Field-Scale Electrical Conductivity Mapping for Delineating Soil Condition

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ABSTRACT

Traditional sampling methods are inadequate for assessing the interrelated physical, chemical, and biological soil properties responsible for variations in agronomic yield and ecological potentials across a landscape. Recent advances in computers, global positioning systems, and large-scale sensors offer new opportunities for mapping heterogeneous patterns in soil condition. We evaluated field-scale apparent electrical conductivity (EC_a) mapping for delineating soil properties correlated with productivity and ecological properties. A contiguous section of farmland (250 ha), managed as eight fields in a no-till winter wheat (*Triticum aestivum* L.)–corn (*Zea mays* L.)–millet (*Panicum miliaceum* L.)–fallow rotation, was EC_a mapped (≈0- to 30-cm depth). A geo-referenced soil-sampling scheme separated each field into four EC_a classes that were sampled (0- to 7.5- and 7.5- to 30-cm depths) in triplicate. Soil physical parameters (bulk density, moisture content, and percentage clay), chemical parameters (total and particulate organic matter [POM], total C and N, extractable P, laboratory-measured electrical conductivity [$EC_{1:1}$], and pH), biological parameters (microbial biomass C [MBC] and N [MBN], and potentially mineralizable N), and surface residue mass were significantly different among EC_a classes ($P \leq 0.06$) at one or both depths (0–7.5 and 0–30 cm). Bulk density, percentage clay, $EC_{1:1}$, and pH were positively correlated with EC_a; all other soil parameters and surface residue mass were negatively correlated. Field-scale EC_a classification delimits distinct zones of soil condition, providing an effective basis for soil sampling. Potential uses include assessing temporal impacts of management on soil condition and managing spatial variation in soil-condition and yield-potential through precision agriculture and site-specific management.

Tʜᴇ ʜᴇᴛᴇʀᴏɢᴇɴᴇᴏᴜs ɴᴀᴛᴜʀᴇ of soil across a landscape has long been recognized; however, the lack of sensitive tools to detect subtle shifts among soil properties has limited spatial delineation of this variability. Recent technological advances in computer hardware and software, global positioning systems, and sensors for field-scale measurements offer new opportunities to map the complex patterns in soil condition that underlie and define agronomic yield potential. Field-scale sensor maps may provide a basis for soil-sampling strategies that accurately reflect spatial variation. Such sampling strategies may be useful in temporal analyses to monitor ecological trends and for managing inherent soil variability through precision agriculture. Site-specific management has the potential to maximize agricultural production and economic return while conserving soil and water resources and enhancing soil quality (Wallace, 1994). An essential first step to the successful implementation of site-specific management is the evaluation of new technologies at the field-scale (Vanden Heuvel, 1996).

Complex inter-relationships exist between physical, chemical, and biological soil properties and their response to land management; these factors are responsible for crop productivity and ecological potential (Bauer and Black, 1994; Gardner and Clancy, 1996; Olson et al., 1996). Soil condition is the combined characteristics of a given soil that define its level of function as a medium for crop production and a contributor to air and water quality. In this paper, we define ecological potential as the complementary interactions between the soil biological community and the soil environment that optimize soil condition and are determined by land management.

Different approaches have been used to detect and map soil condition patterns related to spatial variation in productivity. Lark (1997) used intensive grid sampling (20-m intervals), based upon soil texture and depth, to identify seven map units across a 6-ha field. He found significant differences among map units for several yield-related soil properties including percentage moisture and organic matter, mineral N, and pH at 0- to 20-cm depths ($P \leq 0.003$). However, this type of intensive grid sampling is both labor intensive and costly, making it impractical at the farm-scale. Francis and Schepers (1997) used selective soil sampling based on soil color, texture, depth, slope, and erosion characteristics to produce fertilizer recommendation zones. These zones effectively partitioned concentrations of the nonmobile nutrients P, K, and Zn. Studies, such as these, underscore a need for cost-effective technology to assess spatial variation in soil condition at the field-scale.

Laboratory measurement of $EC_{1:1}$ is a useful integrator of soil physical, chemical, and biological factors that regulate soil function (Smith and Doran, 1996). Geo-referenced in situ estimates of EC_a are now being made at the field scale using both direct contact sensors to measure resistance and noncontact sensors based upon electromagnetic induction technology (Dolittle et al., 1995; Jaynes et al., 1995; Jaynes, 1996). These two approaches provide highly correlated measures of EC_a and both have been shown to correlate with crop productivity at topsoil depths to 90 cm (Fritz et al., 1999; Sudduth et al., 1999).

Measured soil EC_a is determined by clay type and percentage, soil moisture (in conjunction with pore size,

Abbreviations: $EC_{1:1}$, laboratory-measured electrical conductivity using a 1:1 soil:water ratio; EC_a, field-scale apparent electrical conductivity; MBC, microbial biomass C; MBN, microbial biomass N; POM, particulate organic matter.

tortuosity, and water-filled space as they vary with depth), salinity of the soil solution, and temperature (Rhoades et al., 1989; McNeill, 1980). For individual soils, one or more of these factors will dominate measured EC_a. Substantial research effort has been directed toward understanding location-specific relationships between EC_a and those factors contributing to its measurement, including moisture (Khakural and Robert, 1998; Sheets and Hendrickx, 1995; Kachanoski et al., 1988), salinity (Lesch et al., 1992; Rhoades and Corwin, 1981; Rhoades and Ingvalson, 1971), and salinity and clay content (Williams and Hoey, 1987).

