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Apparent soil electrical conductivity: applications for designing and evaluating field-scale experiments

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Abstract

On-farm field-scale research has become increasingly common with the advent of new technologies. While promoting a realistic systems perspective, field-scale experiments do not lend themselves to the traditional design concepts of replication and blocking. Previously, a farm-scale dryland experiment in northeastern Colorado was conducted to evaluate apparent electrical conductivity (EC_a) classification (within-field blocking) as a basis for estimating plot-scale experimental error. Comparison of mean-square (MS) errors for several soil properties and surface residue mass measured at this site, with those from a nearby plot-scale experiment, revealed that EC_a-classified within-field variance approximates plot-scale experimental error. In the present study, we tested these findings at a second and disparate experimental site, Westlake Farms (WLF) in central California. This 32 ha site was EC_a mapped and partitioned into four and five classes using a response-surface model. Classification based on EC_a significantly delineated most soil properties evaluated (0–0.3 and/or 0–1.2 m) and effectively reduced MS error ($P \leq 0.10$). The MS's for several soil properties evaluated at the site were then compared with those of an associated plot-scale experiment; most MS's were not significantly different between the two levels of scale ($P \leq 0.05$), corroborating results from the Colorado experiment. These findings support the use of within-field EC_a-classified variance as a surrogate for plot-scale experimental error and a basis for roughly evaluating treatment differences in non-replicated field-scale experiments. This alternative statistical design may promote field-scale research and encourage a reversal in research direction wherein research questions identified in field-scale studies are pursued at the plot-scale.

Keywords: Agricultural systems; Classified management maps; Statistical analyses; Geographic information systems; Soil electrical conductivity

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1. Introduction

In recent years, heightened understanding of the interdependence between farm economics, environmental quality, and production potential has encouraged the expansion of agronomic research to evaluate farm management as it impacts an agroecosystem. Systems research can be defined as an experimental approach used to broadly appraise land management for a variety of short- and long-term outcomes that may include economic return; sociological implications; soil biological response, chemical composition, and physical structure; crop biomass and yield; pest pressure; and off-site environmental consequences. Moreover, global positioning systems (GPS), geographic information systems (GIS), and field-scale sensors allow examination of temporal shifts in many of these factors within a spatial context. Largely due to these technologies, systems research is increasingly conducted on farms at the field scale (Fraisse et al., 2001; Johnson et al., 2001; Mueller et al., 2002; Corwin et al., 2003b).

Systems research provides the “opportunity to test broad, integrated hypotheses” (Drinkwater, 2002, p. 355). Experiments typically involve multidisciplinary teams of researchers and rely on farmer input for planning, execution, and evaluation. Farmer involvement minimizes (1) research trials that prove ineffective on farms, and (2) rejection of experiment station trials that might have performed well on farms (Stroup et al., 1993). Field-scale systems experiments may hasten the adoption of sustainable management practices because positive outcomes are demonstrated at a scale to which farmers can relate (Rzewnicki, 1991).

To identify best management practices, the traditional research model uses highly controlled small-plot experiments, followed by multiple location trials (still using small plots), and finally realistic on-farm systems experiments. Yet, many investigators now suggest that research direction be reversed to begin with the system (Sumberg and Okali, 1988; Hargrove and Pickering, 1992; Johnson et al., 2003b), a strategy particularly appropriate for experiments in site-specific management (Vanden Heuvel, 1996; Crawford et al., 1997) and for assessing management-induced changes in soil, water, and air quality at farm or regional scales (Nielsen et al., 1995). Field-scale experiments used to broadly evaluate new management approaches can be followed by controlled small-plot experiments to test the nuances of system response.

A major barrier to field-scale experimentation is the perception of excessive and unmanageable variability. An acceptable level of experimental error has been documented in several experiments involving research plots up to 36 m × 366 m (Rzewnicki et al., 1988), plots large enough to accommodate typical farm equipment. Yet, these experiments used replication and randomization, design features rarely feasible in increasingly larger experiments. One of the greatest limitations to field-scale experimentation is a dearth of acceptable methods for design and statistical evaluation.

Experimental error is the “failure of repeated observations, under similar conditions, to be identical” (LeClerg et al., 1962), and soil heterogeneity is the principle source in agronomic research (Harris, 1915). In classic experimentation, small plots are arranged in a randomized complete block design where blocks serve to increase precision by reducing experimental error due to soil heterogeneity. Blocks are placed in homogeneous areas based upon measurements of yield-significant properties. While topography, soil fertility, and

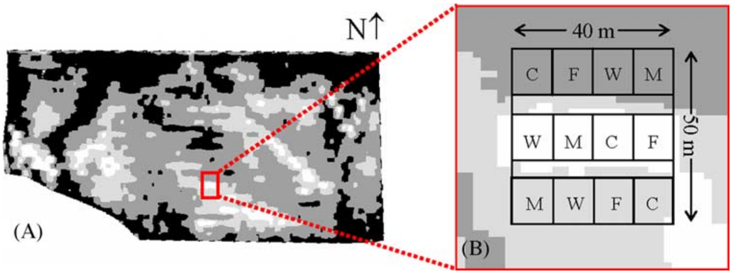

Fig. 1. Relationship between bulk soil electrical conductivity (EC_a) classification and plot-scale blocking. (A) An EC_a-classified map of a ≈32 ha field at the Farm-Scale Intensive Cropping Study and (B) a typical plot-scale experiment identified within the field using EC_a classification as a basis for blocking.

soil series exemplify traditional blocking factors, any method can be used that effectively partitions an existing fertility gradient. In some cases, apparent soil electrical conductivity (EC_a) mapping can be used for this purpose.

Soil factors affecting EC_a vary among locations and may include one or more of the following: salinity, clay type and percentage, bulk density, moisture, and temperature (Rhoades et al., 1989). In locations where soil factors contributing to EC_a are also yield limiting, classified EC_a maps can be used to design and place plot-scale experiments (Fig. 1). This is appropriate because EC_a classes are related to outcome (crop yield) differences expected in the absence of treatments, the rationale for blocking. Classified EC_a maps have been used to identify homogeneous areas within a field to both locate and block plot-scale experiments (personal communication, Newell Kitchen).

