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Relating apparent electrical conductivity to soil properties across the north-central USA

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Abstract

Apparent electrical conductivity (EC_a) of the soil profile can be used as an indirect indicator of a number of soil physical and chemical properties. Commercially available EC_a sensors can efficiently and inexpensively develop the spatially dense datasets desirable for describing within-field spatial soil variability in precision agriculture. The objective of this research was to relate EC_a data to measured soil properties across a wide range of soil types, management practices, and climatic conditions. Data were collected with a non-contact, electromagnetic induction-based EC_a sensor (Geonics EM38) and a coulter-based sensor (Veris 3100) on 12 fields in 6 states of the north-central United States. At 12–20 sampling sites in each field, 120-cm deep soil cores were obtained and used for soil property determination. Within individual fields, EM38 data collected in the vertical dipole orientation (0–150 cm

Abbreviations: CEC, cation exchange capacity; DGPS, differential global positioning system; EC, electrical conductivity; EC_a, apparent soil electrical conductivity; $EC_{a\text{-sh}}$, 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 (0–150 cm) EC_a measured by Geonics EM38; EM, electromagnetic induction; GPS, global positioning system; MLRA, major land resource area; PSD, profile standard deviation

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depth) and Veris 3100 deep (0–100 cm depth) data were most highly correlated. Differences between EC_a sensors were more pronounced on more layered soils, such as the claypan soils of the Missouri fields, due to differences in depth-weighted sensor response curves. Correlations of EC_a with clay content and cation exchange capacity (CEC) were generally highest and most persistent across all fields and EC_a data types. Other soil properties (soil moisture, silt, sand, organic C, and paste EC) were strongly related to EC_a in some study fields but not in others. Regressions estimating clay and CEC as a function of EC_a across all study fields were reasonably accurate ($r^2 \geq 0.55$). Thus, it may be feasible to develop relationships between EC_a and clay and CEC that are applicable across a wide range of soil and climatic conditions.

Keywords: Soil electrical conductivity; Precision agriculture; Sensors; EM38; Veris 3100

1. Introduction

Efficient and accurate methods of measuring within-field variations in soil properties are important for precision agriculture. Sensors that can collect dense datasets while traversing a field provide several advantages over traditional measurement methods that involve soil sample collection and analysis. These advantages may include lower cost, increased efficiency, and more timely results. In addition, the ability to obtain data at many more points with a sensor, as compared to sampling methods, means that overall spatial estimation accuracy can increase even if the accuracy of individual measurements is lower (Sudduth et al., 1997).

Apparent electrical conductivity (EC_a) of the soil profile is a 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, and soil moisture content are some of the factors that affect EC_a (McNeill, 1992; Rhoades et al., 1999). Most of the variation in EC_a can be related to salt concentration for saline soils (Williams and Baker, 1982). In non-saline soils, conductivity variations are primarily a function of soil texture, moisture content, and CEC (Rhoades et al., 1976). A theoretical basis for the relationship between EC_a and soil properties was developed by Rhoades et al. (1989). In this model, EC_a was a function of soil water content, the electrical conductivity of the soil water, soil bulk density, and the electrical conductivity of the soil particles. Recently, techniques have been developed to use this model for predicting the expected correlation structure between EC_a data and multiple soil properties of interest (Lesch and Corwin, 2003).

Two types of portable, within-field EC_a sensors are commercially available for agriculture, an electrode-based sensor requiring soil contact and a non-contact electromagnetic induction (EM) sensor. In an early report of the electrode-based approach, Halvorson and Rhoades (1976) measured EC_a with a four-electrode sensor and used these measurements to create maps of soil salinity variations in a field. Later, a version of the electrode-based sensor was tractor-mounted for mobile, georeferenced measurements of EC_a (Rhoades, 1993). A commercial device implementing the electrode-based approach is the Veris 3100[1] (Veris

[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 US Department of Agriculture or its cooperators.

Technologies, Salina, KS), which uses six rolling coulters for electrodes and provides two simultaneous EC_a measurements (Lund et al., 1999).

The EM-based EC_a sensor most often used in agriculture is the EM38 (Geonics Limited, Mississauga, Ont., Canada), which was initially developed for root-zone salinity assessment (Rhoades and Corwin, 1981). Details of the EM sensing approach are given by McNeill (1992). The EM38 is a lightweight bar 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 transport mechanism and data collection system (e.g., Cannon et al., 1994; Sudduth et al., 2001). As reported by Sudduth et al. (2003), each type of commercial EC_a sensor has its own operational advantages and disadvantages.

Soil EC_a can be used to indirectly estimate soil properties if the contributions of the other soil properties affecting the EC_a measurement are known or can be estimated. In some cases, the within-field variations in EC_a due to one soil property predominate and EC_a can be calibrated directly to that dominant factor. Examples of this direct calibration approach include estimating soil salinity in California (e.g., Lesch et al., 1995a, 1995b) and topsoil depth above a subsoil claypan horizon in Missouri (Doolittle et al., 1994; Kitchen et al., 1999; Sudduth et al., 2001).

Researchers have related EC_a to a number of different soil properties either within individual fields or across closely related soil landscapes. Examples include soil moisture (Kachanoski et al., 1988; Sheets and Hendrickx, 1995), clay content (Williams and Hoey, 1987), and CEC and exchangable Ca and Mg (McBride et al., 1990). Mapping of areas of differing soil texture (Kitchen et al., 1996; Doolittle et al., 2002) and soil type (Jaynes et al., 1993; Anderson-Cook et al., 2002) have also been reported. Johnson et al. (2001) evaluated EC_a for delineating a number of soil physical, chemical, and biological properties related to yield and ecological potential and concluded that EC_a was useful for delimiting distinct zones of soil condition. Although many soil factors affecting EC_a are relatively fixed over time (e.g., clay content), others may exhibit strong seasonal dynamics. For example, Eigenberg et al. (2002) related a time sequence of EC_a maps to temporal changes in available soil nitrogen and hypothesized that it might be possible to use EC_a measurements as an indicator of soluble nitrogen gains and losses in the soil over time.

Since EC_a integrates texture and moisture availability, two characteristics that both vary over the landscape and also affect productivity, EC_a has been related to grain yield variations. In a topographically diverse area of Iowa with highly contrasting soil drainage classes, Jaynes et al. (1993) reported strong negative correlations between EC_a and corn and soybean grain yield in a wet year, but no significant correlation in a year of more normal precipitation. In a study conducted on claypan soils in Missouri, Sudduth et al. (1995) found that grain yield was negatively related to EC_a in a dry year, with little effect found in a year with more optimum precipitation patterns. As these studies show, the relationship between EC_a and crop yields may vary both spatially due to soil differences and temporally due to climatic differences.

