# 16 Delineating Site-Specific Management Units Using Geospatial EC<sub>a</sub> Measurements

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### CONTENTS

16.1	Introduction	
16.2	Materials and Methods	248
	16.2.1 Study Site	248
	16.2.2 Yield Monitoring and EC <sub>a</sub> Survey	
	16.2.3 Sample Site Selection, Soil Sampling, and Soil Analyses	
	16.2.4 Statistical and Spatial Analyses	
16.3	Results and Discussion	249
	16.3.1 Correlation between Crop Yield and EC <sub>a</sub>	249
	16.3.2 Exploratory Statistical Analysis	
	16.3.3 Crop Yield Response Model Development	
16.4	Delineated Site-Specific Management Units	
References		

## 16.1 INTRODUCTION

Site-specific crop management (or site-specific management, SSM) is a means of managing the spatial variability of edaphic (i.e., soil related), anthropogenic, topographic, biological, and meteorological factors influencing crop yield. The aim of SSM is to increase crop productivity, sustain the soil-plant environment, optimize inputs, increase profitability, and minimize detrimental environmental impacts. The spatial variability of edaphic factors is a consequence of pedogenic and anthropogenic activities, which produce variation in soil physical and chemical properties within agricultural fields. In the arid southwestern United States, the primary soil properties influencing crop yield are salinity, soil texture and structure, plant-available water, trace elements (particularly B), and ion toxicity from Na<sup>+</sup> and Cl<sup>-</sup> (Tanji, 1996).

Bullock and Bullock (2000) indicated that efficient, reliable methods for measuring within-field variations in soil properties are important for precision agriculture. Because apparent soil electrical conductivity (EC<sub>a</sub>) is influenced by a variety of soil properties (i.e., salinity, water content, texture, bulk density, organic matter, and temperature) and is a reliable measurement that is easy to take, geospatial measurements of EC<sub>a</sub> have become one of the most frequently used measurements to characterize within-field variability for agricultural applications (Corwin and Lesch, 2003). Geospatial measurements of EC<sub>a</sub> have been used to characterize spatial variation in soil salinity and nutrients such as  $NO_3^-$ , water content, texture-related properties, bulk density-related properties such as compaction, leaching, and organic matter-related properties (Corwin and Lesch, 2005a).

In the past, geo-referenced  $EC_a$  measurements have been correlated to associated yield-monitoring data with mixed results (Corwin et al., 2003; Jaynes et al., 1993; Johnson et al., 2001; Kitchen et al., 1999; Sudduth et al., 1995). These mixed results are due, in part, to a misunderstanding of the relationship between  $EC_a$  measurements and variations in crop yield. As pointed out by Corwin and Lesch (2003), crop yield inconsistently correlates with  $EC_a$  due to the influence of soil properties (e.g., salinity, water content, texture, etc.) that are being measured by  $EC_a$ , which may or may not influence crop yield within a particular field, and because a temporal component of yield variability is poorly captured by a state variable such as  $EC_a$ . Corwin and Lesch (2005a) provide a recent review of the application of geo-referenced  $EC_a$  measurements in agriculture with particular attention to precision agriculture applications.

Site-specific management units (SSMUs) have been proposed as a means of dealing with the spatial variability of edaphic properties influencing crop productivity to achieve the goals of SSM. A SSMU is simply a mapped unit of soil that is managed the same to achieve SSM goals. In a strict sense, the task of delineating SSMUs is extremely complicated because all edaphic, anthropogenic, topographic, biological, and meteorological factors influencing a crop's yield must be considered. One means of simplifying the complexity of delineating SSMUs is to define SSMUs based on a single factor, such as edaphic properties, and determine the extent of the variability of crop yield due to the single factor.

It is hypothesized that in instances where  $EC_a$  correlates with crop yield, spatial  $EC_a$  information can be used to direct a soil sampling plan that identifies sites that adequately reflect the range and variability of various soil properties thought to influence crop yield. The objective of this study is to utilize an intensive geo-referenced  $EC_a$  survey to direct soil sampling and to identify edaphic properties influencing cotton yield, and to use this spatial information to make recommendations for SSM of cotton by delineating SSMUs based solely on edaphic properties influencing cotton yield. This paper draws from previous more detailed work conducted and published by Corwin and colleagues (Corwin and Lesch, 2003, 2005b; Corwin et al., 2003).

