields of a state were combined, correlations were similar, and better in some cases, than correlations calculated within individual fields. When data were combined for all fields, correlations between the two deeper EC_a readings did not decrease, but correlations of $EC_{a\text{-sh}}$ to the other EC_a readings were much lower (Table 3). These results indicate that although the shallow ($EC_{a\text{-sh}}$) and deep ($EC_{a\text{-dp}}$ or $EC_{a\text{-em}}$) EC_a data were strongly related within a field or soil association (the fields from each state had similar soils and were

Table 2. Statistical summary of apparent soil electrical conductivity (EC_a) data.

Field and year	EC_a data†	EC_a Mean	Median	SD	CV
		mS m^{-1}			%
F1(1997)‡	$EC_{a\text{-em}}$	41.2	40.5	5.7	13.8
	$EC_{a\text{-sh}}$	15.2	14.3	4.7	30.9
	$EC_{a\text{-dp}}$	21.9	21.2	9.3	42.5
F1(1999)	$EC_{a\text{-em}}$	30.7	30.0	3.8	12.4
	$EC_{a\text{-sh}}$	9.7	9.3	3.1	32.0
	$EC_{a\text{-dp}}$	19.6	18.7	8.5	43.4
GV(1997)	$EC_{a\text{-em}}$	–	–	–	–
	$EC_{a\text{-sh}}$	30.9	27.1	12.2	39.5
	$EC_{a\text{-dp}}$	35.5	35.2	13.2	37.2
GV(1999)	$EC_{a\text{-em}}$	34.8	35.3	6.4	18.4
	$EC_{a\text{-sh}}$	15.2	13.0	7.5	49.3
	$EC_{a\text{-dp}}$	23.7	23.5	11.6	48.9
WN(1999)	$EC_{a\text{-em}}$	30.7	28.8	8.5	27.7
	$EC_{a\text{-sh}}$	27.7	25.7	8.0	28.9
	$EC_{a\text{-dp}}$	39.3	37.4	12.0	30.5
WS(1999)	$EC_{a\text{-em}}$	32.8	32.2	8.0	24.4
	$EC_{a\text{-sh}}$	27.9	26.9	6.9	24.7
	$EC_{a\text{-dp}}$	41.1	39.5	11.8	28.7

† $EC_{a\text{-em}}$, vertical-mode EC_a measured by Geonics EM38; $EC_{a\text{-sh}}$, shallow EC_a measured by Veris 3100; $EC_{a\text{-dp}}$, deep EC_a measured by Veris 3100.
‡ Field characteristics and locations are given in Table 1.

Table 3. Correlation coefficients (r) between different apparent soil electrical conductivity (EC_a) measurements for study fields.

Field and year	Data†	1999 $EC_{a\text{-em}}$	1999 $EC_{a\text{-sh}}$	1999 $EC_{a\text{-dp}}$	1997 $EC_{a\text{-em}}$	1997 $EC_{a\text{-sh}}$	1997 $EC_{a\text{-dp}}$
Field F1‡							
1999	$EC_{a\text{-em}}$‡	1					
	$EC_{a\text{-sh}}$	0.60	1				
	$EC_{a\text{-dp}}$	0.74	0.74	1			
1997	$EC_{a\text{-em}}$	0.80	0.67	0.83	1		
	$EC_{a\text{-sh}}$	0.64	0.82	0.69	0.71	1	
	$EC_{a\text{-dp}}$	0.79	0.71	0.86	0.81	0.79	1
Field GV							
1999	$EC_{a\text{-em}}$	1					
	$EC_{a\text{-sh}}$	0.67	1				
	$EC_{a\text{-dp}}$	0.84	0.75	1			
1997	$EC_{a\text{-em}}$	–	–	–	–		
	$EC_{a\text{-sh}}$	0.66	0.84	0.74	–	1	
	$EC_{a\text{-dp}}$	0.83	0.69	0.88	–	0.80	1
Both Missouri fields							
1999	$EC_{a\text{-em}}$	1					
	$EC_{a\text{-sh}}$	0.78	1				
	$EC_{a\text{-dp}}$	0.71	0.72	1			
1997	$EC_{a\text{-em}}$	–	–	–	–		
	$EC_{a\text{-sh}}$	0.78	0.87	0.66	–	1	
	$EC_{a\text{-dp}}$	0.71	0.76	0.84	–	0.84	1
Field WN							
1999	$EC_{a\text{-em}}$	1					
	$EC_{a\text{-sh}}$	0.79	1				
	$EC_{a\text{-dp}}$	0.88	0.82	1			
Field WS							
1999	$EC_{a\text{-em}}$	1					
	$EC_{a\text{-sh}}$	0.78	1				
	$EC_{a\text{-dp}}$	0.84	0.80	1			
Both Illinois fields							
1999	$EC_{a\text{-em}}$	1					
	$EC_{a\text{-sh}}$	0.77	1				
	$EC_{a\text{-dp}}$	0.86	0.80	1			
All fields							
1999	$EC_{a\text{-em}}$	1					
	$EC_{a\text{-sh}}$	0.61	1				
	$EC_{a\text{-dp}}$	0.86	0.46	1			