Commercial operators are using EC_a sensing systems to provide soil variability information to producers. Often, the tendency is to relate EC_a maps directly to crop yield maps, with the same variable results documented above. A more thorough, and more generally applicable, procedure would be to first relate sensor data to soil profile properties and then to relate soil variability and climatic conditions to yields. This research was undertaken to provide information needed for the first step in this procedure by documenting the relationship of EC_a to soil properties on 12 research fields in 6 north-central US states. Objectives were to (i) interpret differences in EC_a data obtained with two commercial sensors, the non-contact Geonics EM38 and the coulter-based Veris 3100, (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.

2. Materials and methods

2.1. Study fields

Data were collected on 12 soybean-corn fields, 2 each in Missouri (MO), Illinois (IL), Michigan (MI), Wisconsin (WI), South Dakota (SD), and Iowa (IA). Table 1 gives locations and characteristic information for the twelve fields, which were part of a regional precision agriculture research project. These fields were selected in part due to the degree of within-field soil and production variability present, and to represent the range of climate, soil, and landscape characteristics typical of the north-central US. This natural diversity is evidenced by the fact that the 12 fields are included in 7 different "major land resource areas" (MLRAs, Table 1), as defined by the U.S. Department of Agriculture (1981). For convenience, the fields will be referred to herein by the states in which they were located, rather than the MLRAs. However, it should be noted that any transferability of the results of this study to other sites would be on the basis of the natural boundaries defined by the MLRAs, irrespective of man-made political boundaries.

Soils of the study fields exhibited differences in terms of texture, parent material, and mineralogy. For example, prevailing surface soil texture varied across the research sites as follows: loam (Michigan), silt loam (Wisconsin), loam to clay loam (Iowa), silt loam to silty clay loam (Illinois; Missouri; South Dakota). Subsoil texture was even more variable, ranging from loamy sand at the Michigan fields to clay at the Missouri fields. Complete taxonomic descriptions of the predominant soils in the study fields are given in Table 2.

2.2. EC_a sensors and response curves

The Geonics EM38 can be operated in two orientations, vertical dipole and horizontal dipole, with effective measurement depths of approximately 1.5 m and 0.75 m, respectively (McNeill, 1992). In this research, the EM38 was operated only in the vertical dipole mode. We chose not to use the EM38 horizontal dipole mode because this would have required a second data collection operation. Additionally, since the effective measurement depth of the EM38 horizontal reading is between those of the two Veris 3100 readings, we expected that little additional information would be obtained.

The EC_a measurement from the EM38 vertical dipole mode (designated as $EC_{a\text{-em}}$ in this study) is averaged over a lateral area approximately equal to the measurement depth (McNeill, 1992). The theoretical instrument response to soil conductivity varies as a non-

Table 1
Study field descriptions

State	Field	Size (ha)	Location		Major Land Resource Area (MLRA)	Predominant Soils	Average annual precip. (mm)	Average May–September temperature (°C)
			County	Coordinates				
MO	F1	36	Boone	39°13′48″N, 92°07′01″W	113 Central claypan areas	Mexico, Adco, Leonard	1026	21.6
	GV	14	Boone	39°14′05″N, 92°08′48″W	113 Central claypan areas	Mexico, Adco, Leonard	1026	21.6
IL	WS	16	McLean	40°18′01″N, 88°32′38″W	110 Northern Illinois and Indiana heavy till plain	Varna, Drummer, Chenoa	960	20.8
	WN	16	McLean	40°18′18″N, 88°32′38″W	110 Northern Illinois and Indiana heavy till plain	Varna, Swygert, Drummer	960	20.8
MI	CW	20	Kalamazoo	42°22′25″N, 85°35′55″W	98 Southern Michigan and Northern Indiana drift plain	Kalamazoo	940	20.0
	CE	28	Kalamazoo	42°22′25″N, 85°35′42″W	98 Southern Michigan and Northern Indiana drift plain	Kalamazoo	940	20.0
WI	Z2	16	Columbia	43°20′29″N, 89°20′16″W	95B Southern Wisconsin and Northern Illinois drift plain	Plano, Ripon, Channahon	790	18.4
	Z1	16	Columbia	43°21′16″N, 89°18′55″W	95B Southern Wisconsin and Northern Illinois drift plain	St. Charles, Knowles	790	18.4
SD	BR	65	Brookings	44°13′41″N, 96°39′04″W	102A Rolling till prairie	Kranzburg, Vienna, Brookings	576	17.6
	MY	65	Moody	44°10′15″N, 96°37′25″W	102B Loess uplands and till plains	Kranzburg, Waubay, Cubden	582	18.2
IA	HH	20	Boone	41°56′19″N, 94°05′16″W	103 Central Iowa and Minnesota till prairies	Canisteo, Okoboji, Harps	805	19.8
	MG	20	Boone	41°55′55″N, 94°04′34″W	103 Central Iowa and Minnesota till prairies	Clarion, Nicollet, Canisteo	805	19.8

Table 2
Taxonomic descriptions of study field soils

Soil	State	Taxonomic description
Adco	MO	Fine, smectitic, mesic Vertic Albaqualfs
Brookings	SD	Fine-silty, mixed, superactive, frigid Aquic Hapludolls
Canisteo	IA	Fine-loamy, mixed, superactive, calcareous, mesic Typic Endoaquolls
Channahon	WI	Loamy, mixed, superactive, mesic Lithic Argiudolls
Chenoa	IL	Fine, illitic, mesic Aquic Argiudolls
Clarion	IA	Fine-loamy, mixed, superactive, mesic Typic Hapludolls
Cubden	SD	Fine-silty, frigid Aeric Calciaquolls
Drummer	IL	Fine-silty, mixed, superactive, mesic Typic Endoaquolls
Harps	IA	Fine-loamy, mixed, superactive, mesic Typic Calciaquolls
Kalamazoo	MI	Fine-loamy, mixed, semiactive, mesic Typic Hapludalfs
Knowles	WI	Fine-silty, mixed, mesic Typic Hapludalfs
Kranzburg	SD	Fine-silty, mixed, superactive, frigid Calcic Hapludolls
Leonard	MO	Fine, smectitic, mesic Vertic Epiaqualfs
Mexico	MO	Fine, smectitic, mesic Aeric Vertic Epiaqualfs
Nicollet	IA	Fine-loamy, mixed, superactive, mesic Aquic Hapludolls
Okoboji	IA	Fine, smectitic, mesic Cumulic Vertic Endoaquolls
Plano	WI	Fine-silty, mixed, superactive, mesic Typic Argiudolls
Ripon	WI	Fine-silty, mixed, superactive, mesic Typic Argiudolls
St. Charles	WI	Fine-silty, mixed, superactive, mesic Typic Hapludalfs
Swygert	IL	Fine, mixed, active, mesic Aquic Argiudolls
Varna	IL	Fine, illitic, mesic Oxyaquic Argiudolls
Vienna	SD	Fine-loamy, mixed, superactive, frigid Calcic Hapludolls
Waubay	SD	Fine-silty, mixed, superactive, frigid Pachic Hapludolls

linear function of depth, as given by Eq. (1) (McNeill, 1980).

$$R_{em} = 4z(4z^2 + 1)^{3/2} \tag{1}$$

where R_{em} is the relative response of EM38 and z the distance below sensor (m).