At the Farm-Scale Intensive Cropping Study (FICS) in northeastern Colorado significant relationships were found between EC_a, soil characteristics, and crop yields (Johnson et al., 2001, 2003c), supporting EC_a-classified zones as a basis for blocking and statistically evaluating plot-scale experiments. Background information for the FICS is provided in Table 2. At the FICS, EC_a zones provided a framework through which measurements taken at different levels of scale (microbe, sampling-site, field, and farm) can be integrated (Johnson et al., 2004). Johnson et al. (2003b) hypothesized that if EC_a classification can be used to block plot-scale experiments, EC_a-classified within-field blocking can be used to statistically evaluate field-scale experiments.

Fig. 1 illustrates a clear relationship between EC_a-partitioned soil heterogeneity at the plot and field scales. The 32 ha field shown on the left is separated into four classes of EC_a (A), three of which form the basis for blocks in the traditional plot-scale experiment set in a randomized complete block design (B). Since blocks are homogeneous, plots need not be adjacent but could be placed anywhere in field (A) within assigned blocks. Thus, the entire 32 ha field can be conceptualized as an enlarged version of the plot-scale experiment, where within EC_a-class variance is equivalent to experimental error in the plot-scale experiment. To test this, Johnson et al. (2003b) evaluated numerous soil physical, chemical, and biological properties measured at both the FICS and a nearby traditional plot-scale experiment (Peterson et al., 1993). The EC_a-classified within-field mean square error (MS) of each property measured at the FICS was compared with MS error (derived from blocking) for that property measured in the plot-scale experiment. Experimental errors were similar,

Table 1
Within apparent electrical conductivity (EC_a) class means and significance for selected soil properties (0–30 cm depth) measured at the Farm-Scale Intensive Cropping Study

	EC_a ranges ($dS\,m^{-1}$)	Productivity-associated factors						Erosion-associated factors		
		Water content ($kg\,kg^{-1}$)	SOM[a] ($Mg\,ha^{-1}$)	Total C ($Mg\,ha^{-1}$)	Total N ($Mg\,ha^{-1}$)	P[a] ($kg\,ha^{-1}$)	PMN[a] ($kg\,ha^{-1}$)	Bulk density ($g\,cm^{-3}$)	Clay (%)	pH
EC_a zone		*	**	**	**	**	*	+	*	**
Low	0.00–0.17	0.207	124.8	43.8	4.08	111.8	86.4	1.32	22.8	6.33
Medium low	0.12–0.23	0.187	115.9	35.2	3.45	69.2	67.0	1.39	24.3	6.42
Medium high	0.14–0.29	0.185	110.4	32.2	3.09	27.8	59.3	1.39	27.3	6.72
High	0.18–0.78	0.178	112.6	32.7	3.10	26.7	54.4	1.42	28.1	6.92

[a] SOM: total soil organic matter; P: extractable P; PMN: potentially-mineralizable NH_4^+.
+ Comparisons of EC_a class treatments are significant at the 0.10 level.
* Comparisons of EC_a class treatments are significant at the 0.05 level.
** Comparisons of EC_a class treatments are significant at the 0.01 level.

indicating that field-scale EC_a-classified variability effectively estimated soil heterogeneity partitioned by plot-scale blocking. These findings support the use of field-scale systems experiments to broadly evaluate treatments and identify research needs requiring further study at the plot scale.

The geographic extent to which these results are transferable remains untested. Data sets suitable for assessment are difficult to find because they must meet two criteria. First, data must include a variety of soil indices from both an EC_a-classified field-scale site and an associated blocked plot-scale experiment. Second, the soil characteristics driving EC_a at the sites must be yield limiting. Data sets from 32.4 and 8.1 ha sites at Westlake Farms (WLF) in the San Joaquin Valley of central California met these criteria (Corwin et al., 2003a,b). A positive correlation between EC_a and cotton yield at WLF ($r = 0.51$; $P \leq 0.01$) (Corwin et al., 2003b) indicates potential utility of EC_a classification as a basis for blocking. The objective of this paper was to determine whether EC_a-classified within-field variability can be used to approximate plot-scale experimental error in a second and contrasting environment, the San Joaquin Valley.

2. Materials and methods

2.1. Field-scale study

The WLF study site is a 32.4 ha field located on the west side of California's San Joaquin Valley and comprised of Panoche silty clay thermic Xerothents soil. The site has been used in a drainage water reuse study since 1999. Eight 4 ha rectangular paddocks with dimensions of 75 m × 364 m comprise the study site (Fig. 2A). To characterize the spatial variability of soil properties, an EC_a survey was conducted in 1999 using an EM-38 electrical conductivity meter (Geonics, Ltd., Mississauga, Ontario, Canada)[1] following the survey guidelines outlined by Corwin and Lesch (2003). Approximately 4000 EC_a measurements were taken across the site.

The EC_a survey consisted of a grid of 384 sites arranged in a 4 × 12 pattern within each of the eight paddocks. At each site, EC_a measurements were taken using electromagenetic induction (EM) with the coil configuration oriented in the vertical (EM_v) and in the horizontal (EM_h) position. The horizontal coil configuration concentrates the EM reading nearer to the soil surface and penetrates to a depth of roughly 0.75–1.0 m, whereas the EM reading in the vertical configuration penetrates to a depth of roughly 1.5 m and concentrates the reading less at the surface. From the EM measurements the geometric mean and profile ratio were calculated for each site. The geometric mean EM levels were defined as the SQRT ($EM_v \times EM_h$). The profile ratios were defined as EM_h/EM_v. In essence, the profile ratio is analogous to the leaching fraction, while the geometric mean approximates relative salinity in the root zone (Corwin et al., 1999).

Utilizing the EM data and ESAP statistical software (ESAPv2.0) developed by Lesch et al. (1995), 40 soil sampling sites were selected by means of a response surface sample

[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.