## 16.2 MATERIALS AND METHODS

### 16.2.1 STUDY SITE

A 32.4-ha field located in the Broadview Water District of the San Joaquin Valley's west side in central California was used as the study site. The soil at the site is a Panoche silty clay (thermic Xerorthents), which is slightly alkaline with good surface and subsurface drainage. The subsoil is thick, friable, calcareous, and easily penetrated by roots and water.

## 16.2.2 YIELD MONITORING AND EC, SURVEY

Spatial variation of cotton yield was measured at the study site in August 1999 using a four-row cotton picker equipped with a yield sensor and Global Positioning System (GPS) receiver. The yield sensors measured average seed cotton yield. All subsequent references to cotton yield are with respect to seed cotton yield. A total of 7706 cotton yield readings were collected (Figure 16.1a). Each yield observation represented a total area of approximately 42 m². From August 1999 through March 2000 the field was fallow. On March 2000, an intensive EC<sub>a</sub> survey was conducted using mobile fixed-array electrical resistivity equipment developed by Rhoades and colleagues (Carter, 1993; Rhoades, 1992). The fixed-array electrodes were spaced to measure EC<sub>a</sub> to a depth of 1.5 m. Over 4000 EC<sub>a</sub> measurements were collected (Figure 16.1b).

# 16.2.3 SAMPLE SITE SELECTION, SOIL SAMPLING, AND SOIL ANALYSES

Data from the EC<sub>a</sub> survey were used to direct the selection of sixty sample sites. A spatial statistics software package, ESAP-95 version 2.01, developed by Lesch et al. (2000) was used to determine

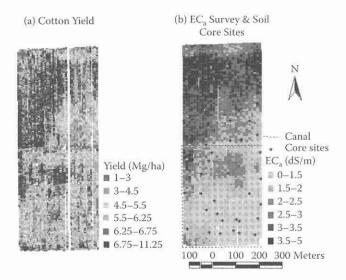


FIGURE 16.1 Maps of (a) cotton yield and (b) EC<sub>a</sub> measurements including sixty soil core sites. (Modified from Corwin, D.L., Lesch, S.M., Shouse, P.J., Soppe, R., Ayars, J.E., Agron. J., 95, 352–364, 2003. With permission.)

the sample sites from the  $EC_a$  survey data. The software uses a model-based response-surface sampling strategy. The selected sites reflect the observed spatial variability in  $EC_a$  while simultaneously maximizing the spatial uniformity of the sampling design across the study area. Figure 16.1b shows the spatial  $EC_a$  survey data and the locations of the sixty core sites. Soil samples were collected at 0.3 m increments to a depth of 1.8 m. Soil samples were analyzed for physical and chemical properties thought to influence cotton yield including gravimetric water content ( $\theta_g$ ), bulk density ( $\rho_b$ ), pH, B, NO<sub>3</sub>-N, Cl<sup>-</sup>, electrical conductivity of the saturation extract ( $EC_e$ ), leaching fraction (LF), percentage clay, and saturation percentage (SP). All samples were analyzed for physical and chemical properties following the methods outlined in Agronomy Monograph No. 9 (Page et al., 1982).

## 16.2.4 STATISTICAL AND SPATIAL ANALYSES

Statistical analysis was conducted using SAS software (SAS, 1999). The statistical analysis consisted of three stages: (1) determination of the correlation between EC<sub>a</sub> and cotton yield using data from the sixty sites, (2) exploratory statistical analysis to identify the significant soil properties influencing cotton yield, and (3) development of a crop yield response model based on ordinary least squares regression (OLS) adjusted for spatial autocorrelation with restricted maximum likelihood. Because the location of EC<sub>a</sub> and cotton yield measurements did not exactly overlap, ordinary kriging was used to determine the expected cotton yield at the sixty sites.

Spatial analysis was accomplished with a geographic information system (GIS). The commercial GIS software ArcView 3.3 (ESRI 2002) was used to compile, manipulate, organize, and display all spatial data. Delineation of SSMUs was accomplished using the GIS, exploratory statistical analyses, and crop yield response model adjusted for spatial autocorrelation.