Sensitivity in the vertical mode is highest at about 0.4 m below the instrument (Fig. 1). The EC_a measurement is an integrated response to changes in soil conductivity with depth, as weighted by this instrument response function (McNeill, 1992). The EM38 was combined

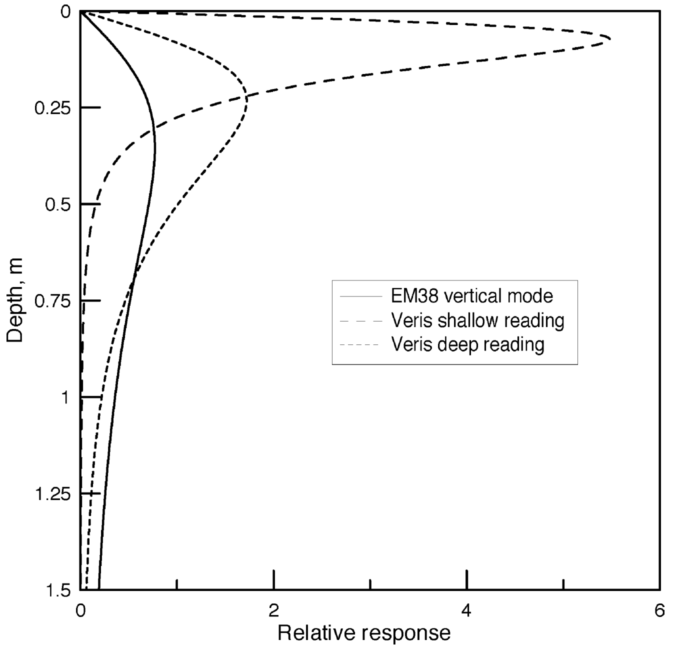

Fig. 1. Relative response of EC_a sensors as a function of depth. Responses are normalized to yield a unit area under each curve.

with a data acquisition computer and differential GPS (DGPS) system for mobile data collection, as described by Sudduth et al. (2001).

The Veris 3100 (Lund et al., 1999) uses rolling coulter electrodes to directly sense soil electrical conductivity. Measurement electrodes are configured to provide both shallow and deep readings of EC_a (designated as $EC_{a\text{-sh}}$ and $EC_{a\text{-dp}}$, respectively). As with the EM38, the Veris 3100 response to soil conductivity varies as a nonlinear function of depth. The electrodes of the Veris 3100 are configured in a Wenner array, an arrangement commonly used for geophysical surveys (Milsom, 1996). The theoretical response of the Wenner array is given by Eq. (2) (Roy and Apparao, 1971).

$$R_w = \left(\frac{8Lz}{3}\right)\left(\left(\frac{L^2}{9}+4z^2\right)^{-3/2} - \left(\frac{4L^2}{9}+4z^2\right)^{-3/2}\right) \tag{2}$$

where R_w is the relative response of Wenner array, L the distance between outermost electrodes (m) and z is the distance below sensor (m).

For the Veris 3100 shallow reading, the value of L in Eq. (2) is 0.7 m; for the deep reading it is 2.2 m. The graph of these responses (Fig. 1) shows them to be similar in shape to the response of the EM38, although the two Veris responses reach a maximum nearer the soil surface and then decrease more rapidly with depth.

Integrating the response curves of Fig. 1 with respect to depth clearly shows the different soil volumes examined by the sensors (Fig. 2). With the Veris shallow reading ($EC_{a\text{-sh}}$),

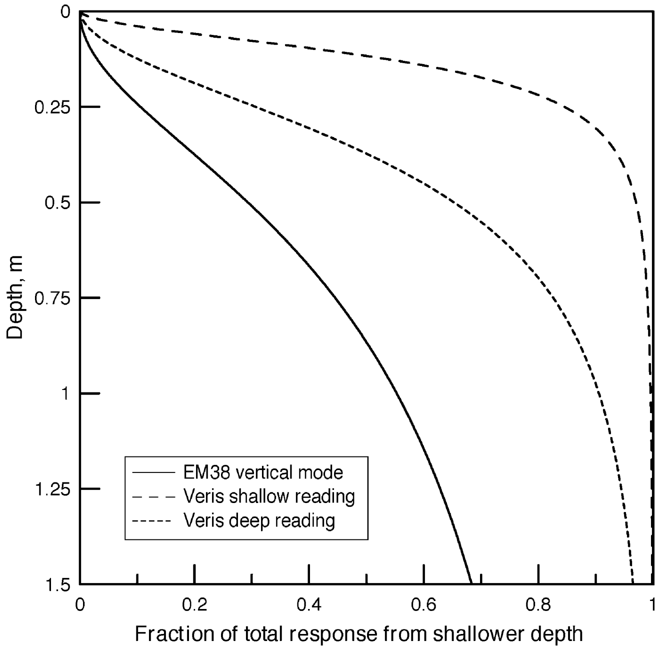

Fig. 2. Cumulative response of EC_a sensors as a function of depth.

90% of the response is obtained from the soil above the 30-cm depth. With the Veris deep reading ($EC_{a\text{-}dp}$), 90% of the response is obtained from the soil above the 100-cm depth. With the EM38 vertical reading ($EC_{a\text{-}em}$), 70% of the response is obtained above about 1.5 m. By integrating Eq. (1), it can be shown that 90% of the EM38 vertical response is obtained above about 5 m. The response curves of Figs. 1 and 2 are based on equations that assume a homogeneous soil volume. Actual weighting functions will vary somewhat due to EC_a differences among soil layers, with a highly conductive surface layer reducing the response depth (Barker, 1989).

2.3. Data collection

The EC_a data for each field were collected with both sensors on the same date, either after harvest or prior to planting (Table 3). The Veris 3100 and Geonics EM38 were operated in tandem, taking measurements on transects spaced approximately 10 m apart. Soil EC_a, in milliSiemens per meter (mS m^{-1}), was recorded on a 1-s interval, corresponding to a 4–6 m data spacing. Between 4400 and 13,000 individual EC_a measurements were obtained for each field. Data obtained by differential GPS was associated with each sensor reading to provide positional information with an accuracy of 1.5 m or better. Raw EC_a data were offset by 1 s to compensate for the position of the GPS antenna ahead of the sensor and for time lags in the data acquisition system (Sudduth et al., 2001).