In addition to use as a direct indicator of those soil properties affecting it, it is also possible to use EC_a as an indirect measure of other soil properties and productivity (Jaynes, 1996). The effectiveness of EC_a mapping for predicting crop yield appears to depend upon the degree to which soil properties affecting yield are correlated with the soil factors affecting EC_a. Sudduth et al. (1995) found strong correlations during relatively dry years between both EC_a and depth to claypan, and depth to claypan and yield. However, EC_a was found to be a poor predictor of yield for claypan soils in a wet year. Strong correlations have also been shown between EC_a and soil attributes linked to forest productivity including soil saturated-extract electrical conductivity, exchangeable Ca and Mg, and cation-exchange capacity (McBride et al., 1990).

Most published research applies EC_a mapping to the appraisal of one or two specific factors contributing to soil condition and productivity. However, there is little information in the literature regarding the use of EC_a sensors to evaluate spatial variation in overall soil condition for arable land; where soil condition encompasses both soil characteristics that affect EC_a, and other soil characteristics affecting yield potential with which they may be correlated. The objective of this study was to assess EC_a mapping as a basis for soil sampling design and for spatially delineating soil physical, chemical, and biological properties (0- to 7.5- and 0- to 30-cm depths) related to yield and ecological potential. This information is essential for monitoring the impact of management on temporal trends in soil condition and for the successful implementation of site-specific management.

MATERIALS AND METHODS

Study Site

This research was conducted as part of the newly established Farm-Scale Intensive Cropping Study. The site consists of a contiguous section of farmland, ≈250 ha, located 30 km east of Sterling, CO (40.6° N, 103.0° W). Centered within the semiarid Central Great Plains, the site receives highly variable rates of precipitation, ranging between 250 and 680 mm and averaging 420 mm annually. Typically, 80% of precipitation falls during the growing season between April and September. Soils are mapped as a complex of Platner (fine, smectitic, mesic Aridic Paleustolls), Weld (fine, smectitic, mesic Aridic Argiustolls), and Rago loam (fine, smectitic, mesic Pachic Argiustolls) and range in slope from 0 to 5%.

The site was managed for nearly 70 yr as a winter wheat–fallow rotation under conventional-tillage. During most of this time, it was farmed as eight fields of ≈31 ha, four planted to wheat and four in fallow each year. Beginning in 1999, cropping was intensified to a wheat–corn–millet–fallow rotation using strict no-till management. By retaining the eight-field subdivisions within the section, each phase of the 4-yr rotation is duplicated each year (Fig. 1). Fields 1 and 4, 2 and 7, and 3 and 6 are paired (i.e., replicates) with regard to recent management history. Fields 5 and 8 have identical histories except
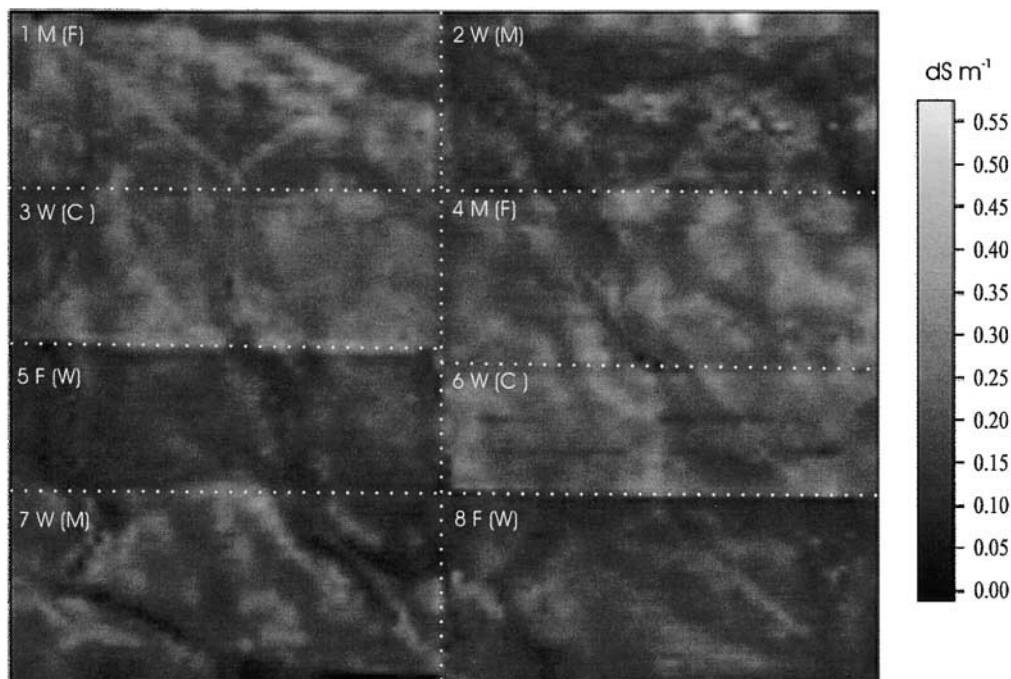

Fig. 1. Experimental layout superimposed on the March 1999 EC_a map of the 250-ha site. Field numbers, followed by cropping treatments winter wheat (W), corn (C), proso millet (M), and fallow (F), for the 1998 and 1999 (in parenthesis) growing seasons are shown in the upper left-hand corner of each field.

for 1997 when field 8 was planted to conventionally-tilled millet, while field 5 was left fallow.