### 16.3 RESULTS AND DISCUSSION

# 16.3.1 CORRELATION BETWEEN CROP YIELD AND EC.

The correlation of EC<sub>a</sub> to yield at the sixty sites was 0.51. The moderate correlation between yield and EC<sub>a</sub> suggests that some soil properties influencing EC<sub>a</sub> measurements may also influence cotton yield, making an EC<sub>a</sub>-directed soil sampling strategy a potentially viable approach at this site. The

similarity of the spatial distributions of EC<sub>a</sub> measurements and cotton yield in Figure 16.1 visually confirms their close relationship.

## 16.3.2 EXPLORATORY STATISTICAL ANALYSIS

Exploratory statistical analysis was conducted to determine the significant soil properties influencing cotton yield and to establish the general form of the cotton yield response model. The exploratory statistical analysis consisted of three stages: (1) a preliminary multiple linear regression (MLR) analysis, (2) a correlation analysis, and (3) scatter plots of yield versus potentially significant soil properties. Both preliminary MLR and correlation analysis showed that the 0 to 1.5 m soil depth increment resulted in the best correlations and best fit of the data; consequently, the 0 to 1.5 depth increment was considered to correspond to the active root zone. Preliminary MLR analysis indicated that the following soil properties were most significantly related to cotton yield: EC, LF, pH, percentage clay,  $\theta_e$ , and  $\rho_b$ . Table 16.1 reveals that the correlation coefficients between EC<sub>a</sub> and  $\theta_{g}$ , EC<sub>e</sub>, B, percentage clay,  $\rho_{b}$ , Cl<sup>-</sup>, LF, and SP were significant at the 0.01 level. The correlation coefficients were 0.79, 0.87, 0.88, 0.76, -0.38, 0.61, -0.50, and 0.77, respectively, indicating high correlations between EC<sub>a</sub> and the properties of  $\theta_e$ , EC<sub>e</sub>, B, percentage clay, and SP. However, B is a property not measured by EC<sub>a</sub>. Rather, the high correlation of B to EC<sub>a</sub> is an artifact due to its close correspondence to salinity (i.e., EC<sub>e</sub>) stemming from the leaching process. The high correlation of EC, to both percentage clay and SP is expected because it reflects the influence of texture on the EC, reading. So, in this particular field, EC<sub>a</sub> is highly correlated with salinity,  $\theta_g$ , and texture. Table 16.1 also indicates the correlation between cotton yield and soil properties, with the highest correlation occurring with salinity (ECe).

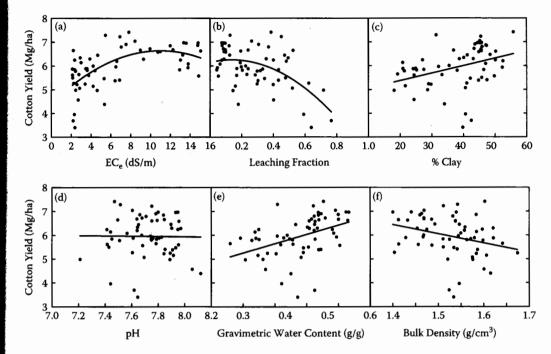
TABLE 16.1
Simple Correlation Coefficients between EC<sub>a</sub> and Soil Properties and between Cotton Yield and Soil Properties

Soil Property <sup>a</sup>	Fixed Array ECab	Cotton Yield <sup>c</sup>
$\theta_{\mathbf{g}}$	0.79**	0.42**
EC <sub>e</sub>	0.87**	0.53**
В	0.88**	0.50**
pН	0.33*	-0.01
% clay	0.76**	0.36*
$\rho_{b}$	-0.38**	-0.29*
NO₃-N	0.22	-0.03
Cl-	0.61**	0.25*
LF	-0.50**	-0.49**
SP	0.77**	0.38*

Notes: \* Significant at the P < 0.05 level; \*\* significant at the P < 0.01 level.  $\theta_g$  = gravimetric water content;  $EC_e$  = electrical conductivity of the saturation extract (dS m<sup>-1</sup>); LF = leaching fraction; SP = saturation percentage.

- a Properties averaged over 0 to 1.5 m.
- b Pearson correlation coefficients based on sixty observations.
- c Pearson correlation coefficients based on fifty-nine observations.

Source: Modified from Corwin, D.L., Lesch, S.M., Shouse, P.J., Soppe, R., Ayars, J.E., Agron. J., 95, 352-364, 2003. With permission.