Table 3
Summary of whole-field EC_a datasets

State	Field	Sampling date	$EC_{a\text{-em}}$		$EC_{a\text{-sh}}$		$EC_{a\text{-dp}}$		0–60 cm soil temperature (°C)
			Mean (mS m^{-1})	CV	Mean (mS m^{-1})	CV	Mean (mS m^{-1})	CV	
MO	F1	16 November 1999	30.7	0.12	9.7	0.32	19.6	0.43	15.3
	GV	17 November 1999	34.8	0.18	15.2	0.49	23.7	0.49	13.8
IL	WS	14 October 1999	32.8	0.24	27.9	0.25	41.1	0.29	15.5
	WN	14 October 1999	30.7	0.28	27.7	0.29	39.3	0.31	16.2
MI	CW	1 May 2001	7.6	0.28	5.2	0.58	6.1	0.49	16.5
	CE	1 May 2001	7.1	0.21	6.8	0.29	8.6	0.26	16.5
WI	Z2	2 May 2001	15.5	0.17	15.1	0.34	20.8	0.27	17.9
	Z1	2 May 2001	15.3	0.11	12.3	0.41	21.0	0.19	17.9
SD	BR	27 October 2000	26.7	0.12	12.1	0.45	18.9	0.29	6.0
	MY	20 October 2000	28.3	0.26	15.1	0.62	27.4	0.43	11.2
IA	HH	11 November 1999	36.7	0.31	35.2	0.46	46.3	0.46	14.0
	MG	10 November 1999	31.3	0.33	23.3	0.57	36.3	0.55	14.8

Using our previously reported approach (Sudduth et al., 2001), a calibration transect was established to monitor EC_a sensor drift during each field 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 prone to instrument drift than was the EM38; in fact none of the Veris data collected in this study required adjustment. In practice, drift compensation would probably not be required for Veris EC_a surveys. However, drift evaluation and/or compensation should be a routine operation to maintain the quality of EM38 surveys.

To document soil temperature at the time of data collection, multiple readings were obtained with a handheld thermocouple probe. Data were collected on a 15-cm depth increment and averaged to a 60-cm depth. Soil temperature data were obtained and averaged by field, except for the MI and WI fields, where a single set of temperature data was collected representing both fields (Table 3).

After EC_a data were mapped, between 12 and 20 calibration sampling sites were selected within each field. These sites were chosen by a soil scientist familiar with the soils in the particular field to provide EC_a values distributed similarly to those in the EC_a map, with the additional goal of including samples from all the landscape positions and soil map units present in the field. One 4.0-cm diameter core 120 cm in length 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 (ammonium acetate method); organic C; and saturated paste EC.

2.4. Data analysis

To allow comparison between EC_a sensors, a combined dataset was created for each field. Each Veris data point was paired 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 comparison dataset. Pearson correlation coefficients (r) were calculated between the data obtained with the different EC_a sensors.

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. These horizon values were also used to calculate the profile standard deviation (PSD) at each calibration point, providing a measure of the variability in each soil property with depth. Because EC_a sensor response is not constant with depth, three additional sets of data were created by weighting each soil property profile by the sensor response curve (Fig. 1).

Analysis of the relationship between EC_a and soil properties was carried out for each data source ($EC_{a\text{-}em}$, $EC_{a\text{-}sh}$, and $EC_{a\text{-}dp}$) and soil property. In previous work with a subset of these data (Sudduth et al., 2003), we found a lack of significant spatial autocorrelation, likely caused by the small number (12–20) and spatial dispersion of the calibration points in each field; therefore, we conducted a non-spatial analysis between EC_a and soil properties. Pearson correlation coefficients were calculated between EC_a and soil properties (soil 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 statistically significant ($P \leq 0.05$) parameters were retained in the final regression equations.

3. Results and discussion

3.1. Comparison of EC_a data

Soil EC_a data obtained with each sensor exhibited similar qualitative trends at the field scale. As expected, field mean EC_a (Table 3) was highest for the fields with finer-textured soils (MO, IL, IA, SD) and lower for the fields with coarser-textured soils (MI and WI). The most variation (in terms of CV) in EC_a values was found in the Iowa fields, which had the widest range in soil texture, from loam to clay loam. In general, EC_a measured by EM38 was either less variable (MO, MI, WI, SD, IA) or exhibited a similar level of variation (IL) as Veris 3100 data (Table 3).

Correlation coefficients between the various EC_a measurements for each field are shown in Table 4. With the exception of two fields, the highest correlations were found between $EC_{a\text{-}em}$ data and $EC_{a\text{-}dp}$ data. Correlations between $EC_{a\text{-}em}$ data and $EC_{a\text{-}sh}$ data were consistently the lowest, while correlations of $EC_{a\text{-}dp}$ to $EC_{a\text{-}sh}$ were intermediate. The reason behind this ranking can be discerned from the differences between the response curves for the various sensors (Figs. 1 and 2), where the $EC_{a\text{-}dp}$ response curve lies between the $EC_{a\text{-}sh}$ curve and the $EC_{a\text{-}em}$ curve. Because the two fields in each state were generally similar in terms of parent material, mineralogy, and management, combining these data yielded cor-

Table 4
Correlation coefficients (r) between different EC_a measurements

State	Field	By-state correlations[a]			By-field correlations[a]		
		$EC_{a\text{-em}}$ vs. $EC_{a\text{-dp}}$	$EC_{a\text{-em}}$ vs. $EC_{a\text{-sh}}$	$EC_{a\text{-dp}}$ vs. $EC_{a\text{-sh}}$	$EC_{a\text{-em}}$ vs. $EC_{a\text{-dp}}$	$EC_{a\text{-em}}$ vs. $EC_{a\text{-sh}}$	$EC_{a\text{-dp}}$ vs. $EC_{a\text{-sh}}$
MO	F1	0.78	0.69	0.71	0.74	0.60	0.74
	GV				0.84	0.66	0.75
IL	WS	0.86	0.77	0.80	0.84	0.78	0.80
	WN				0.88	0.79	0.82
MI	CW	0.67	0.54	0.76	0.85	0.64	0.78
	CE				0.75	0.59	0.65
WI	Z2	0.72	0.27	0.47	0.71	0.24	0.45
	Z1				0.78	0.42	0.62
SD	BR	0.84	0.79	0.85	0.75	0.69	0.79
	MY				0.89	0.81	0.89
IA	HH	0.95	0.88	0.91	0.95	0.89	0.92
	MG				0.95	0.89	0.91
IL, MI, WI, IA		0.96	0.92	0.94			
All states		0.79	0.70	0.92			

[a] All correlations are highly significant ($P < 0.001$).

relations that were usually similar, and higher in some cases, than correlations calculated within individual fields (Table 4).