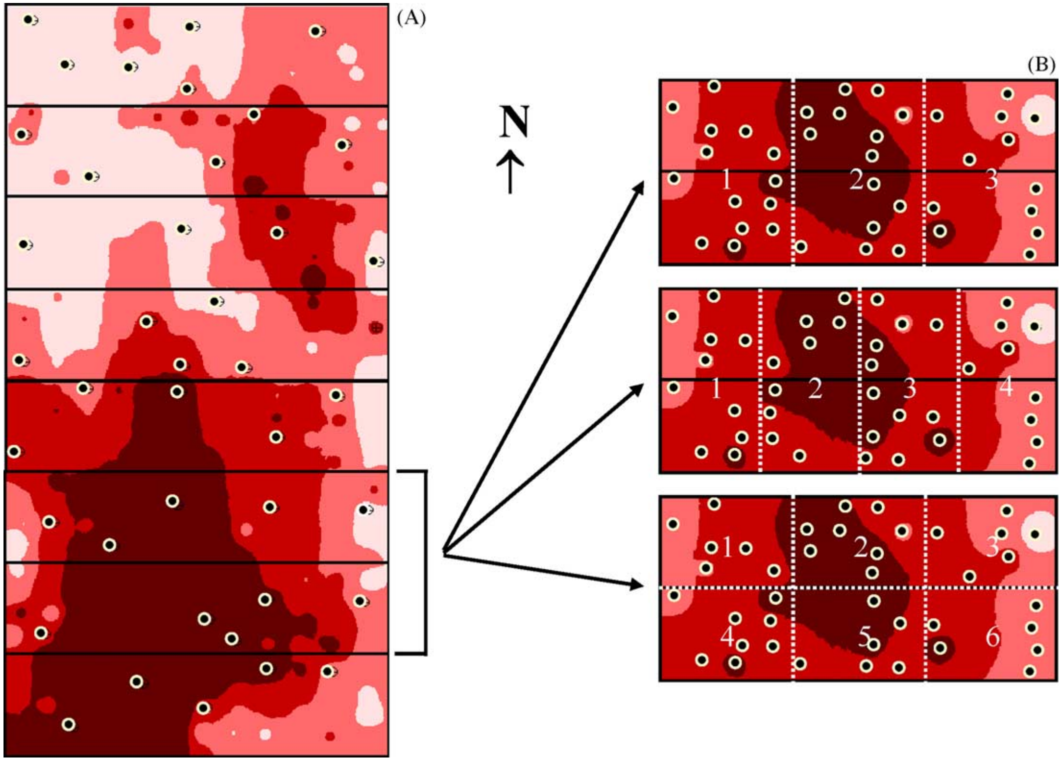

Fig. 2. The 32.4 ha field-scale Westlake Farms Study separated into eight paddocks (A). The site is partitioned into four classes of apparent electrical conductivity (EC_a) based upon a response surface. Class color, from light to dark, corresponds to increasing conductivity. Forty soil sampling points (●) are identified. Two paddocks on the south end of the study site were selected for more intensive soil sampling and were used to simulate a traditional plot-scale study (8.1 ha) (B). These are shown with three different blocking schemes (three, four, and six blocks) superimposed over a map of laboratory-measured salinity (EC_e). Light to dark coloration indicates low to high salinity where salinity ranges are: 6.988–13.288, 13.288–18.42, 18.42–26.435, and 26.435–35.6 dS m^{-1} for the four zones shown. Thirty randomly selected soil sampling sites, in addition to the ten response surface sites, are identified on each map (●).

design (Fig. 2). Conceptually, 40 sites were selected to characterize the observed spatial variability in EM measurements that satisfy the following three criteria: (i) to represent about 95% of the observed range in the geometric mean EM data, (ii) to represent about 95% of the observed range in the EM profile ratio data, and (iii) to be spatially distributed across the eight paddocks in an approximately uniform manner with about five sites within each paddock. A more detailed discussion on how a spatial response surface sample design is used to simultaneously achieve these criteria is found in Lesch et al. (1995).

At each of the 40 sites, soil core samples were taken in 1999 and again in 2002. Soil cores were taken at 0.3 and 1.2 m depth increments and analyzed for a variety of physical and chemical soil properties listed in Table 3. Methods of analysis are provided by Corwin et al. (2003a). The 2002 data set was used for this study with the exception of soil texture and bulk density assessments, which were only available in the 1999 data set.

The WLF field-scale experiment was partitioned into four and five EC_a classes. To accomplish this, EM_v and EM_h measurements were log transformed and decorrelated to determine principal component scores by the same process used in ESAP to create a response surface. Resultant scores were then separated into quartiles or quantiles. All spatial data were entered into a geographic information system (GIS) using the commercial GIS software ArcView 3.1 (ESRI, Redlands, CA).[1]

2.2. Plot-scale study

Two paddocks on the south end of the WLF study (8.1 ha) were used to simulate a typical plot-scale experiment set in a randomized complete block design (Fig. 2B). We selected salinity as the blocking factor because it is the major soil property limiting crop production at WLF (Corwin et al., 2003b), and it represents an obvious basis for a traditionally designed plot-scale experiment. Salinity was assessed for soil samples (0–1.2 m) from 40 sampling sites by measuring electrical conductivity in a 1:1 saturated paste (EC_e). Soil analyses from all available sampling points within the two paddocks were evaluated to increase degrees of freedom. Consequently, thirty samples came from random sampling sites, selected using SAS (SAS Institute, 1997), while the remaining ten were taken from the response surface sites described above. Using ArcView 3.1 GIS software (ESRI, Redlands, CA)[1], a map of EC_e was produced, classified, and interpolated using inverse-distance-weighting, and the resulting EC_e map used to position experimental blocks (Fig. 2).

2.3. Experimental approach

The same general approach taken at the FICS experiment in northeastern Colorado (Johnson et al., 2003b) was applied to the WLF study in central California. Within-field variability delineated using EC_a classification (i.e. within-field blocking) was evaluated as an estimate of traditional small-plot experimental error. Our strategy was to compare field- and plot-scale experimental error to determine the significance of scale to experimental outcome (crop yield) occurring in the absence of treatments.