† $EC_{a\text{-em}}$, vertical-mode EC_a measured by Geonics EM38; $EC_{a\text{-sh}}$, shallow EC_a measured by Veris 3100; $EC_{a\text{-dp}}$, deep EC_a measured by Veris 3100.
‡ Field characteristics and locations are given in Table 1.

located near each other), their relationship was not consistent across different soil associations. Thus, the shallow ($EC_{a\text{-}sh}$) and deeper ($EC_{a\text{-}dp}$ and $EC_{a\text{-}em}$) sensors provide unique information, and data from one cannot be inferred from data obtained with the other. However, because the two deeper EC_a readings were highly correlated both within and across fields, it appears that little additional information would be gained on these soils by collecting both EM38 and Veris data.

Relationship of Apparent Soil Electrical Conductivity to Measured Soil Properties

A statistical summary of profile-average soil property data measured for the calibration points in each field is shown in Table 4. Analysis of variance indicated that profile-average clay and paste EC were significantly higher for the Missouri fields while sand, organic C, and CEC were significantly higher ($P \leq 0.05$) for the Illinois fields. Profile CVs of clay, silt, CEC, and paste EC were significantly higher for the Missouri fields while profile CVs of organic C were significantly higher ($P \leq 0.05$) for the Illinois fields. These higher CVs showed that the claypan soils of the Missouri fields were more layered in terms of the soil properties affecting EC_a. To further investigate this layering, mean A-horizon and first B-horizon clay and CEC were calculated for the calibration points on each field. For the Illinois fields, mean clay and CEC for the first B-horizon were within 2% of the means for the A horizons. For the Missouri fields, mean clay was 215% greater and mean CEC 185% greater for the first B horizon compared with the A horizons. This significant layering, combined with differences in response functions (Fig. 3) for the different sensors, explains the nonlinear relationship between data from the different sensors seen on the Missouri fields (Fig. 6). The similarity of clay and CEC levels between the A horizon and B horizon for the Illinois fields helps to explain the linear relationship between EC_a data obtained from the different sensors on those fields (Fig. 6).

Significant ($P \leq 0.05$) correlation coefficients between EC_a and profile-weighted soil properties for each field are shown in Table 5. Correlations of EC_a with sensor-weighted clay content and sensor-weighted CEC were generally highest and most persistent across all fields and EC_a data types. This higher correlation with sensor-weighted data supports our hypothesis that transformation of soil property data by weighting with the sensor response function is an appropriate way to help account for curvilinearity in the functional relationship. Other soil properties that exhibited a significant correlation in most cases were clay, silt, and CEC of the upper soil horizon. Some properties, such as profile-average organic C and CEC were significant on the Missouri fields but not on the Illinois fields. Significant correlations with soil moisture, sand content, and paste EC were observed less frequently.