Electrical Conductivity Mapping

Each of the eight fields comprising the study was individually mapped for EC_a, during mid-March 1999, using a Veris 3100 Sensor Cart (Veris Technologies, Salina, KS)[1]. At the time of mapping, winter wheat was growing in Fields 5 and 8; all other fields had been fallow since the summer of 1998. The Veris 3100 Sensor Cart was pulled across each field behind a pick-up truck in a series of parallel transects spaced ≈15 m apart. The instrument was calibrated, as per manufacturer instructions, prior to data collection for each field.

The Veris 3100 uses three pairs of coulter-electrodes to determine soil EC_a. The coulters penetrate the soil surface to a depth of ≈6 cm. One pair of electrodes functions to emit an electrical current into the soil, while the other two pairs detect decreases in the emitted current due to its transmission through soil (resistance). The depth of measurement is based upon the spacing of the coulter-electrodes. The center pair, situated closest to the emitting (reference) coulter-electrodes, integrates resistance between depths of 0 and ≈30 cm, while the outside pair integrates between 0 and ≈90 cm. Output from the Veris Data Logger reflects the conversion of resistance to conductivity (1/resistance = conductivity). We used only surface data (≈0–30 cm) in this study since it corresponded most closely to soil sampling depths (described later).

A Trimble AG132 DGPS system (Trimble Navigation Ltd., Sunnyvale, CA) with submeter accuracy was used to geo-reference EC_a measurements. The Veris data logger records latitude, longitude, and shallow and deep EC_a data (mS m^{-1}) at 1-s intervals in an ASCII text format. For reporting purposes, EC_a units were converted to dS m^{-1} by dividing mS m^{-1} by 100. Given the average collection speed of 0.44 m sec^{-1}, ≈250 EC_a measurements were taken per hectare.

Electrical Conductivity Class and Soil Sampling Point Determination

The soil sampling design used in this study represents a stratified sampling approach (Cook and Stubbendieck, 1986) with allocation into four geo-referenced EC_a ranges. Data were sorted into EC_a ranges in the following manner: Veris data were downloaded and saved as an image file using ERDAS Imagine (ERDAS Inc., Atlanta, GA). In this format, unsupervised classification (ERDAS, 1997) was performed to individually recode the eight fields in the study into four classes (EC_a ranges). Four was determined to be the number of classes that could be evaluated with a manageable number of soil samples given the large area of land encompassed by this

[1] Mention of a trademark, proprietary product or vendor does not constitute a guarantee of or warranty of the product by USDA nor imply its approval to the exclusion of other products that may be suitable.
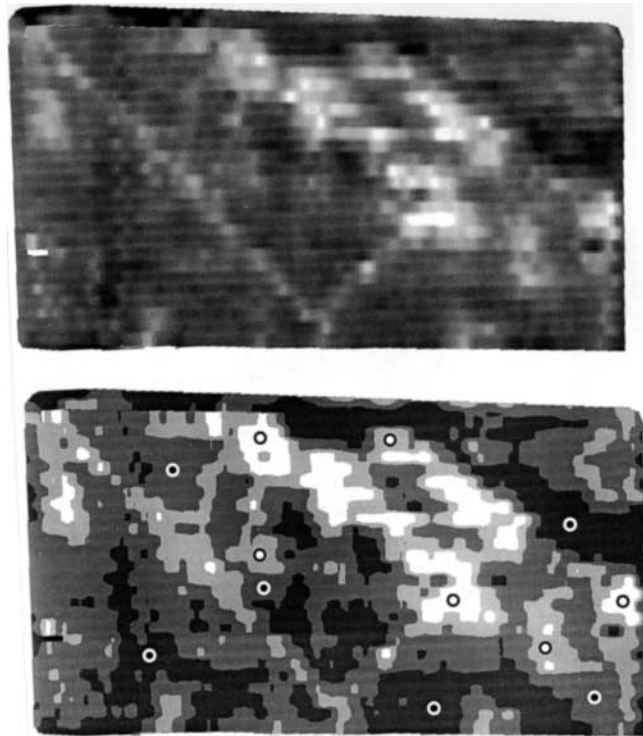

Fig. 2. A gray-scale electrical conductivity map for field 1 (top) and the same map following recoding into four electrical conductivity classes (bottom). Variations in color, from dark to light, correspond to increasing conductivity, and "○" symbols represent selected soil sampling sites.

study. Ranges of EC_a were assigned to each class (e.g., field #1 in Fig. 2, bottom) to reflect spectral patterns seen in the original gray-scale EC_a maps (Fig. 2, top). In this way, unsupervised classification served to group EC_a pixels into naturally occurring clusters. Table 1 shows EC_a class ranges for individual fields, as well as EC_a class means across all eight fields.

Three representative geo-referenced soil-sampling points were selected within each of the four EC_a classes identified in each individual field (Fig. 2, bottom). Selections were made in distinct, nonadjoining areas within each class with the intent to provide comprehensive coverage of the experimental site. Sampling points were centered within EC_a class areas to avoid transition zones. This process was used to identify 12 soil-sampling points within each of the eight fields for a total of 96 points across the study site.