Both field- and plot-scale experiments in this study were analyzed as complete blocks. The field-scale experiment was separated into four and five EC_a classes, and the plot-scale experiment into three, four, and six EC_e blocks (Fig. 2), numbers of blocks typically used in

Table 2
Comparison of the Farm-Scale Intensive Cropping Study and the Westlake Farms research sites: site characteristics and EC_a mapping/classification methods

	Farm-Scale Intensive Cropping Study[a]	Westlake Farms Study[b]
Location	Northeast Colorado	Central California
Climate	Semiarid	Arid
Soil classification	Platner, Weld, and Rago loam (fine, smectitic, mesic Aridic Paleustolls, Aridic Argiustolls, and Pachic Argiustolls)	Lethent clay loam (fine, smectitic, thermic, Typic Natrargid)
Cropping system	Dryland Winter wheat–corn–proso millet–fallow rotation	Irrigated Bermuda grass rotational forage
Regional production challenges	Maximizing precipitation-use-efficiency	Saline drainage water disposal
	Minimizing wind/water erosion	Controlling toxic ion and trace element buildup in soil and crops
	Maintaining/increasing soil organic matter	Maintenance of soil quality
Primary soil factors limiting yield	Depth, organic matter, water-holding capacity, pH	Salinity, leaching fraction, water content, pH
Size of field-scale study site (ha)	250	32.4
Size of plot-scale study site (ha)	5.5	8.1
Depth of soil sampling (m)	0.33	1.2
EC_a collection method	Direct contact	Electromagnetic induction: horizontal (EM_H) and vertical (EM_V) modes
Range of measured EC_a (dS m^{-1})	0.03–0.78	EM_H: 1.45–5.19 EM_V: 2.56–7.95
EC_a classification method	Design-based Unsupervised classification	Model-based Response surface
Major soil factors driving EC_a (in order of significance)	Percent clay	Salinity
	Bulk density	Water content
	Water content	Bulk density
	Salinity	Percent clay

[a] Johnson et al. (2001, 2003a).
[b] Corwin et al. (2003a,b).

agronomic research. Different numbers of blocks (or classes) were analyzed to investigate the effect of block number on experimental error. The effectiveness of EC_a as a blocking factor was evaluated in two ways using analysis of variance. First, the means of measured soil properties were pooled over the 40 sites and four depths. For each property, when within EC_a class variability (MS (site(EC_a class))) was significantly smaller than among EC_a class variability (MS (EC_a class)), blocking was considered effective for the property. Secondly, EC_a classes were evaluated for their ability to significantly partition soil properties across the WLF site.

Lastly, the *F*-test was used to compare EC_a-classified within-field MS error, for several soil properties assessed in the field scale experiment, to MS error derived from blocking for those same soil properties assessed at the plot scale. All statistical analyses were conducted using SAS (SAS Institute, 1997).

3. Results and discussion

3.1. EC_a effectiveness as a blocking factor

The effectiveness of EC_a classification as a basis for blocking was evaluated from two perspectives. First, any successful blocking scheme will substantially reduce variability. For individual soil parameters measured at WLF, when within EC_a class variability (MS (site(EC_a class))) was significantly smaller than among EC_a class variability (MS (EC_a class)), EC_a-classified blocking was effective for the parameter. Using this criterion, EC_a proved to be a suitable basis for blocking a majority of measured soil properties (Table 3). Secondly, Corwin et al. (2003b) identified four soil properties exhibiting the greatest effect on cotton yields at WLF, salinity, plant-available water, leaching fraction, and pH. Three of these were evaluated in our study. The variability of salinity and pH (with separation into four or five EC_a classes), and water content, an indicator of plant-available water (with separation into five EC_a classes), was significantly reduced by EC_a classification. The responsiveness of yield-associated soil parameters to EC_a classification supports the use of EC_a as a blocking factor because it verifies the relationship between EC_a classes and outcome (yield) differences expected in the absence of treatments, the rationale for blocking.

Increasing the number of EC_a classes from four to five did not significantly reduce within EC_a class variability (MS (site(EC_a class))) for any of the soil properties evaluated (Table 3). However, partitioning into five classes produced a significant *F*-test (MS (EC_a class)/MS (site(EC_a class))) indicating effective blocking for water content, saturation percentage (SP) and exchangeable sodium percentage (ESP), results not found with four classes. Conversely, partitioning into four classes effectively blocked cation exchange capacity (CEC), $CaCO_3$, and exchangeable K^+, results not found with five classes.

The effectiveness of EC_a as a blocking variable was also evaluated for significant delineation of soil characteristics at two depths of measurement and using four and five classes of EC_a. With partitioning into four classes, a majority of measured soil properties were different among EC_a classes ($P \leq 0.10$) for both surface and root-zone soils (0–0.33 and 0–1.2 m depths) (Table 4). Increasing the number of EC_a classes from four to five added water content and pH to the list of significantly partitioned soil properties at the surface, and saturation percentage and ESP to those significantly partitioned in deeper soils (data not shown).

3.2. MS error comparisons: field-scale EC_a classification versus plot-scale blocking

Comparisons of soil property MS errors, calculated for the field-scale experiment separated into four and five EC_a classes, and the plot-scale experiment separated into three, four,

Table 3
The 32.4 ha Westlake Study was partitioned into four and five classes based on apparent electrical conductivity (EC_a)