Quadratic regression analysis was performed to estimate soil properties as a function of each of the EC_a variables. Properties estimated were profile-average and top-layer clay, silt, CEC, organic C, paste EC, and soil moisture (Missouri fields only). The effect of field was not statistically significant in the analysis ($P \leq 0.05$), so regressions were performed for three data sets: (i) Missouri data, (ii) Illinois data, and (iii) all data. Table 6 shows the regression statistics for each analysis. Regressions for some soil properties were more predictive for Missouri fields while others were more predictive for Illinois fields. The most accurate estimates were obtained for clay, silt, and CEC. Estimates of soil moisture, organic C, and paste EC obtained by regression on a single EC_a variable were of relatively low accuracy.

Top-layer clay, silt, and CEC were estimated with considerably more accuracy than were profile-average values. In most cases, $EC_{a\text{-}sh}$ provided the best estimates of the top-layer soil properties, as would be expected from the shape of the $EC_{a\text{-}sh}$ weighting function (Fig. 3). Profile-average soil properties were usually estimated with the highest accuracy using $EC_{a\text{-}em}$ data although $EC_{a\text{-}dp}$ data were most predictive for some cases (Table 6). Quadratic equations were significant for less than half of the soil parameters; for the others, only the linear EC_a term was significant.

A second series of regression analyses included multiple EC_a data sources for estimating the same soil properties listed above. Stepwise quadratic (plus interaction) analyses included (i) both Veris data sets—$EC_{a\text{-}sh}$ and $EC_{a\text{-}dp}$—and (ii) all three EC_a data sets (Table 6). In

Table 4. Means and coefficients of variation (CVs indicating variation with depth) for soil properties obtained from by-horizon analysis of calibration point cores. Means and CVs were calculated for each calibration point and then averaged over all calibration points in each field.

	Field†							
	F1 (MO)		GV (MO)		WS (IL)		WN (IL)	
Property	Mean	CV	Mean	CV	Mean	CV	Mean	CV
Soil moisture, g kg^{-1}	146	0.26	146	0.18	–‡	–	–	–
Clay, g kg^{-1}	354	0.38	321	0.22	300	0.13	298	0.14
Silt, g kg^{-1}	594	0.23	622	0.11	587	0.09	603	0.10
Sand, g kg^{-1}	32	0.84	58	0.39	113	0.43	99	0.64
Organic C, g kg^{-1}	6.4	0.58	6.7	0.60	8.9	0.77	8.0	0.86
CEC, cmol kg^{-1}§	18.8	0.33	18.2	0.20	21.0	0.17	20.8	0.25
Paste EC, mS m^{-1}¶	22	0.27	22	0.31	10	0.17	17	0.28

† Field characteristics and locations are given in Table 1.
‡ Soil moisture data not available for Illinois fields.
§ CEC, cation exchange capacity.
¶ EC, electrical conductivity.