Scatter plots comparing EC_a data across all states (Fig. 3a) showed that the two Veris readings were highly correlated ($r = 0.92$; Table 4). However, the relationship of Veris EC_a data to $EC_{a\text{-em}}$ (Fig. 3b and c) was not as strong ($r < 0.8$; Table 4). Examination of Fig. 3 shows that a common, strongly linear relationship was apparent between $EC_{a\text{-em}}$ and $EC_{a\text{-dp}}$ across all states except Missouri and South Dakota. In fact, when data from those two states were removed from the analysis, correlations between all pairs of EC_a data sources were ≥ 0.92 (Table 4).

This phenomenon may be explained by differences in the degree of soil layering among the fields. The claypan soils of the Missouri fields are highly layered in terms of clay and CEC, two soil properties with a major effect on EC_a (Sudduth et al., 2003). In fact, claypan soils are defined as those soils where clay content doubles within a 3-cm depth increment. This abrupt layering, combined with differences in response functions for the different sensors (Fig. 1), explains the lower correlations seen among the data collected with the different sensors on the Missouri fields (Table 4) and the departure of those data from the general linear trends seen in Fig. 3. Abrupt layering of EC_a-affecting soil properties was also hypothesized as a reason for the similar, but weaker, nonlinear behavior of data from South Dakota (Fig. 3).

Over a wide range of soil conditions found in the north-central US, the data obtained from the various EC_a sensors was very similar (i.e., high correlation coefficients, Table 4), perhaps indicating some degree of “interchangeability” between the sensors. However,

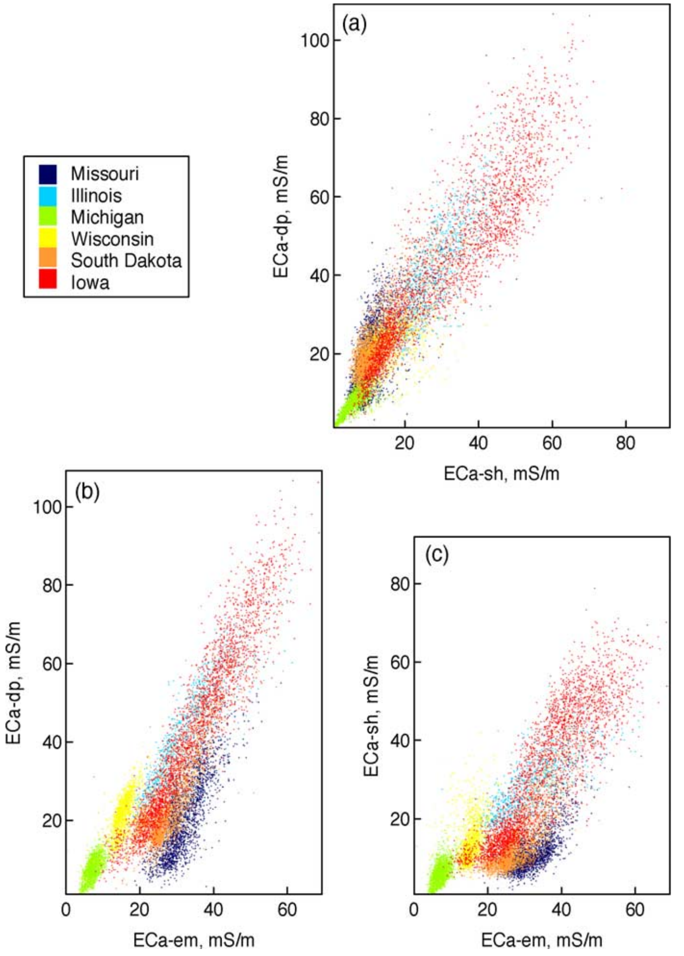

Fig. 3. Relationships between EC_a data types over all fields: (a) $EC_{a\text{-sh}}$ vs. $EC_{a\text{-dp}}$, (b) $EC_{a\text{-em}}$ vs. $EC_{a\text{-dp}}$, and (c) $EC_{a\text{-em}}$ vs. $EC_{a\text{-sh}}$.

lower correlations were often obtained on a field-by-field or state-by-state basis, particularly when relating shallow ($EC_{a\text{-sh}}$) to deeper ($EC_{a\text{-dp}}$ and $EC_{a\text{-em}}$) sensor data. At least for some of the soils datasets investigated in this study, it appears that integration of EC_a data representing at least two different sensing depths may provide additional information related to soil variability.

3.2. *Relationship of EC_a to measured soil properties*

A statistical summary of profile-average soil property data for the calibration points in each field is shown in Table 5. Many of the soil properties were highly variable within and among fields. Considerable variation was also apparent as a function of depth, as

Table 5
Means and mean profile standard deviations (PSDs, in parentheses) for soil properties obtained from by-horizon analysis of calibration point cores

State	Field	Number of points	Soil moisture ($g\,kg^{-1}$)	Clay ($g\,kg^{-1}$)	Silt ($g\,kg^{-1}$)	Sand ($g\,kg^{-1}$)	Organic C ($g\,kg^{-1}$)	CEC ($cmol\,kg^{-1}$)	Paste EC ($mS\,m^{-1}$)
MO	F1	19	149 (37)	354 (135)	594 (135)	32 (26)	6.4 (3.5)	24.2 (8.1)	24 (7.0)
	GV	15	156 (29)	321 (76)	620 (67)	60 (22)	6.5 (3.9)	22.5 (5.0)	22 (7.1)
IL	WS	17	–[a]	298 (41)	585 (55)	113 (54)	10.1 (7.1)	21.5 (4.7)	11 (2.0)
	WN	12	–	298 (40)	605 (61)	96 (68)	8.4 (6.8)	20.2 (4.6)	17 (5.0)
MI	CW	16	167 (33)	130 (39)	318 (105)	552 (126)	7.5 (5.0)	10.1 (3.2)	67 (36)
	CE	17	164 (30)	154 (55)	328 (161)	504 (187)	5.8 (4.6)	10.1 (3.3)	63 (37)
WI	Z2	15	231 (38)	217 (40)	670 (55)	114 (61)	8.2 (5.7)	17.2 (3.0)	42 (9.2)
	Z1	16	228 (15)	216 (54)	662 (97)	122 (105)	3.8 (3.1)	15.8 (3.8)	27 (5.2)
SD	BR	17	126 (38)	254 (38)	430 (82)	317 (115)	8.4 (7.8)	18.8 (6.3)	32 (8.3)
	MY	20	183 (24)	263 (41)	572 (61)	165 (71)	10.8 (7.8)	22.8 (5.6)	41 (11)
IA	HH	15	213 (36)	261 (52)	377 (51)	354 (87)	11.4 (8.4)	24.5 (6.7)	66 (36)
	MG	18	191 (32)	240 (44)	348 (34)	412 (73)	9.4 (7.3)	20.6 (5.3)	91 (42)

[a] Soil moisture data not available for Illinois fields.

measured by the PSD (Table 5). Mean PSDs for clay were significantly higher (Duncan's Multiple Range Test, $P \leq 0.05$) for the Missouri fields, compared to all others. For CEC, the highest-PSD grouping included Missouri, South Dakota, and Iowa. Thus, the Missouri, South Dakota, and Iowa fields were more layered in terms of one or both of these soil properties that are strongly related to EC_a.