Soil and Residue Sampling

Given the significant amount of time required for EC_a mapping, classification, and sample-site identification, particularly for an experiment of this size, simultaneous mapping and soil sampling were not possible. Soil samples were collected on

Table 1. Field-scale apparent electrical conductivity (EC_a) class ranges within each field at the study site.

EC_a Class	EC_a Class Means† (dS m^{-1})	Field							
		1	2	3	4	5‡	6	7	8‡
		EC_a Ranges (dS m^{-1})							
I	.116	0–.17	0–.12	0–.17	0–.15	0–.10	0–.17	0–.12	0–.12
II	.168	.17–.23	.12–.17	.17–.21	.15–.23	.10–.14	.17–.21	.12–.16	.12–.17
III	.227	.23–.29	.17–.28	.21–.27	.23–.28	.14–.18	.21–.28	.16–.24	.17–.21
IV	.305	.29–.56	.28–.78	.27–.51	.28–.42	.18–.39	.28–.45	.24–.43	.21–.44

† Mean EC_a for each class across all fields.
‡ Fields planted to winter wheat at the time of EC_a measurement.

two different dates based upon crop status. Wheat and fallow fields were sampled in mid-August following wheat harvest. Corn and millet fields were sampled in mid-November after corn harvest. The rationale for two different sampling times is presented in the results and discussion section.

Soil samples were collected at depths of 0 to 7.5 and 7.5 to 30 cm. Seven 4-cm diameter cores were taken at each sampling site, separated by depth, composited, and mixed. Because of high moisture contents, the 7.5- to 30-cm samples were sieved through a 4-mm screen, while the drier surface samples were sieved to 2 mm. A portion of each sample was refrigerated at 4°C, while the remainder was air dried. Deep samples were run through a soil grinder (M.G. Johnston Industries, Lakeville, MN) to pass a 2-mm sieve after air drying. The crushing action of this type of grinder leaves residues intact, and so does not interfere with the measurement of POM.

Soil temperature is known to fluctuate seasonally and to affect the measurement of EC_a. For this reason, duplicate soil temperature measurements were taken in surface soils (0–7.5 cm) at each sampling site for both sampling dates.

As an estimate of productivity, surface residue cover was measured in wheat and fallow fields (Fields 1, 4, 5, and 8) at the time of soil sampling in mid-August. A representative area was selected 3 m south of each soil-collection site, and above-surface residues were removed from an 85-cm diameter area. Samples were oven-dried and mass per unit area was calculated (kg ha^{-1}).

Soil Analyses

Physical, chemical, and biological soil attributes were assessed as per the minimum data set proposed by Doran and Parkin (1996). Physical measurements included soil texture (Kettler et al., in review), gravimetric water content, and bulk density. Bulk density was calculated for the composited soil cores collected at each site by dividing oven-dried mass by sample volume. Chemical measurements consisted of whole-soil organic matter and POM (0.053- to 0.5- and 0.5- to 2-mm size fractions) by loss on ignition (Cambardella et al., 2001), pH and $EC_{1:1}$ using a 1:1 water:soil mixture, 2 M KCl-extracted NO_3-N and NH_4-N measured on a LACHAT FIA auto-analyzer (Zellweger Analytics, Milwaukee, WI), total C and N analyzed with a Carlo Erba NA 100 (CE Elantech, Lakewood, NJ), and P by the Bray-1 method (Bray and Kurtz, 1945). Biological measurements included MBC and MBN by microwave irradiation (Islam et al., 1998) and anaerobically-incubated potentially-mineralizable N (Waring and Bremmer, 1964; Keeney, 1982). Microbial biomass C, MBN, pH, $EC_{1:1}$, and anaerobic potentially-mineralizable N analyses were made on fresh soil within 2 wk of collection. All other testing was performed on air-dried soil. Data were expressed on a volumetric basis except for KCl-extracted NO_3-N and NH_4-N, reported as mg kg^{-1} soil; and soil moisture, reported as kg kg^{-1} soil.

Statistical Analyses

While soil laboratory analyses were conducted on 0- to 7.5- and 7.5- to 30-cm depth samples as collected, statistical comparisons were made on 0- to 7.5- and 0- to 30-cm increments. Data from 0- to 7.5- and 7.5- to 30-cm analyses were combined and weighted to calculate 0- to 30-cm depth measurements. The significance of classification by EC_a ranges was determined for each of the soil attributes measured using an ANOVA for a randomized complete block strip-split plot design with crop (wheat, corn, millet or fallow) and EC_a class as treatment factors. Pearson correlation coefficients were

estimated, across replicates and crops, for all pairs of soil variables using both values from all sampling points ($n = 96$) and EC_a class sample means ($n = 4$). In addition, ANOVA by sampling date were run to compare mean soil gravimetric moisture, water-filled-pore space, and temperature for the two sampling times.

The significance of EC_a classification to surface residue cover was determined for wheat and fallow fields only with the ANOVA run by crop in order to separate cropped and noncropped effects. Differences were declared significant at the 0.05 level, unless stated otherwise. Correlations between EC_a and residue were analyzed across replicates by crop, using all sampling points ($n = 24$) and EC_a class sample means ($n = 4$). All statistical analyses were performed using SAS (SAS Institute, 1997).