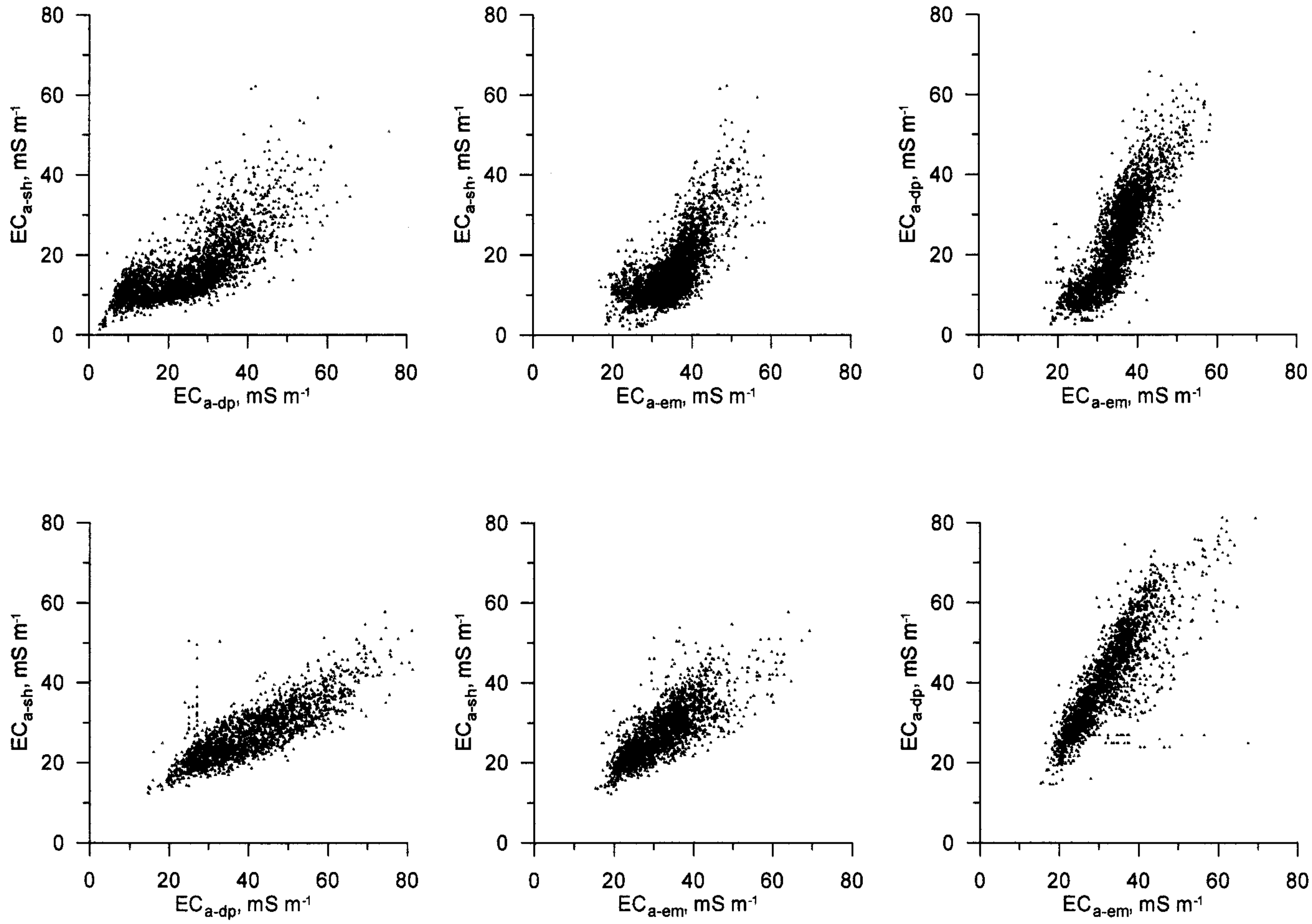

Fig. 6. Relationships between apparent soil electrical conductivity (EC_a) data for (top) Missouri field GV and (bottom) Illinois field WS. Relationships appear more linear for WS (40°18′5″ N, 88°32′38″ W; Varna, Drummer, and Chenoa soils) than for GV (39°14′5″ N, 92°8′49″ W, Mexico and Adco soils). $EC_{a\text{-sh}}$, shallow (0–30 cm) EC_a measured by Veris 3100; $EC_{a\text{-dp}}$, deep (0–100 cm) EC_a measured by Veris 3100; $EC_{a\text{-em}}$, vertical-mode EC_a measured by Geonics EM38.

general, this approach provided little, if any, improvement over single-factor EC_a regressions for top-layer clay, silt, and CEC, reinforcing our observation that $EC_{a\text{-sh}}$ data were a reasonable estimator of these properties. Estimates of single-state, profile-average clay and silt were generally improved by including both Veris EC_a data sets and were further improved somewhat by including the $EC_{a\text{-em}}$ data. For multistate analyses, estimates were improved when all three EC_a variables were allowed to enter the regression but were not improved by including just Veris data.

Estimates of paste EC and profile-average soil moisture were of low accuracy and were not improved by including additional EC_a variables. Estimates of organic C for Illinois fields were improved by including additional EC_a terms while estimates for Missouri fields were not. Estimates of top-layer soil moisture, available only for Missouri fields, also improved when additional EC_a terms were included. For both single EC_a and multiple EC_a regressions, better estimates of soil properties were obtained within a single state than across both states. For best results, site-specific (or soil-specific) equations relating soil properties to EC_a should be used.