3.2.1. Correlation analysis

Correlation coefficients between EC_a and profile soil properties were determined by state and for the dataset as a whole (Fig. 4). In general, highest correlations were observed for clay and CEC. The only exception was for the South Dakota data (Fig. 4e), where highest correlations were with soil moisture. Some soil properties were strongly related ($|r| \geq 0.5$) to EC_a for some states but not for others. Examples included soil moisture (SD, IA), silt (MO, IL, IA), sand (IA), organic C (IA), and saturated paste EC (SD).

When comparing the different weighting functions, correlations of EC_a with sensor-weighted clay content and sensor-weighted CEC were generally highest and most persistent across all states and EC_a data types (Fig. 4). 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. We previously reported similar results for the Illinois–Missouri subset of this data (Sudduth et al., 2003).

3.2.2. Regression analysis using individual EC_a variables

Second-order polynomial regression analysis was performed to estimate soil properties as a function of EC_a, both using each EC_a variable independently and then (see Section 3.2.3) using combinations of the three EC_a variables. Properties estimated were profile-

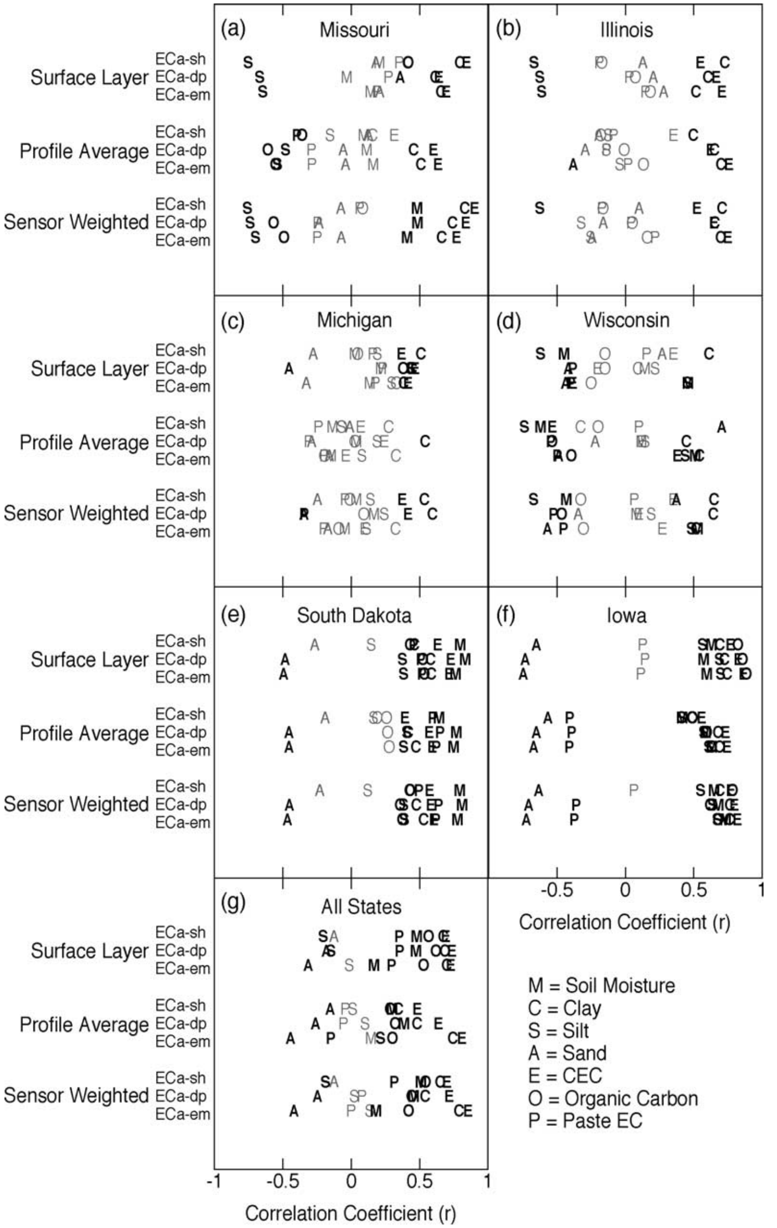

Fig. 4. Correlations between weighted (surface-layer, profile-average, and sensor) soil properties and EC_a data types for each state and over all states: (a) MO, (b) IL, (c) MI, (d) WI, (e) SD, (f) IA and (g) all states. Bold letters designate significant ($P \leq 0.05$) correlations. Soil moisture (M) not available in Illinois data set.

Table 6
Regression statistics for the estimation of surface-layer soil properties as a function of EC_a, using individual and multiple-variable datasets

Soil Property	State	Best single-EC_a model			Veris shallow + deep		Veris + EM38	
		EC_a data	r^2	S.E.[a]	r^2	S.E.	r^2	S.E.
Soil moisture	MO	$EC_{a\text{-sh}}$	0.24	29	0.48	25	0.69	19
	IL	–[b]	–	–	–	–	–	–
	MI	$EC_{a\text{-dp}}$, q[c]	0.30	30	0.30	30	0.30	30
	WI	$EC_{a\text{-sh}}$, q	0.33	19	0.45	17	0.52	16
	SD	$EC_{a\text{-dp}}$	0.70	23	0.79	20	0.79	20
	IA	$EC_{a\text{-sh}}$	0.39	32	0.39	33	0.39	33
	All	$EC_{a\text{-sh}}$	0.23	42	0.23	42	0.50	34
Clay	MO	$EC_{a\text{-sh}}$	0.63	35	0.63	35	0.74	30
	IL	$EC_{a\text{-sh}}$	0.53	26	0.54	25	0.70	21
	MI	$EC_{a\text{-dp}}$, q	0.38	32	0.46	30	0.46	30
	WI	$EC_{a\text{-sh}}$	0.37	43	0.50	39	0.54	38
	SD	$EC_{a\text{-dp}}$, q	0.52	17	0.52	17	0.60	16
	IA	$EC_{a\text{-em}}$	0.55	38	0.52	39	0.57	38
	All	$EC_{a\text{-dp}}$, q	0.55	51	0.58	50	0.66	45
Silt	MO	$EC_{a\text{-sh}}$, q	0.62	41	0.62	41	0.63	41
	IL	$EC_{a\text{-dp}}$, q	0.48	34	0.47	34	0.51	32
	MI	$EC_{a\text{-dp}}$, q	0.47	94	0.47	94	0.47	94
	WI	$EC_{a\text{-sh}}$	0.39	59	0.77	38	0.82	35
	SD	$EC_{a\text{-em}}$	0.15	57	0.25	54	0.25	54
	IA	$EC_{a\text{-em}}$	0.48	43	0.47	44	0.48	43
	All	$EC_{a\text{-em}}$, q	0.12	142	0.10	144	0.30	127
CEC	MO	$EC_{a\text{-sh}}$	0.71	2.3	0.82	1.9	0.83	1.8
	IL	$EC_{a\text{-em}}$	0.50	2.9	0.44	3.1	0.61	2.7
	MI	$EC_{a\text{-dp}}$, q	0.36	2.7	0.36	2.7	0.43	2.6
	WI	$EC_{a\text{-em}}$	0.15	3.4	N.S.[d]		0.49	2.8
	SD	$EC_{a\text{-dp}}$, q	0.61	2.6	0.61	2.6	0.80	2.0
	IA	$EC_{a\text{-em}}$, q	0.77	3.5	0.72	3.8	0.77	3.5
	All	$EC_{a\text{-dp}}$, q	0.58	5.4	0.58	5.4	0.70	4.6