**FIGURE 16.2** Scatter plots of soil properties and cotton yield: (a) electrical conductivity of the saturation extract (EC<sub>e</sub>, dS m<sup>-1</sup>), (b) leaching fraction, (c) percentage clay, (d) pH, (e) gravimetric water content, and (f) bulk density (Mg m<sup>-3</sup>). (Taken from Corwin, D.L., Lesch, S.M., Shouse, P.J., Soppe, R., Ayars, J.E., *Agron. J.*, 95, 352–364, 2003. With permission.)

A scatter plot of EC<sub>e</sub> and yield indicates a quadratic relationship where yield increases and then decreases (Figure 16.2a). The scatter plot of LF and yield shows a negative, curvilinear relationship (Figure 16.2b). Yield shows a minimal response to LF below 0.4 and falls off rapidly for LF > 0.4. Clay percentage, pH,  $\theta_g$ , and  $\rho_b$  appear to be linearly related to yield to various degrees (Figure 16.2c through Figure 16.2f, respectively). Even though there was clearly no correlation between yield and pH (r = -0.01; see Figure 16.2d), pH became significant in the presence of the other variables, which became apparent in both the preliminary MLR analysis and in the final yield response model. Based on the exploratory statistical analysis, it became evident that the general form of the cotton yield response model was

$$Y = \beta_0 + \beta_1(EC_e) + \beta_2(EC_e)^2 + \beta_3(LF)^2 + \beta_4(pH) + \beta_5(\% \text{ clay}) + \beta_6(\theta_g) + \beta_7(\rho_b) + \varepsilon$$
 (16.1)

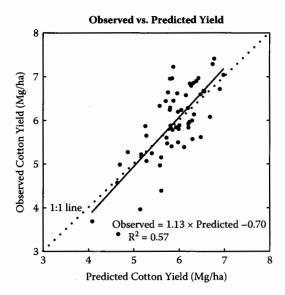
where, based on the scatter plots of Figure 16.2, the relationships between cotton yield (Y) and pH, percentage clay,  $\theta_g$ , and  $\rho_b$  are assumed linear; the relationship between yield and  $EC_e$  is assumed to be quadratic; the relationship between yield and LF is assumed to be curvilinear;  $\beta_0$ ,  $\beta_1$ ,  $\beta_2$ , ...,  $\beta_7$  are the regression model parameters; and  $\varepsilon$  represents the random error component.

## 16.3.3 CROP YIELD RESPONSE MODEL DEVELOPMENT

Ordinary least squares regression based on Equation (16.1) resulted in the following crop yield response model:

$$Y = 20.90 + 0.38(EC_e) - 0.02(EC_e)2 - 3.51(LF)2 - 2.22(pH) + 9.27(\theta_g) + \varepsilon$$
 (16.2)

where the nonsignificant t test for percentage clay and  $\rho_b$  indicated that these soil properties did not contribute to the yield predictions in a statistically meaningful manner and dropped out of the



**FIGURE 16.3** Observed versus predicted cotton yield estimates using Equation (16.3). Dotted line is a 1:1 relationship. (Taken from Corwin, D.L., Lesch, S.M., Shouse, P.J., Soppe, R., Ayars, J.E., *Agron. J.*, 95, 352–364, 2003. With permission.)

regression model, while all other parameters were significant near or below the 0.05 level. The  $R^2$  value for Equation (16.2) is 0.61, indicating that 61 percent of the estimated spatial yield variation is successfully described by Equation (16.2). However, the residual variogram plot indicates that the errors are spatially correlated, which implies that Equation (16.2) must be adjusted for spatial autocorrelation.

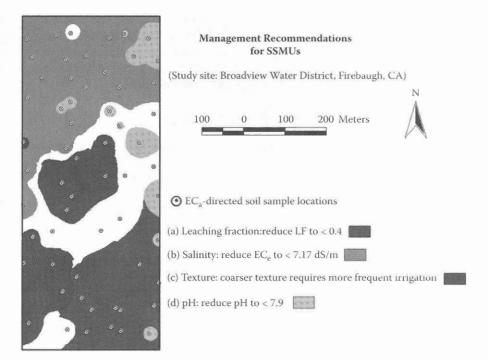
Using a restricted maximum likelihood approach to adjust for spatial autocorrelation, the most robust and parsimonious yield response model for cotton was Equation (16.3):

$$Y = 19.28 + 0.22(EC_e) - 0.02(EC_e)^2 - 4.42(LF)^2 - 1.99(pH) + 6.93(\theta_g) + \varepsilon$$
 (16.3)