Regression equations for estimating claypan TD as a function of EC_a yielded standard errors from 6 to 16 cm (Table 7). Comparisons between $EC_{a\text{-em}}$ and $EC_{a\text{-dp}}$ data were variable between fields. For field F1, $EC_{a\text{-dp}}$ data were more predictive of TD while $EC_{a\text{-em}}$ data were more predictive of TD on field GV. Variations in the accuracy of TD estimations between years could be explained at least partially by the fact that different calibration points were used between 1997 and 1999. For F1, the 1997 calibration points exhibited a reasonably uniform distribution in TD across the range from 0 to 100 cm. However, in 1999, the calibration-point TDs were clustered between 20 and 50 cm. For GV, a more uniform distribution of calibration points was obtained in 1999. These results point out the importance of properly selecting calibration points for relating EC_a data to soil physical properties. One way to remove the subjectivity from this process was proposed by Lesch et al. (1995b), who described an algorithmic approach to the selection of optimized locations for calibrating EC_a measurements.

SUMMARY AND CONCLUSIONS

Sensor-based measurements of EC_a can provide important information on within-field soil variability. In

Table 5. Significant ($P \leq 0.05$) correlations between soil properties and apparent soil electrical conductivity (EC_a) data for each study field.

		Field F1‡			Field GV			Field WN			Field WS		
Soil property	Weighting†	$EC_{a\text{-}em}$§	$EC_{a\text{-}sh}$¶	$EC_{a\text{-}dp}$#	$EC_{a\text{-}em}$	$EC_{a\text{-}sh}$	$EC_{a\text{-}dp}$	$EC_{a\text{-}em}$	$EC_{a\text{-}sh}$	$EC_{a\text{-}dp}$	$EC_{a\text{-}em}$	$EC_{a\text{-}sh}$	$EC_{a\text{-}dp}$
Soil moisture	Sensor‡		0.54	0.60				–††	–	–	–	–	–
	Profile avg.							–	–	–	–	–	–
	Top layer							–	–	–	–	–	–
Clay	Sensor	0.60	0.76	0.74	0.88	0.89	0.83	0.59	0.70		0.78	0.76	0.74
	Profile avg.				0.81		0.70				0.80	0.55	0.73
	Top layer		0.62		0.75	0.83	0.74	0.60	0.74	0.66	0.54	0.77	0.62
Silt	Sensor	−0.65	−0.71	−0.73	−0.84		−0.79					−0.60	
	Profile avg.	−0.50			−0.74		−0.61						
	Top layer	−0.52	−0.66	−0.60	−0.68	−0.79	−0.72	−0.63	−0.75	−0.64	−0.60	−0.64	−0.61
Sand	Sensor												
	Profile avg.							−0.60					
	Top layer	0.46		0.59									
CEC‡‡	Sensor	0.76	0.61	0.79	0.88	0.88	0.88	0.63	0.76	0.66	0.60	0.51	
	Profile avg.	0.68	0.54	0.53	0.82		0.79						
	Top layer				0.74	0.83	0.77	0.79	0.77	0.83	0.78	0.54	0.63
Organic C	Sensor				−0.75		−0.72						
	Profile avg.	−0.54		−0.60	−0.72	−0.55	−0.60			0.62			
	Top layer												
Paste EC	Sensor		0.79										
	Profile avg.												
	Top layer		0.85	0.74									

† Weighting applied to soil property data before calculating correlations: sensor = weighting function from Fig. 3 for the respective sensor; profile avg. = depth-weighted average for 120-cm-deep profile sample; top layer = value from top layer of profile sample.
‡ Field characteristics and locations are given in Table 1.
§ $EC_{a\text{-}em}$, vertical-mode EC_a measured by Geonics EM38.
¶ $EC_{a\text{-}sh}$, shallow EC_a measured by Veris 3100.
# $EC_{a\text{-}dp}$, deep EC_a measured by Veris 3100.
†† Soil moisture data not available for Illinois fields.
‡‡ CEC, cation exchange capacity.