RESULTS AND DISCUSSION

Soil Analyses

The main effect of crop treatment (data not shown) had little effect on soil parameters measured. Differences among crops ($P \leq 0.05$) were found for $EC_{1:1}$ and pH at the surface (0–7.5 cm) and for NO_3-N at both surface and 0–30 cm depths. It is reasonable that NO_3-N would differ among cropping treatments given variation in recommended application rates for the different crops. Cornfields received the highest N rates and showed the highest levels of NO_3-N following harvest probably due to drought stress and the inability of the plants to fully utilize available N. Both $EC_{1:1}$ and pH are affected by NO_3-N levels in soil, causing them to show corresponding differences among cropping treatments for surface soils.

Crop $\times$ EC_a class interactions ($P \leq 0.05$) were found for only pH and large-fraction POM (0.5–2 mm) at the 0–30 cm depth. Levels of POM were highest in the millet and corn treatments as compared with wheat and fallow. This can be attributed to greater residue production by these crops, as well as to the fact that both were preceded by wheat in 1998 (Fig. 1). Conversely, the wheat and fallow treatments produce less (or no) residue and had been cropped during only one of the 1998 and 1999 growing seasons.

With the exception of KCl-extracted NO_3-N and NH_4-N, all measured soil physical, biological, and chemical parameters were significantly different among EC_a classes ($P \leq 0.06$) at one or both sampling depths (Table 2). In general, the greatest differences were shown for soil chemical properties, probably because of greater across-site variation. Chemical parameters associated with residue inputs, whole soil organic matter, large-fraction POM (0.5–2 mm), and total C and N, were significantly different among EC_a classes at both soil depths. These and other measured parameters, including percentage silt, water content, extractable P, MBC, MBN, and anaerobic potentially-mineralizable NH_4, were negatively correlated with EC_a at one or both soil depths, suggesting an negative relationship between EC_a and yield (Table 3).

It is reasonable to expect a significant relationship between $EC_{1:1}$ and EC_a since both integrate the effects of clay (type and percentage) and salt content (including

Table 2. Within-class means and significance of field-scale apparent electrical conductivity (EC$_a$) classification for various soil attributes. The 250-ha experimental site was divided into eight fields planted to two replications of wheat, corn, proso millet, and fallow.

		Soil attribute means within EC$_a$ classes									
		EC$_a$ classes†									
		0- to 7.5-cm depth					0- to 30-cm depth				
Soil attribute	Units	I	II	III	IV	$Pr > F$	I	II	III	IV	$Pr > F$
Physical											
Bulk density	g cm^{-3}	1.38	1.47	1.51	1.56	0.06	1.32	1.39	1.39	1.42	0.06
Sand	%	39.8	41.9	43.4	41.3	0.06	36.4	37.3	36.9	36.2	n.s.‡
Silt	%	42.0	39.1	36.6	36.2	0.05	40.8	38.4	35.8	35.7	0.04
Clay	%	18.2	19.0	20.0	22.5	0.07	22.8	24.3	27.3	28.1	0.02
Water content	kg kg^{-1}	.160	.135	.124	.118	0.002	.207	.187	.185	.178	.03
Chemical											
EC$_{1:1}$§	dS m^{-1}	0.18	0.14	0.16	0.17	n.s.	0.16	0.15	0.19	0.22	0.006
NH$_4$–N	mg kg^{-1}	0.071	0.028	0.081	0.071	n.s.	0.222	0.223	0.214	0.184	n.s.
NO$_3$–N	mg kg^{-1}	7.2	5.3	5.5	6.1	n.s.	5.6	4.0	4.2	4.5	n.s.
SOM¶	Mg ha^{-1}	34.1	31.3	28.4	28.3	0.05	124.8	115.9	110.4	112.6	0.05
PH		6.22	6.21	6.38	6.51	n.s.	6.33	6.42	6.72	6.92	0.01
Extractable P	kg ha^{-1}	41.9	29.8	15.7	13.0	0.004	111.8	69.2	27.8	26.7	0.002
POM# (0.05–0.5 mm)	Mg ha^{-1}	5.93	5.36	4.18	3.96	0.01	14.42	11.94	11.08	12.02	0.04
POM (0.5–2 mm)	Mg ha^{-1}	2.30	2.16	1.60	1.70	0.02	4.22	3.78	3.28	3.37	n.s.
POM (0.05–2 mm)	Mg ha^{-1}	7.69	7.05	5.36	5.24	0.001	17.73	14.89	13.67	14.76	n.s.
Total C	Mg ha^{-1}	13.4	11.3	9.5	9.2	0.004	43.8	35.2	32.2	32.7	0.009
Total N	Mg ha^{-1}	1.20	1.04	0.91	0.87	0.006	4.08	3.45	3.09	3.10	0.001
Biological											
Microbial biomass C	kg ha^{-1}	418.6	357.8	293.7	286.5	0.04	545.3	544.8	425.8	442.0	n.s.
Microbial biomass N	kg ha^{-1}	45.1	40.3	36.0	31.6	0.002	57.9	53.1	54.9	52.4	n.s.
PMN NH$_4$††	kg ha^{-1}	45.1	36.0	32.7	26.9	0.02	86.4	67.0	59.3	54.4	.04