Figure 16.3 shows the observed versus predicted cotton yield estimates from Equation (16.3). Figure 16.3 suggests that the estimated regression relationship has been reasonably successful at reproducing the predicted yield estimates with an  $R^2$  value of 0.57. Sensitivity analysis reveals that LF is the most significant factor influencing cotton yield with the degree of predicted yield sensitivity to one standard deviation change resulting in a percentage yield reduction for EC<sub>e</sub>, LF, pH, and  $\theta_g$  of 4.6, 9.6, 5.8, and 5.1 percent, respectively. The point of maximum yield with respect to salinity is calculated by setting the first partial derivative of Equation (16.3) to zero with respect to EC<sub>e</sub>, which results in a value of 7.17 dS m<sup>-1</sup>, which is similar to the salinity threshold for cotton of 7.7 dS m<sup>-1</sup> reported by Maas and Hoffman (1977).

### 16.4 DELINEATED SITE-SPECIFIC MANAGEMENT UNITS

From Equation (16.3) and scatter plots of cotton yield versus properties (Figure 16.2), management recommendations were made that spatially prescribed what could be done to increase cotton yield at those locations with less than optimal yield. Four recommendations can be made to improve cotton productivity at the study site: (1) reduce the LF in highly leached areas (i.e., areas where LF > 0.5), (2) reduce salinity by increased leaching in areas where the average root zone (0 to 1.5 m) salinity is >7.17 dS m<sup>-1</sup>, (3) increase the plant-available water in coarse-texture areas by more frequent irrigation, and (4) reduce the pH where pH > 7.9.



**FIGURE 16.4** Site-specific management units for a 32.4 ha cotton field in the Broadview Water District of central California's San Joaquin Valley. Recommendations are associated with the SSMUs for (a) leaching fraction, (b) salinity, (c) texture, and (d) pH. (Taken from Corwin, D.L., Lesch, S.M., *Comput. Electron. Agric.* 46(1–3), 11–43, 2005a.)

Subsequently, Corwin and Lesch (2005a) delineated SSMUs, which are depicted in Figure 16.4. Figure 16.4 indicates the areas pertinent to the above recommendations. All four recommendations can be accomplished by improving water application timing and distribution with variable-rate irrigation technology (Evans, 1997; Perry et al., 2003) and by the precision application of soil amendments. Highly leached zones were delineated where the LF needed to be reduced to <0.5; high-salinity areas were defined where the salinity needed to be reduced below the salinity threshold for cotton, which was established from Equation (16.3) to be  $EC_e = 7.17$  dS m<sup>-1</sup> for this field; areas of coarse texture were defined that needed more frequent irrigations; and areas were pinpointed where the pH needed to be lowered below a pH of 8 with a soil amendment such as OM. This work brought an added dimension because it delineated within-field units where associated site-specific management recommendations would optimize the yield, but it still falls short of integrating meteorological, economic, and environmental impacts on within-field crop-yield variation. Furthermore, these SSMUs have not been tested to evaluate whether their use would actually increase yield.

In instances where crop yield correlates with EC<sub>a</sub>, the spatial distribution of EC<sub>a</sub> provides a means of directing soil sampling to determine edaphic properties influencing yield. This information provides a basis for delineating SSMUs. The method for delineating SSMUs consists of the following general steps: (1) intensive yield monitoring and EC<sub>a</sub> survey; (2) EC<sub>a</sub>-directed soil sampling; (3) statistical analyses to determine the correlation between EC<sub>a</sub>-directed soil sampling and crop yield, to identify the significant soil properties influencing crop yield, and to develop a crop yield response model adjusted for spatial autocorrelation; and (4) use of GIS to define SSMUs based on scatter plots and crop yield response model.

Even though EC<sub>a</sub>-directed soil sampling provides a viable means of identifying some soil properties that influence within-field variation of yield, it is only one piece of a complicated puzzle of interacting factors that result in observed within-field crop variation. Crop yield is influenced by

complex interactions of meteorological, biological, anthropogenic, topographic, and edaphic factors. Furthermore, SSM requires more than just a myopic look at crop productivity. It must balance sustainability, profitability, crop productivity and quality, optimization of inputs, and minimization of environmental impacts. Nevertheless, the presented approach is a step forward because it provides spatial information for use in site-specific soil and crop management.

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