Table 6. Regression statistics for the estimation of soil properties as a function of apparent soil electrical conductivity (EC_a).

		Best single-EC_a model			Veris EC_a		Veris + EM38	
Soil property	Locations	EC_a data†	R^2	SE‡	R^2	SE	R^2	SE
Top layer								
Moisture	MO§	$EC_{a\text{-}sh}$, q¶	0.20	49.7	0.30	47.2	0.60	37.4
Clay	MO	$EC_{a\text{-}sh}$	0.63	34.7	0.63	34.7	0.70	31.9
	IL	$EC_{a\text{-}sh}$	0.53	25.6	0.55	25.6	0.55	25.6
	All	$EC_{a\text{-}sh}$, q	0.78	31.2	0.78	31.2	0.78	31.2
Silt	MO	$EC_{a\text{-}sh}$, q	0.62	41.2	0.62	41.2	0.63	40.7
	IL	$EC_{a\text{-}dp}$, q	0.48	34.2	0.47	33.7	0.51	32.4
	All	$EC_{a\text{-}sh}$, q	0.73	39.1	0.73	39.1	0.74	38.7
CEC#	MO	$EC_{a\text{-}sh}$	0.56	3.40	0.56	3.40	0.56	3.40
	IL	$EC_{a\text{-}em}$	0.61	2.80	0.46	3.30	0.61	2.80
	All	$EC_{a\text{-}sh}$	0.60	3.44	0.60	3.44	0.61	3.36
Organic C	MO	$EC_{a\text{-}sh}$	0.17	1.90	0.17	1.90	0.17	1.90
	IL	NS††			NS		NS	
	All	$EC_{a\text{-}sh}$, q	0.46	3.56	0.51	3.42	0.58	3.22
Paste EC	MO	$EC_{a\text{-}dp}$, q	0.28	5.9	0.28	5.9	0.31	5.8
	IL	NS			NS		NS	
	All	$EC_{a\text{-}dp}$	0.15	10.7	0.15	10.7	0.30	9.8
Profile average								
Moisture	MO	$EC_{a\text{-}sh}$	0.20	14.8	0.20	14.8	0.20	14.8
Clay	MO	$EC_{a\text{-}em}$	0.23	49.2	0.33	46.7	0.60	37.4
	IL	$EC_{a\text{-}em}$	0.47	29.6	0.53	28.3	0.50	28.6
	All	$EC_{a\text{-}em}$	0.30	44.5	0.20	48.3	0.43	40.5
Silt	MO	$EC_{a\text{-}em}$	0.28	46.4	0.37	44.0	0.44	41.7
	IL	$EC_{a\text{-}em}$, q	0.15	52.5	NS		NS	
	All	$EC_{a\text{-}dp}$	0.10	52.1	0.10	52.1	0.10	52.1
CEC	MO	$EC_{a\text{-}em}$	0.48	2.86	0.44	3.00	0.48	2.86
	IL	NS			NS		NS	
	All	$EC_{a\text{-}dp}$	0.20	4.26	0.20	4.26	0.28	4.06
Organic C	MO	$EC_{a\text{-}em}$, q	0.41	1.40	0.32	1.48	0.41	1.40
	IL	$EC_{a\text{-}em}$	0.20	2.86	0.50	2.30	0.62	2.01
	All	NS			0.19	2.43	0.19	2.43
Paste EC	MO	$EC_{a\text{-}sh}$	0.18	4.2	0.18	4.2	0.18	4.2
	IL	NS			NS		NS	
	All	$EC_{a\text{-}sh}$, q	0.43	5.1	0.43	5.1	0.43	5.1

† $EC_{a\text{-}sh}$, shallow EC_a measured by Veris 3100; $EC_{a\text{-}dp}$, deep EC_a measured by Veris 3100; $EC_{a\text{-}em}$, vertical-mode EC_a measured by Geonics EM38.
‡ Standard errors are in the units of g kg^{-1} (moisture, clay, silt, and organic C), cmol kg^{-1} (CEC), and mS m^{-1} (paste EC).
§ Field characteristics and locations are given in Table 1.
¶ The letter "q" denotes quadratic regression; all others are linear.
# CEC, cation exchange capacity.
†† NS, no significant ($P \leq 0.05$) regression.