[a] Standard errors (S.E.) are in units of $g\,kg^{-1}$ (soil moisture, clay, silt) and $cmol\,kg^{-1}$ (CEC).
[b] No soil moisture data available for Illinois fields.
[c] The letter "q" denotes a quadratic regression, all others are linear.
[d] N.S. denotes no significant ($P \leq 0.05$) regression.

average and surface-layer soil moisture, clay, silt, CEC, organic C, and paste EC. Estimates for sand were not developed, since sand content is merely a linear combination of clay and silt. Regressions were performed individually for data from each state and also for all data combined. Table 6 shows the regression statistics for surface-layer data, while Table 7 includes statistics for profile-average data, both for single-variable and multiple-variable analyses. Only results for the best-fit EC_a variable are shown for each soil property. The most accurate estimates were generally obtained for clay, silt, and CEC. Estimates of soil moisture were variable, while estimates of organic C and paste EC obtained by regression

Table 7
Regression statistics for the estimation of profile-average soil properties as a function of EC_a, using individual and multiple-variable datasets.

Soil Property	State	Best single-ECa model			Veris shallow + deep		Veris + EM38	
		ECa data	r^2	S.E.[a]	r^2	S.E.	r^2	S.E.
Soil moisture	MO	N.S.[d]			N.S.		N.S.	
	IL	–[b]	–	–	–	–	–	–
	MI	N.S.			N.S.		0.49	34
	WI	$EC_{a\text{-sh}}$	0.38	27	0.71	19	0.75	18
	SD	$EC_{a\text{-dp}}$, q[c]	0.68	28	0.73	26	0.68	28
	IA	$EC_{a\text{-em}}$	0.40	36	0.34	38	0.58	31
	All	$EC_{a\text{-dp}}$	0.15	45	0.15	45	0.24	42
Clay	MO	$EC_{a\text{-em}}$	0.26	49	0.60	39	0.60	38
	IL	$EC_{a\text{-em}}$	0.48	28	0.43	30	0.51	28
	MI	$EC_{a\text{-dp}}$, q	0.42	30	0.42	30	0.42	30
	WI	$EC_{a\text{-em}}$	0.29	20	0.54	16	0.54	16
	SD	$EC_{a\text{-em}}$	0.22	35	0.25	35	0.22	35
	IA	$EC_{a\text{-em}}$	0.47	49	0.52	47	0.68	39
	All	$EC_{a\text{-em}}$, q	0.61	48	0.34	63	0.72	42
Silt	MO	$EC_{a\text{-em}}$	0.29	46	0.38	44	0.44	42
	IL	N.S.			0.22	54	0.36	50
	MI	N.S.			N.S.		0.40	107
	WI	$EC_{a\text{-sh}}$	0.55	66	0.81	45	0.81	45
	SD	$EC_{a\text{-dp}}$, q	0.26	91	0.35	85	0.35	85
	IA	$EC_{a\text{-em}}$	0.37	73	0.33	77	0.50	66
	All	$EC_{a\text{-em}}$, q	0.18	143	0.12	148	0.28	136
CEC	MO	$EC_{a\text{-em}}$	0.40	3.4	0.47	3.3	0.70	2.5
	IL	$EC_{a\text{-em}}$	0.57	3.5	0.59	3.5	0.79	2.6
	MI	$EC_{a\text{-em}}$, q	0.21	3.9	N.S.		0.65	2.7
	WI	$EC_{a\text{-em}}$	0.14	2.0	0.66	1.3	0.66	1.3
	SD	$EC_{a\text{-em}}$, q	0.44	3.6	0.44	3.6	0.51	3.4
	IA	$EC_{a\text{-em}}$	0.55	4.5	0.54	4.6	0.66	4.0
	All	$EC_{a\text{-em}}$	0.66	3.8	0.49	4.7	0.70	3.6

[a] Standard errors (S.E.) are in units of $g\,kg^{-1}$ (soil moisture, clay, silt) and $cmol\,kg^{-1}$ (CEC).
[b] No soil moisture data available for Illinois fields.
[c] The letter "q" denotes a quadratic regression, all others are linear.
[d] N.S. denotes no significant ($P \leq 0.05$) regression.

on a single EC_a variable were of relatively low accuracy. Only in two cases were coefficients of determination greater than 0.42 obtained for organic C or paste EC—Missouri profile-average organic C was estimated with $r^2 = 0.48$ and Iowa surface-layer organic C was estimated with $r^2 = 0.78$. Because of this, data for organic C and paste EC were not included in Tables 6 and 7.

Surface-layer clay, silt, and CEC were usually estimated with higher or similar accuracy levels than profile-average values. Best estimates of surface-layer soil properties were obtained with each of the three datasets ($EC_{a\text{-em}}$, $EC_{a\text{-sh}}$, and $EC_{a\text{-dp}}$) several times, depending