Soil property	4 EC_a classes			5 EC_a classes		
	MS (EC_a class) (d.f. = 3)	MS (site(EC_a class)) (d.f. = 36)	MS (error) (d.f. = 120)	MS (EC_a class) (d.f. = 4)	MS (site(EC_a class)) (d.f. = 35)	MS (error) (d.f. = 12)
Water content ($kg\ kg^{-1}$)	0.324	0.339	0.276	0.664[+]	0.301	0.276
Sand[b] (%)	1136[*]	197	92.8	738[*]	220	92.8
Silt[b] (%)	637[*]	166	40.7	472[*]	172	40.7
Clay[b] (%)	103	49.2	53.8	32.3	57.0	53.8
Bulk density[b] ($g\ cm^{-3}$)	0.0239	0.0159	0.0250	0.0248	0.0155	0.0250
SP[a] (%)	519	256	117	710[*]	227	117
pH	0.585[*]	0.126	0.077	0.449[*]	0.129	0.077
EC_e[a] ($dS\ m^{-1}$)	1009[*]	67	53	940[*]	48	53
CEC[a] ($mmol_c\ kg^{-1}$)	2310[*]	510	190	1150	590	190
ESP (%)	1475	3155	1525	7327[*]	2534	1525
SAR	5306[*]	442	325	5189[*]	317	325
Total C ($g\ kg^{-1}$)	2.850[*]	0.447	0.630	1.56[*]	0.525	0.630
Total N ($g\ kg^{-1}$)	0.0057[*]	0.00195	0.00437	0.00509[*]	0.00192	0.00437
$CaCO_3$ ($g\ kg^{-1}$)	123[*]	30.8	9.20	65.7	34.6	9.20
Gypsum ($g\ kg^{-1}$)	179	171	155	291	158	155
Mo ($mg\ L^{-1}$)	1.04	0.507	0.0938	0.812	0.518	0.0939
B ($mg\ L^{-1}$)	356[*]	80.5	33.0	265[*]	83.1	33.0
Anions in the saturation extract						
Cl^- ($mmol_c\ L^{-1}$)	5611[*]	896	428	5151[*]	814	428
HCO_3^- ($mmol_c\ L^{-1}$)	6.176[*]	0.504	0.393	4.959[*]	0.481	0.393
NO_3^- ($mmol_c\ L^{-1}$)	0.144	0.068	0.043	0.114	0.069	0.043
SO_4^- ($mmol_c\ L^{-1}$)	172,925[*]	10,020	8,208	15,7871[*]	7,086	8,208

Cations in the saturation extract						
Ca^{2+} ($mmol_c\ L^{-1}$)	1.29	8.28	4.12	5.55	7.99	4.12
K^{+} ($mmol_c\ L^{-1}$)	4.291*	0.649	0.127	5.375*	0.422	0.127
Mg^{2+} ($mmol_c\ L^{-1}$)	1721*	109	58	1170*	126	58
Na^{+} ($mmol_c\ L^{-1}$)	205,035*	12,835	10,252	191,248*	8,919	10,252
Exchangeable cations						
Ca^{2+} ($mmol_c\ kg^{-1}$)	75.0	94.0	153	186+	81.0	153
K^{+} ($mmol_c\ kg^{-1}$)	1.88+	0.840	1.95	1.78	0.830	1.95
Mg^{2+} ($mmol_c\ kg^{-1}$)	117.7	60.5	22.8	70.4	64.2	22.8
Na^{+} ($mmol_c\ kg^{-1}$)	2550*	310	140	2690*	230	140

Comparisons were made between among site (within EC_a class) and among EC_a class mean squares (MS's) for several soil properties using these classification schemes. The MS's were calculated on the means of measured soil properties pooled over 40 sites and four depths, 0–0.3, 0.3–0.6, 0.6–0.9, and 0.9–1.2 m (160 observations).

[a] EC_e: laboratory-measured EC using a 1:1 water saturated paste; SP: saturation percentage; CEC: cation exchange capacity.

[b] Degrees of freedom for MS(EC class), 4 or 5 classes; MS (site(EC class)), 4 or 5 classes; and MS(error) are 3 or 4, 30 or 29, and 102 for sand, silt, and clay, and 3 or 4, 31 or 30, and 105 for bulk density.

* MS (EC_a class) is significantly larger than MS (site(EC_a class)) at the 0.05 level.

+ MS (EC_a class) is significantly larger than MS (site(EC_a class)) at the 0.10 level.

Table 4
Significance of EC_a classification/EC_e blocking and comparison of soil property (0–0.3 m and 0–1.2 m depths) means and mean square errors (MSE's) within field-scale apparent electrical conductivity (EC_a) classes (with partitioning into four classes) and plot-scale blocks (with partitioning into four blocks) at the Westlake Farms Study site

Soil property	Units	Field-scale experiment						Plot-scale experiment					
		Within EC_a class means				$Pr > F$	MSE	Within block means				$Pr > F$	MSE
		I	II	III	IV			I	II	III	IV		
0–0.3 m depth													
Water[b] content	$kg\,kg^{-1}$	0.193	0.192	0.185	0.196	n.s.	0.136	0.199	0.201	0.188	0.233	0.02	0.102
Saturation percentage	%	56.9	62.0	66.0	74.2	0.0001	46.7	73.8	79.0	72.3	66.1	0.001	39.4
pH		7.45	7.70	7.76	7.78	n.s.	0.125	7.93	8.00	7.83	7.74	n.s.	0.0666
EC_e	$dS\,m^{-1}$	7.36	8.91	11.0	19.1	0.0001	15.9	14.0	17.4	13.8	8.19	0.0005	17.9
CEC	$mmol_c\,kg^{-1}$	177	185	217	240	0.02	2111	256	247	223	249	n.s.	3704
ESP	%	23.4	36.3	33.2	50.6	0.03	399	34.7	55.5	44.0	18.7	0.02	583
SAR		12.8	17.5	23.5	42.0	0.0001	92.9	34.1	41.4	30.8	14.9	0.0001	123
Total C	$g\,kg^{-1}$	9.42	8.65	7.79	6.48	0.01	3.44	5.37	6.69	7.40	9.01	n.s.	1.87
Total N	$g\,kg^{-1}$	0.775	0.760	0.735	0.626	n.s.	0.0214	0.597	0.658	0.729	0.804	0.06	0.0092[a]
$CaCO_3$	$g\,kg^{-1}$	20.9	14.5	10.6	5.16	0.008	92.1	1.13	1.33	6.67	11.1	0.0001	14.6[a]
Gypsum	$g\,kg^{-1}$	23.0	36.4	34.7	59.3	0.0005	288	52.9	69.5	57.0	38.8	0.0004	159
Mo	$\mu g\,L^{-1}$	498	457	668	885	n.s.	275	657	817	493	345	0.006	81.9[a]
B	$mg\,L^{-1}$	8.79	12.4	15.7	19.8	0.002	33.8	19.3	17.6	14.1	11.8	0.04	25.1
Exchangeable Na^+	$mmol_c\,kg^{-1}$	39.2	58.2	71.8	122	0.0001	852	101	108	97.0	94.7	n.s.	1002