† Each of the eight fields within the study site was individually classified into four conductivity ranges, and each range was sampled in triplicate at two depths. Analyses were made across crops and field replicates ($n = 96$). Class 1 = low EC$_a$, Class II = medium low EC$_a$, Class III = medium high EC$_a$, and Class IV = high EC$_a$.
‡ n.s. = Non-significant F-value at the 0.1 level.
§ EC$_{1:1}$ = laboratory measured EC using a 1:1 water saturated paste.
¶ SOM = total soil organic matter by loss-on-ignition.
# POM = particulate organic matter by loss-on-ignition.
†† PMN NH$_4$ = potentially mineralizable NH$_4^+$.

soluble anions and cations). The two measures differ in that EC$_{1:1}$ allows for the standardization of soil water. While this difference will affect the magnitude of measured EC, a degree of correlation should still exist between EC$_{1:1}$ and EC$_a$, dependent upon the extent to which clay type and percentage and salt content contribute to measured conductivity. In this study, surface soil analyses of EC$_{1:1}$ were not related to EC$_a$ classification. However, EC$_{1:1}$ was differentiated by EC$_a$ classification when the two analyses were based upon a similar depth of measurement (0–30 cm) (Table 2 and 3). Soil pH, which typically shows a strong relationship with EC$_{1:1}$ (Patriquin et al., 1993), was also significantly different among EC$_a$ classes in deep (0–30 cm) soils.

Potassium chloride-extracted NO$_3$-N and NH$_4$-N were not significantly partitioned by EC$_a$ classification and exhibited a narrow range of variability across the experimental site. Nitrogen transformations in soil are controlled by soil water content, texture, biological activity, cropping, and the composition and quantity of organic matter (Stevenson, 1982). These soil characteristics impact the discordant processes of volatilization, nitrification, immobilization, and leaching (losses) or mineralization (gains) that define levels of soil inorganic N (Jansson and Persson, 1982; Stevenson, 1982). Our analyses indicate that, at the time of sample collection, available N levels were not related to variability in soil condition. In this study it should also be noted that, prior to soil sampling, millet and corn crops were severely drought stressed at critical growth stages during July

and August. Since adequate moisture is essential for effective crop uptake of N (Olson, 1984), erratic across-field crop demand for available N may have altered its spatial variation. It is also possible that for this location, factors other than inorganic N dominate measured EC$_a$.

Physical soil attributes of texture and bulk density, although less effectively partitioned than chemical and biological attributes, were still different among the EC$_a$ classes (Table 2). The one exception was percentage sand at the 0- to 30-cm depth, which was uniform across sampling sites. As per other reports (Kachanoski et al., 1988; Khakural and Robert, 1998), positive correlations were found between EC$_a$ and clay content (Table 3), with clay content ranging between 12.2 and 38.8 % in sampled soils.

All measured biological parameters, MBC, MBN, and anaerobic potentially-mineralizable NH$_4$, were significantly different among EC$_a$ classes in the 0- to 7.5-cm depth only (Table 2). Correlations between EC$_a$ ($\approx$30-cm depth) and soil surface measurements (0–7.5 cm) of moisture and biological activity were stronger than those between EC$_a$ and the same measurements taken at 0- to 30-cm (Table 3). This may suggest some EC$_a$ bias toward soil surface conditions.

It is interesting to note that when correlation analyses were conducted using EC$_a$ class means ($n = 4$) for soil parameters, as opposed to using values from all sampling points ($n = 24$), the relationships between EC$_a$ and those parameters improved dramatically (data not shown). All measured parameters, except percentage

Table 3. Correlation matrix ($r \times 100$) for measured soil attributes, 0- to 30-cm sampling depth ($n = 96$).

Soil attributes

Attribute	Physical						Chemical										Biological		
	EC$_a$†	Bulk density	Sand	Silt	Clay	Water	EC$_{1:1}$‡	NH$_4$	NO$_3$	SOM§	pH	P	POM¶ 0.05–0.5	POM 0.5–2 mm	Total C	Total N	MBC#	MBN††	PMN NH$_4$‡‡
EC$_a$	100																		
Bulk density	49***	100																	
Sand	-5	1	100																
Silt	-28**	-16	-83***	100															
Clay	50***	20*	-59***	4	100														
Water	-33***	-41***	-22*	24	5	100													
EC$_{1:1}$	44***	12	2	-17	21*	18	100												
NH$_4$	-1	19	-5	0	9	-18	-17	100											
NO$_3$	16	13	-12	10	7	30**	59***	-19	100										
SOM	-34***	-25**	-8	20*	-15	34***	-5	-23*	-14	100									
pH	37***	3	15	-33***	21*	2	55***	-13	-7	4	100								
P	-58***	-43***	-10	44***	-45***	39***	-17	-21*	26**	22*	-43***	100							
POM (0.05–0.5)	-13	-32***	15	6	-35***	23*	30**	-9	16	16	15	42***	100						
POM (0.5–2 mm)	-25**	-33***	7	14	-32**	-10	-17	15	-27**	6	-6	19	49***	100					
Total C	-36***	-38***	2	28**	-44***	17	3	-6	-1	25**	-7	58***	74***	53***	100				
Total N	-38***	-26**	-13	44***	-40***	12	-15	-2	6	24*	-42***	64***	54***	43***	83***	100			
MBC	-26	-6	-28	38**	-12	13	-30*	-23	13	7	-47***	58***	39**	34*	35*	45***	100		
MBN	-2	0	8	6	-32*	6	29*	-18	40**	-13	6	20	64***	47***	56***	43***	36*	100	
PMNNH$_4$	-50***	-35**	-13	38**	-50***	20	-10	-7	10	18	-21	56***	68***	56***	71***	63***	44**	56***	100