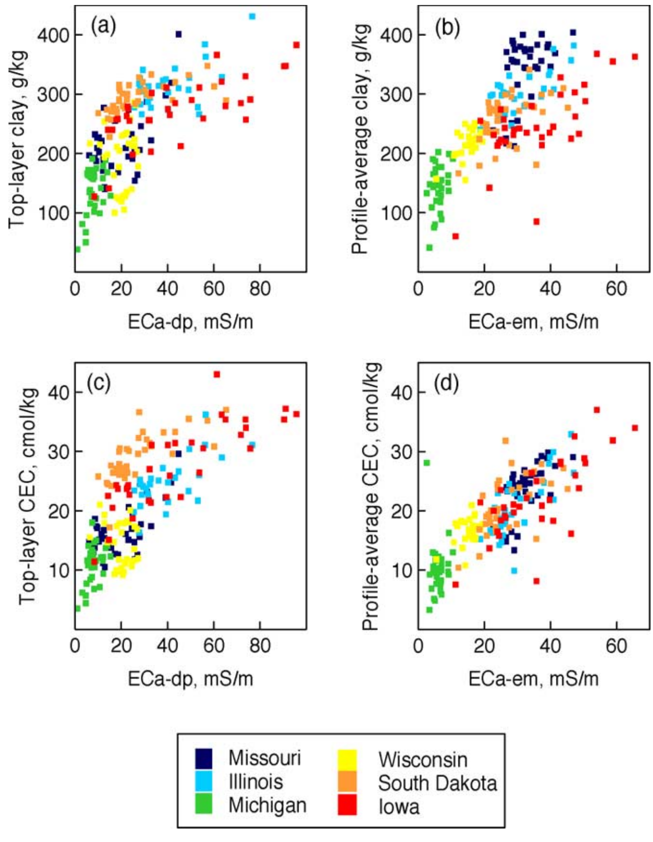

Fig. 5. Relationships between EC_a data and CEC and clay content measured at calibration points for all study fields: (a) $EC_{a\text{-}dp}$ vs. top-layer clay, (b) $EC_{a\text{-}em}$ vs. profile-average clay, (c) $EC_{a\text{-}dp}$ vs. top-layer CEC, and (d) $EC_{a\text{-}em}$ vs. profile-average CEC.

on the specific property and state (Table 6). Profile-average soil properties were usually estimated with the highest accuracy using $EC_{a\text{-}em}$ data, although $EC_{a\text{-}dp}$ and (rarely) $EC_{a\text{-}sh}$ data were most predictive for some cases (Table 7). Quadratic equations were significant for less than half of the soil parameters; for the others only the linear EC_a term was significant.

When considering data across all states, regressions for soil moisture, silt, organic C, and paste EC were of low accuracy ($r^2 < 0.4$). However, regressions for clay and CEC were of reasonable accuracy ($r^2 \geq 0.55$) across all states, both for surface-layer (Table 6) and profile-average (Table 7) datasets. Fig. 5 shows the relationship of the best-fit EC_a dataset to each of these clay and CEC datasets. In all four cases, the data from the various states merged into a single, relatively unified data distribution. The clay-EC_a relationship appeared to be somewhat different for the Iowa data than for the other states (Fig. 5a and b). However, this difference was not apparent when considering the CEC-EC_a relationship (Fig. 5c and d). The relationships of EC_a data to CEC and clay were surprisingly good, considering that data were collected on the different fields at different times of the year (Table 3) and under different soil moisture conditions (Table 4). These results indicate that it may be possible to develop general calibrations relating EC_a to CEC and clay content that are applicable across a wide range of soil and climatic conditions.

Because studies have found soil temperature to have an effect on EC_a (e.g., McKenzie et al., 1989; Slavich and Petterson, 1990; Sudduth et al., 2001), we investigated the effect of soil temperature differences among the different fields (Table 3) on the regression estimates of soil properties. Although an equation is available (Rhoades et al., 1999) for correcting solution electrical conductivity to a standard temperature, researchers (McKenzie et al., 1989; Sudduth et al., 2001) have measured temperature effects on EC_a that are considerably smaller than the approximately 2% per degree C indicated by this equation. Due to our uncertainty about the applicability of the solution equation to field EC_a measurements, we included soil temperature as a multiplicative effect on EC_a in the regression analysis rather than using it to make an explicit temperature correction. In all cases, little or no improvement in soil property estimates (increase in $r^2 < 0.04$) was seen when comparing these regressions to those that did not include soil temperature (Tables 6 and 7). Therefore, we concluded that the soil temperature differences (approximately 12 °C) seen among study fields had a relatively minor effect on the relationship of EC_a to soil properties. This conclusion is supported by earlier work on one of the Missouri study fields (Sudduth et al., 2001), where EC_a data were collected over a wide range of soil temperatures (4–28 °C). EC_a-based estimates of topsoil depth were only slightly improved when temperature was included explicitly in the regression model, compared to modeling the temperature effect by dividing the dataset into two temperature classes (4–16 °C and 16–28 °C).

3.2.3. Regression analysis using multiple EC_a variables

Another series of regression analyses included multiple EC_a data sources for estimating the same soil properties listed above. Stepwise second-order polynomial (including interactions) analyses included (i) both Veris datasets—$EC_{a\text{-sh}}$ and $EC_{a\text{-dp}}$ and (ii) all three EC_a datasets. Single-state estimates of soil properties were improved by including both Veris EC_a datasets in about 40% of the cases. When including Veris and EM38 data, improved estimates were obtained about 65% of the time, and these estimates were generally better than those obtained using only Veris data. For multi-state analyses, soil property estimates were improved when all three EC_a variables were allowed to enter the regression, but were generally not improved by including just the two types of Veris data. For both single EC_a and multiple EC_a regressions, better estimates of soil properties were most often obtained within a single state than across multiple states (Tables 6 and 7).

Integration of multiple EC_a variables can provide an increased understanding of soil variability. However, collection of multiple datasets involves practical and economic considerations. The Veris 3100 is attractive in this regard because it provides two EC_a measurements in a single pass over the field. Alternatively, EM-based sensors that simultaneously provide data from two measurement depths have recently become available. Although collecting data with two distinct sensors (i.e., Veris 3100 and EM38) can increase information content, the added effort and expense is probably justifiable only in limited circumstances.

4. Conclusions

We found both similarities and differences in EC_a data obtained with the Geonics EM38 ($EC_{a\text{-em}}$) and the Veris 3100 ($EC_{a\text{-sh}}$ and $EC_{a\text{-dp}}$). 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. Because the claypan soils of the Missouri fields exhibited the greatest by-depth variation in clay content and CEC, two primary drivers of EC_a, differences between EC_a data types were most pronounced on these fields.

Correlations of EC_a with clay content and CEC were generally highest and most persistent across fields and EC_a data types. Correlations with other soil properties (soil moisture, silt, sand, organic C and paste EC) were lower and more variable for the fields used in the study. Within a single state, profile-average clay and CEC could be estimated reasonably well as a function of a single EC_a variable, usually $EC_{a\text{-em}}$. Surface-layer clay and CEC were also estimated reasonably well with a single variable, generally either $EC_{a\text{-sh}}$ or $EC_{a\text{-dp}}$. Soil property estimates were often improved by using a combination of multiple EC_a variables.

Regressions estimating clay and CEC as a function of EC_a across all study fields were reasonably accurate ($r^2 \geq 0.55$). These field sites from six states included soils of differing parent material (e.g., glacial till, loess), variable soil weathering (e.g., with and without carbonates, varying degree of clay formation), dissimilar levels of organic matter accumulation, and variations in management (e.g., tilled versus no-till, number of years in crop production). Given these dissimilarities, it is quite surprising and significant that such strong relationships between EC_a and clay and CEC were obtained for the combined multi-state dataset.

Acknowledgements

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