0–1.2 m depth													
Water content	kg kg^{-1}	0.241	0.249	0.233	0.254	n.s.	0.0845	0.251	0.249	0.248	0.260	n.s.	0.0497
Saturation percentage	%	59.1	65.9	64.6	67.6	n.s.	64.0	69.6	66.9	65.0	62.9	n.s.	35.9
pH		7.74	7.94	8.02	7.94	0.008	0.0316	8.08	8.09	7.98	7.92	0.09	0.0275
EC_e	dS m^{-1}	13.7	17.1	19.9	24.2	0.0001	16.7	20.7	27.8	25.3	16.0	0.0001	20.0
CEC	mmol$_c$ kg^{-1}	144	168	163	204	0.006	1267	207	207	197	202	n.s.	1926
ESP	%	60.9	70.1	73.0	70.5	n.s.	788	60.9	68.6	60.8	48.5	n.s.	408
SAR		30.7	40.1	47.8	54.6	0.0001	110	50.4	66.2	56.5	34.7	0.0001	121
Total C	g kg^{-1}	6.11	5.55	4.77	4.13	0.001	1.12	3.18	3.87	4.35	4.77	0.0001	0.311[a]
Total N	g kg^{-1}	0.484	0.500	0.443	0.421	0.06	0.0049	0.385	0.419	0.442	0.494	0.0001	0.0020[a]
$CaCO_3$	g kg^{-1}	19.7	12.7	12.0	5.86	0.02	76.9	1.75	2.51	6.18	5.75	0.01	11.6[a]
Gypsum	g kg^{-1}	50.8	59.6	58.84	65.8	n.s.	42.8	68.5	71.3	70.4	56.9	0.05	144[a]
Mo	μg L^{-1}	467	541	775	812	0.09	128	879	848	550	455	0.008	94.4
B	mg L^{-1}	15.5	17.9	21.9	21.4	0.009	20.1	24.4	24.7	19.5	18.1	0.005	20.7
Exchangeable Na^+	mmol$_c$ kg^{-1}	73.5	102	105	130	0.001	782	104	125	108	88.1	0.02	530

[a] Field- and plot-scale MSE's are significantly different at the 0.05 level.

[b] The number of degrees of freedom for each variable is 36/36 (field-scale/plot-scale).

Table 5
Comparison of field- and plot-scale mean square errors for analyzed soil properties (0–0.3 m depth) at the Westlake Study

Soil property	Units	Field-scale experiment		Plot-scale experiment		
		4 EC_a classes (MS within EC_a class)	5 EC_a classes (MS within EC_a class)	3 Blocks (MS within block)	4 Blocks (MS within block)	6 Blocks (MS within block)
Water content[a]	$kg\,kg^{-1}$	0.136	0.0992	0.113	0.102	0.105
Saturation percentage	%	46.7	36.1	44.9	39.4	46.4
pH		0.125	0.119	0.0713	0.0666	0.0712
EC_e	$dS\,m^{-1}$	15.9	19.0	21.9	17.9	20.2
CEC	$mmol_c\,kg^{-1}$	2111	2236	3527	3704	3201
ESP	%	399	401	691	583	688
SAR		92.9	103	154	123	154
Total C	$g\,kg^{-1}$	3.44	3.73	1.37[4,5]	1.87[5]	0.839[4,5]
Total N	$g\,kg^{-1}$	0.0214	0.0229	0.00784[4,5]	0.00923[4,5]	0.00712[4,5]
$CaCO_3$	$g\,kg^{-1}$	92.1	91.2	14.7[4,5]	14.6[4,5]	11.8[4,5]
Gypsum	$g\,kg^{-1}$	288	341	172[5]	159[5]	163[5]
Mo	$mg\,L^{-1}$	27.5	297	94.8[4,5]	81.9[4,5]	91.7[4,5]
B	$mg\,L^{-1}$	33.8	35.7	27.0	25.1	25.5
Anions in the saturation extract						
Cl^-	$mmol_c\,L^{-1}$	99.4	91.5	173	136	172
HCO_3^-	$mmol_c\,L^{-1}$	0.644	0.623	0.777	0.748	0.823
NO_3^-	$mmol_c\,L^{-1}$	0.0348	0.033	0.0224	0.0222	0.0222
SO_4^-	$mmol_c\,L^{-1}$	2860	3404	2746	2403	2471

Cations in the saturation extract						
Ca^{2+}	$mmol_c\ L^{-1}$	4.16	3.91	2.43	2.27	2.57
K^{+}	$mmol_c\ L^{-1}$	0.205	0.176	0.235	0.224	0.221
Mg^{2+}	$mmol_c\ L^{-1}$	56.8	68.8	20.4[4,5]	20.7[4,5]	14.1[4,5]
Na^{+}	$mmol_c\ L^{-1}$	2986	3509	3718	3107	3452
Exchangeable cations						
Ca^{2+}	$mmol_c\ kg^{-1}$	1290	1034	3308[4,5]	3254[4,5]	3016[4,5]
K^{+}	$mmol_c\ kg^{-1}$	6.62	6.88	3.20[4,5]	3.66	2.60[4,5]
Mg^{2+}	$mmol_c\ kg^{-1}$	171	155	54.0[4,5]	48.6[4,5]	40.8[4,5]
Na^{+}	$mmol_c\ kg^{-1}$	852	933	1209	1002	1249

Field-scale mean square (MS) is the variance among sites within apparent electrical conductivity (EC_a) classes, where the field is partitioned into four or five EC_a classes. Plot-scale MS is the variance among sites within blocks, with partitioning of the plot-scale experiment into three, four, and six blocks. [4,5]Plot-scale MS's are significantly different from field-scale MS's (0.05 level) with partitioning into four or five EC_a classes, respectively.

[a] Degrees of freedom for each variable were 36/37, 36/36, and 36/34 (field-scale/plot-scale), with field-scale experiment partitioning into four EC_a classes and plot-scale experiment partitioning into three, four, and six blocks, respectively. Degrees of freedom were 35/37, 35/36, and 35/34 (field-scale/plot-scale), with field-scale experiment partitioning into five EC_a classes and plot-scale experiment partitioning into three, four, and six blocks, respectively.

and six blocks, are shown in Tables 5 and 6. The MS errors for the majority of measured soil properties were not different ($P \leq 0.05$) between the two levels of scale. Furthermore, most of those that were different showed only a 2–4-fold disparity, a degree of heterogeneity with little effect on ANOVA (Scheffe, 1959). These findings were similar to those at the FICS site in Colorado (Johnson et al., 2003b).