0- to 30-cm depth

* Significant at the 0.05 probability level.
** Significant at the 0.01 probability level.
*** Significant at the 0.001 probability level.
† EC$_a$ = field-scale electrical conductivity.
‡ EC$_{1:1}$ = laboratory measured electrical conductivity using a 1:1 soil to water ratio.
§ SOM = total soil organic matter by loss-on-ignition.
¶ POM = particulate organic matter by loss-on-ignition.
# MBC = microbial biomass C.
†† MBN = microbial biomass N.
‡‡ PMN NH$_4^+$ = potentially mineralizable NH$_4$-N.

sand and NO_3-N, were highly correlated with EC_a ($r \geq 0.80$) at one or both sampling depths. We know that measured EC_a synthesizes the effects of certain static and dynamic soil characteristics; these characteristics are, in turn, correlated with other soil properties that underlie overall soil condition and productivity. Highly variable levels of a specific soil parameter can be associated with a single EC_a value due to the buffering effect of corresponding variations in opposing soil parameters affecting EC_a. Consequently, for this experimental site strong correlations do not exist between EC_a and individual soil parameters at point sources. Field-scale apparent electrical conductivity appears to be a tool most useful for the delineation of overall soil condition.

Under the conditions of this study, primary factors contributing to measured EC_a can be separated into static (clay percentage) and dynamic components (soil moisture and salinity). Soil clay content (0–30 cm) was negatively correlated with parameters associated with productivity including P, POM, total C and N, MBN, and potentially-mineralizable N, all of which are strongly auto-correlated (Table 3). On the other hand, clay content was positively correlated with pH and bulk density. These relationships are likely due to the calcareous nature of soils in northeastern Colorado, where the erosion of topsoil exposes underlying soil horizons that are characterized by increased clay content and $CaCO_3$ and associated elevation of bulk density and pH.

Other potential contributors to EC_a, soil moisture content, and NO_3-N are correlated with both P and POM components of the soil and with each other. The lack of significant correlation between NO_3-N and EC_a suggests that it had minimal impact on EC_a for these sampling times. While soil moisture generally increases with increasing clay content, there is no correlation between the two for the soils under study. For this site, increases in soil water-holding capacity due to the presence of clay are probably offset by concomitant decreases in soil organic matter components and soil depth. Furthermore, in semiarid environments, plant-available water and crop yields are less defined by the ability of soil to store water than by precipitation inputs.

Residue Analyses

As harvest index relationships between wheat grain mass and aboveground biomass are well accepted, it is likely that the measured across-field variation in residue mass mirrors that of crop yields. Surface residue cover measured at each of the wheat and fallow soil-sampling sites was significantly related to EC_a classification and negatively correlated with EC_a (Fig. 3). As would be expected for a collection date shortly after wheat harvest, residue quantity in wheat fields (1375–8459 kg ha^{-1}) was approximately twice that in fallow fields (582–5005 kg ha^{-1}). Residue mass in fallow fields was slightly less correlated with EC_a ($r = -0.91$) than that of wheat fields ($r = -0.95$), probably because of differential decomposition and redistribution by wind and water. Tremendous variability in residue quantity was found within EC_a classes, particularly in low EC_a (high
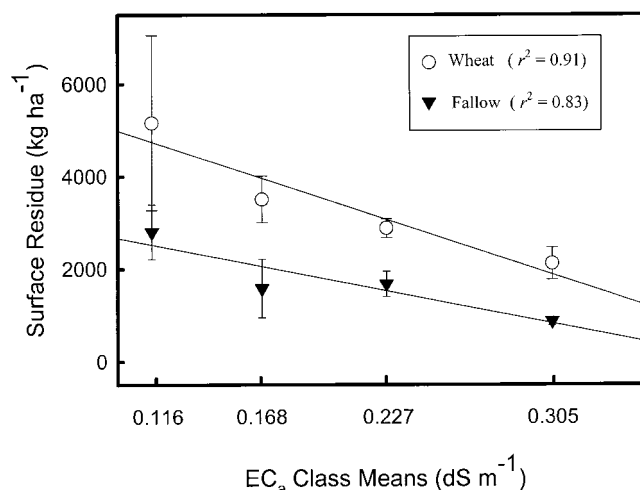

Fig. 3. Relationship between surface residue content and field-scale apparent electrical conductivity (EC_a). Each point represents the mean of six samples. The error bars depict the standard errors of the mean.

residue) zones. Accordingly, correlations between surface residue and EC_a declined ($r = -0.54$ and -0.62, respectively, for wheat and fallow fields) when analyzed using data from all sampling points ($n = 24$).

Electrical Conductivity Mapping and Classification

Apparent vestiges of both historical and recent management are evident in the EC_a map generated in this field study. Careful examination of the map reveals V-shaped patterns in each of the four corner fields of the section (Fig. 1 and 2). These anomalies are believed to be remnants of the plow path followed in the 1930s when the study site was farmed as two half sections. Additionally, each of the four field pairs within the section, having similar recent management histories, is distinguished by varying mean levels of conductivity. The two fields of actively growing wheat, at the time of EC_a mapping, register the lowest overall conductivity. This can not be attributed to soil water content since the water content of soil under a growing crop would be less than that in fallow fields, and water content is negatively correlated with EC_a at this site. Two possible explanations may be offered for this phenomenon. An EC_a bias toward the soil surface may exist where the growing crop and associated microbial activity reduce levels of available N, and hence EC_a (Eigenberg et al., 2001). Alternatively, the loosening of soil during planting or with plant root activity may lower soil bulk density and EC_a (E. Lund, 2001, personal communication).