Table 7. Regression equations and statistics for estimation of claypan soil topsoil depth (TD, depth to the first B horizon) as a function of apparent soil electrical conductivity (EC_a).

Field and year	EC_a data†	Calibration equation	r^2	SE	Calibration points used
				cm	
F1 (1997)‡	$EC_{a\text{-em}}$‡	$TD = 7390\ EC_{a\text{-em}}^{-1} - 137$	0.81	10.7	18
	$EC_{a\text{-dp}}$	$TD = 918\ EC_{a\text{-dp}}^{-1} - 11.7$	0.87	8.9	18
F1 (1999)	$EC_{a\text{-em}}$	$TD = 1560\ EC_{a\text{-em}}^{-1} - 18.6$	0.27	9.0	18
	$EC_{a\text{-dp}}$	$TD = 278\ EC_{a\text{-dp}}^{-1} + 13.8$	0.62	6.5	18
GV (1997)	$EC_{a\text{-dp}}$	$TD = 1670\ EC_{a\text{-dp}}^{-1} - 19.2$	0.66	15.3	13
GV (1999)	$EC_{a\text{-em}}$	$TD = 5220\ EC_{a\text{-em}}^{-1} - 118$	0.86	10.6	13
	$EC_{a\text{-dp}}$	$TD = 646\ EC_{a\text{-dp}}^{-1} - 2.4$	0.69	16.1	13

† $EC_{a\text{-sh}}$, shallow EC_a measured by Veris 3100; $EC_{a\text{-dp}}$, deep EC_a measured by Veris 3100; $EC_{a\text{-em}}$, vertical-mode EC_a measured by Geonics EM38.
‡ Field characteristics and locations are given in Table 1.

this study, we compared two commercial EC_a sensing systems on diverse soil landscapes in Missouri and Illinois. We found both similarities and differences between the results obtained with the Geonics EM38 ($EC_{a\text{-em}}$) and the Veris 3100 ($EC_{a\text{-sh}}$ and $EC_{a\text{-dp}}$).

Within a single field and measurement date, $EC_{a\text{-em}}$ and $EC_{a\text{-dp}}$ were most highly correlated ($r = 0.74$–0.88). Lowest correlations were between $EC_{a\text{-em}}$ and $EC_{a\text{-sh}}$. Differences were attributed to differences between the depth-weighted response functions for the three data types, coupled with differences in the degree of soil profile layering between sites. The claypan soils of the Missouri fields exhibited more variation with depth in clay content and CEC, two primary drivers of EC_a. Because of this, differences between EC_a data types were more pronounced on the Missouri fields.

Correlations of EC_a with clay content and CEC were generally highest and most persistent across fields and EC_a data types. Significant correlations with silt content and, on the Missouri fields, with organic C were also common. Significant correlations with sand content, paste EC, or soil moisture content were observed only about 10% of the time.

Top-layer clay, silt, and CEC could be estimated reasonably well as a function of a single EC_a variable, usually $EC_{a\text{-sh}}$. Profile-average clay and silt were estimated less accurately and often required combination of multiple EC_a variables for best results. Organic C and top-layer soil moisture estimates were of variable accuracy while paste EC and profile-average soil moisture and CEC were not accurately estimated with regressions including single or multiple EC_a variables.

This study showed that, while qualitatively similar, EC_a data obtained with different commercial sensors were quantitatively different. Differences between the two data sources designed to give a deep-profile measurement ($EC_{a\text{-dp}}$ and $EC_{a\text{-em}}$) were more pronounced in more layered soils. Both of these measurements were related to profile CEC and clay content while the $EC_{a\text{-sh}}$ measurement was strongly related to CEC and clay content in the upper soil horizon(s). With these differences, the selection of an EC_a sensing system for a particular application should be based on both practical implementation issues and the intended use of the data.

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