In general, surface soil MS's (0–0.3 m) compared more favorably between plot- and field-scale experiments than did MS's for soil properties evaluated at deeper depths (0–1.2 m) (Tables 5 and 6). This is likely a reflection of increasing heterogeneity with depth at WLF (Corwin et al., 2003b), but is contrary to findings at the FICS in Colorado where variability is greatest at the soil surface (Johnson et al., 2003b). The MS's for soil properties in surface soils (0–0.3 m depth) were most alike when field- and plot-scale experiments were partitioned into four EC_a classes and four blocks, respectively (Table 5). The number of surface soil properties showing different MS's at the field and plot scales increased when the number of EC_a classes was increased from four to five.

As was true for surface soils, MS's for deeper soil (0–1.2 m) properties were most similar between field- and plot-scale experiments when the experimental sites were partitioned into four EC_a classes and four blocks, respectively (Tables 5 and 6). The MS comparisons changed little when partitioning was increased from four to five EC_a classes with four plot-scale blocks. Only extractable Na^+ was added to the list of soil properties with different MS's between the two levels of scale.

The MS for EC_e was expected to compare favorably between the field and plot scales, since EC_e was the basis for plot-scale blocking and the major contributor to measured EC_a at WLF (Corwin et al., 2003b). This was confirmed for surface soils where soil water content, SP, and B, all highly correlated with EC_e (Corwin et al., 2003b), also showed comparable MS's between the field- and plot-scale experiments. Interestingly, these relationships were not as strong at deeper soil depths. Comparisons of field- and plot-scale MS's for EC_e (four or five EC_a classes versus three or six EC_e blocks) and SP (four or five EC_a classes versus six EC_e blocks) revealed significant differences. This may reflect the increasing EC_e and soil heterogeneity found with depth by Corwin et al. (2003b). It is also possible that spatial patterns in salinity changed slightly between 1999, when soils were EC_a mapped, and 2002 when soils were sampled (Johnson et al., 2003a).

3.3. Field-scale within-field blocking versus traditional plot-scale blocking

In a traditional randomized complete block design, blocks are positioned to frame homogeneous regions in a field. Two or more blocks may include soils with similar characteristics as was the case with each of the salinity-based blocking schemes used for the WLF plot-scale site (Fig. 2B). For example, when apportioned into four blocks, the EC_e map shows block 2 to be highest in salinity, block 4 lowest, and blocks 1 and 3 of similar mid-range salinity. This is verified by soil analyses (Table 4).

In contrast, the soil property means within EC_a classes were directionally stratified for most properties examined, indicating a degree of linearity between those properties and EC_a (Table 4). Total C and N, soil properties associated with yield potential, were negatively correlated with EC_a at one or both depths of measurement. Properties indicative of increased salinity and decreased yield (SP, pH, EC_e, CEC, ESP, sodium adsorption ratio (SAR), B,

Table 6
Comparison of field- and plot-scale mean square errors for analyzed soil properties (0–1.2 m depth) at the Westlake Study

Soil property	Units	Field-scale experiment		Plot-scale experiment		
		4 EC_a classes (MS within EC_a class)	5 EC_a classes (MS within EC_a class)	3 Blocks (MS within block)	4 Blocks (MS within block)	6 Blocks (MS within block)
Water content[a]	$kg\,kg^{-1}$	0.0845	0.0748	0.0486	0.0497	0.0441
Saturation percentage	%	64.0	56.6	34.3	35.9	27.0[4,5]
pH		0.0316	0.0322	0.0288	0.0275	0.0259
EC_e	$dS\,m^{-1}$	16.7	11.9	26.8[4,5]	20.0	25.0[4,5]
CEC	$mmol_c\,kg^{-1}$	1267	1471	1801	1926	1471
ESP	%	789	633	442	408	381[4]
SAR		111	79.1	165[5]	121	166[5]
Total C	$g\,kg^{-1}$	1.12	1.31	0.278[4,5]	0.311[4,5]	0.264[4,5]
Total N	$g\,kg^{-1}$	0.00489	0.00479	0.0020[4,5]	0.0020[4,5]	0.0021[4,5]
$CaCO_3$	$g\,kg^{-1}$	76.9	86.6	11.0[4,5]	11.6[4,5]	8.16[4,5]
Gypsum	$g\,kg^{-1}$	428	396	119[4,5]	144[4,5]	128[4,5]
Mo	$mg\,L^{-1}$	127	130	93.5	94.4	78.6
B	$mg\,L^{-1}$	20.1	20.8	22.5	20.7	21.2
Anions in the saturation extract						
Cl^-	$mmol_c\,L^{-1}$	224	203	206	173	211
HCO_3^-	$mmol_c\,L^{-1}$	0.126	0.120	0.330[4,5]	0.279[4,5]	0.356[4,5]
NO_3^-	$mmol_c\,L^{-1}$	0.0170	0.0174	0.490[4,5]	0.515[4,5]	0.519[4,5]
SO_4^-	$mmol_c\,L^{-1}$	2505	1771	7252[4,5]	5949[4,5]	6682[4,5]

Table 6 (*Continued*)