Soil temperatures (0–7.5 cm) were fairly uniform across the study site for each sampling date, but were significantly different among dates (Table 4). Gravimetric water content and water-filled pore space were quite similar, albeit significantly different, among sampling dates. Although both soil temperature and moisture content affect measured EC_a, the design of this experiment is based upon the assumption that the relevance of established EC_a zones does not change over time

Table 4. Mean soil temperature, moisture content, and water-filled pore space for the two sampling dates.

Sampling date	Mean soil temperature 0–7.5 cm	Mean soil moisture		Mean soil water-filled pore space	
		0–7.5 cm	0–30 cm	0–7.5 cm	0–30 cm
	°C	—— kg kg⁻¹ ——		—— % ——	
15 Aug. 1999	26.7†	0.150	0.190	45.8	54.3
16 Nov. 1999	12.0	0.119	0.165	45.0	48.3
SE$_d$‡	0.58	0.004	0.002	1.61	0.87

† Values within a column are significant different ($P = 0.0001$).
‡ SE$_d$ = Standard error of the difference between sample date means.

with fluctuations in dynamic soil properties. It has been demonstrated that, while the magnitude of temporal EC$_a$ measurements varies with soil moisture and temperature, spatial patterns in EC$_a$ remain constant (Sudduth et al., 2000; Veris Technologies, 2001). This finding is essential to the use of EC$_a$ mapping as a basis for identifying soil-sampling zones.

The number of EC$_a$ classes, into which a field is separated for sampling or management purposes, depends upon desired measurement sensitivity and the level of within-field variability. For this study, separation into four EC$_a$ classes (ranges) proved to be a good compromise between sensitivity and visually discernable patterns in EC$_a$ (Fig. 2).

CONCLUSIONS

The EC$_a$ vs. yield relationship varies among published accounts, and inconsistent correlations have been found between EC$_a$ and crop yield across years (Jaynes et al., 1995; Kitchen et al., 1999). However, these studies have been conducted in high-rainfall regions where yield reductions occur due to both drought and excessive precipitation. Typically in the Central Great Plains, where insufficient precipitation poses the primary limitation to crop production, crop yield varies with degree of drought stress. In this environment, EC$_a$ may be a more consistent predictor of yield potential across years.

For this study site, soil parameters associated with erosion phase including percentage clay, bulk density, pH, and EC$_{1:1}$ were positively correlated with EC$_a$ measurements integrated over a soil depth of ≈0 to 30 cm. Other properties related to crop productivity, notably soil moisture, total and POM, total C and N, MBC and MBN, and surface-residue content, were negatively correlated. These results imply a negative relationship between EC$_a$ and productivity. The application of spatial techniques to EC$_a$ and yield maps from the experimental site will provide verification of the statistical associations between EC$_a$ and yield; these analyses will be the focus of a future publication.

In view of the large number of soil samples required for representative estimates of overall-field condition, traditional grid sampling is both expensive and labor intensive. One of the best ways to reduce these costs is to minimize the number of samples required through zone sampling. Zone sampling, based on a combination of soil color, texture, depth, slope, and erosion characteristics, has been shown to be an effective alternative

to grid sampling (Francis and Schepers, 1997). In fact, the EC$_a$–classed soil-sampling scheme used in this study appears to integrate these and other soil characteristics. We found that EC$_a$ classification effectively delimits distinct zones of soil condition, making it an excellent basis for soil sampling to reflect spatial heterogeneity.

Chen et al. (2000) used soil color, quantified through remotely-sensed imaging, to predict C levels as an indicator of soil condition. Like EC$_a$, remote sensing was found to be a cost-effective basis for delineating soil spatial variability. However, while remotely sensed imagery is typically applied to bare (tilled) soil, EC$_a$ has the advantage of effectiveness for cropped land where no-till management is practiced.

Currently, most farmers in the Central Great Plains apply management practices uniformly across a field. In this approach, management decisions are based upon measured soil attributes expressed as whole-field averages. The software used to assign EC$_a$ classes can also generate class areas (ha class⁻¹) within fields. Thus, whole-field means for specific soil analyses can be easily calculated. EC$_a$ class sample means are simply weighted, relative to class area within the whole field, summed, and divided by the number of classes. This approach is superior to traditional random sampling because it accounts for spatial heterogeneity of soil attributes in the sampling design; moreover, whole field means based on stratified sampling have smaller standard errors than are possible with random sampling.

Soil classification using EC$_a$ provides an effective basis for delineating interrelated physical, chemical, and biological soil attributes that are expressed as soil condition, crop productivity, and ecological potential. It offers a useful framework for soil sampling to reflect spatial heterogeneity and can be potentially applied to assess temporal impacts of management on soil condition. Furthermore, as variable rate planters, sprayers, and applicators become more refined and cost effective, classification based on EC$_a$ can provide spatial data regarding soil condition and yield potential that will serve as an essential link between this new technology and effective management.

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