Soil property	Units	Field-scale experiment		Plot-scale experiment		
		4 EC_a classes (MS within EC_a class)	5 EC_a classes (MS within EC_a class)	3 Blocks (MS within block)	4 Blocks (MS within block)	6 Blocks (MS within block)
Cations in the saturation extract						
Ca^{2+}	$mmol_c\ L^{-1}$	2.07	2.00	5.07[4,5]	4.74[4,5]	5.20[4,5]
K^+	$mmol_c\ L^{-1}$	0.162	0.105	0.356[4,5]	0.312[4,5]	0.329[4,5]
Mg^{2+}	$mmol_c\ L^{-1}$	27.3	31.6	99.7[4,5]	89.9[4,5]	68.3[4,5]
Na^+	$mmol_c\ L^{-1}$	3209	2230	7771[4,5]	6146[5]	7362[4,5]
Exchangeable cations						
Ca^{2+}	$mmol_c\ kg^{-1}$	446	411	1098[4,5]	1199[4,5]	1111[4,5]
K^+	$mmol_c\ kg^{-1}$	2.11	2.06	0.740[4,5]	0.842[4,5]	0.690[4,5]
Mg^{2+}	$mmol_c\ kg^{-1}$	151	160	89.8	82.5	61.6[4,5]
Na^+	$mmol_c\ kg^{-1}$	782	580	604	530	611

Field-scale mean square (MS) is the variance among sites within apparent electrical conductivity (EC_a) classes, where the field is partitioned into four or five EC_a classes. Plot-scale MS is the variance among sites within blocks, with partitioning of the plot-scale experiment into three, four, and six blocks. [4,5]Plot-scale MS's are significantly different from field-scale MS's (0.05 level) with partitioning into four or five EC_a classes, respectively.

[a] Degrees of freedom for each variable were 36/37, 36/36, and 36/34 (field-scale/plot-scale), with field-scale experiment partitioning into four EC_a classes and plot-scale experiment partitioning into three, four, and six blocks, respectively. Degrees of freedom were 35/37, 35/36, and 35/34 (field-scale/plot-scale), with field-scale experiment partitioning into five EC_a classes and plot-scale experiment partitioning into three, four, and six blocks, respectively.

and exchangeable Na) were positively correlated with EC_a. Although relationships between specific soil properties and yield potential at the FICS in Colorado are quite different from those of WLF, similar directional stratification of soil properties by EC_a classification was identified (Table 1). In other soils, EC_a predicts yield in a non-linear fashion, where yield is maximized at mid-range EC_a values (Kitchen et al., 1999).

Another important distinction must be made between EC_a-classified within-field blocking and traditional randomized complete block designs. Traditional blocks are defined as grouped sets of experimental units to which treatments are independently applied. As a result, each block encompasses several experimental units. In contrast, with EC_a-classified within-field blocking each treatment is independently applied to a field, where a field is the experimental unit. Each experimental unit encompasses several blocks; hence, the term within-field blocking.

There are frequently limitations associated with conducting an experiment based upon an existing dataset. In this study, a response surface model was applied to identify EC_a classes at WLF because it was the basis previously established to identify soil sampling sites for the data set examined. The response surface approach favors the identification of soil sampling sites at the extremes of EC_a (personal communication, Scott Lesch) and may not be the optimal method for classifying soils for the purpose of blocking (to minimize within-class variance). Yet, despite this possible deficiency MS errors for most soil properties were similar between field-scale EC_a-classified and plot-scale salinity-based blocking schemes. It is possible that field- and plot-scale variances at WLF would show even greater similarity had unsupervised EC_a classification methods been applied as at the FICS in Colorado.

By the same token, the plot-scale study was positioned in a location predetermined by the availability of soil analyses from randomly-selected sampling sites at WLF. More homogeneous blocks may have been possible in another location. Analyses made in this study should be regarded as reasonable estimates of field- and plot-scale experimental errors for WLF.

4. Conclusions

At WLF in the San Joaquin Valley of central California, EC_a classification significantly delineated a majority of soil factors tested and effectively reduced their variance. Additionally, field-scale EC_a-classified MS (within-field) variability and traditional plot-scale MS error were found to be similar. These findings corroborate those from the FICS in Colorado (Johnson et al., 2003b), reinforcing the proposal that EC_a-classified within-field blocking can be used for the statistical design of field-scale studies and as a means to estimate plot-scale experimental error. The fact that the Colorado and California experimental sites exemplify widely contrasting climates, cropping systems, soil characteristics, production challenges, and EC_a classification methods further bolsters the potential application of this alternative statistical approach.

It is important to note that EC_a classification can be used as a basis for blocking only when EC_a and yield are correlated, a relationship found in locations where the soil characteristics driving EC_a also limit yield. At WLF, salinity dominated measured EC_a and best predicted yield, while at the FICS clay content drove EC_a and defined erosion phase/yield potential across fields. Although EC_a and yield are not always correlated (Kitchen et al., 1999; Johnson et al., 2003a), the EC_a-yield relationship has been documented in multiple locations within and outside the U.S. (Kitchen et al., 1999, 2003; Johnson et al., 2003a; Veris Technologies, 2004). This indicates widespread potential application for EC_a in experimental design and analysis.

Within-field blocking, based on EC_a, offers a compelling tool in statistical design. It is well suited for examining environmental response (soil, water, and atmosphere) to a single treatment or management practice and provides a foundation for the study of these responses within a spatial context. For instance, the impact of management on soil quality could be evaluated across a gradient of soil fertility delimited by EC_a classes.

Within-field blocking also offers the opportunity to compare two or more treatments without benefit of replication. Many landowners are understandably hesitant to commit multiple fields and ongoing management to create replicated treatments in on-farm experiments. However, when multiple replicated treatments are not feasible, landowners may be willing to split a field into two parcels to provide room for one additional treatment. Within-field blocking, based on EC_a classification, could then be used to roughly compare the two treatments. Two or three treatments could also be applied to separate fields that could be roughly compared using this approach. In agronomic research, the opportunity to add one or more additional treatments can significantly improve the potential value of an experiment.

Wide-spread acceptance of within-field blocking as a bonafide statistical design will require its continued assessment over space and time. In order to broaden the scope of inference beyond the WLF and FICS, multi-site comparisons of field- and plot-scale experimental error are necessary. For this reason, we take a conservative stance, suggesting that EC_a-classified within-field variance be used in a systems approach to agronomic research, as a rough estimate of plot-scale experimental error and a means to identify questions requiring further research at the plot scale. Such alternative statistical methods will encourage the study of intact agroecosystems that are realistic in terms of scale, management, farm equipment, and soil heterogeneity. Because farmers can relate to experimental goals examined in systems similar to their own, field-scale experiments may also lead to greater acceptance and implementation of sustainable management practices.

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