July 2008
Volume 13, Number 2
www.eegs.org

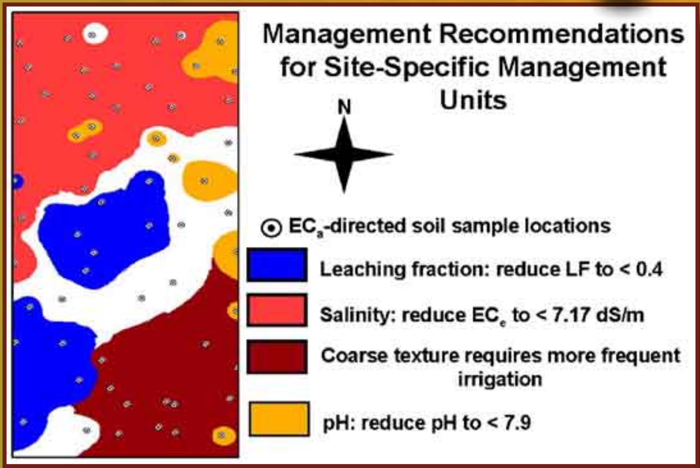
FastTIMES

News for the Near-Surface Geophysical Sciences
Published by the Environmental & Engineering Geophysical Society

ER electrode close-up

Four-electrode ER system

Geophysics and Precision Agriculture



Electrical properties guide cropland management decisions

Recommendation map

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. . . and more!

Non-polarizing electrode

FastTIMES welcomes short articles on applications of geophysics to near-surface engineering or environmental problems. In the article below, Dennis Corwin and Scott Lesch provide a glimpse into the world of precision agriculture, where differences in soil electrical properties can have significant implications for field management and crop yield.

Application of Geo-referenced Geophysical Measurements to Precision Agriculture

by Dennis L. Corwin[1] and Scott M. Lesch[2]
[1]USDA-ARS, U.S. Salinity Laboratory, 450 West Big Springs Road, Riverside, California (Dennis.Corwin@ars.usda.gov)
[2]Department of Environmental Sciences, University of California, Riverside, California (Scott.Lesch@ars.usda.gov)

Introduction

Conventional agriculture treats an entire field uniformly with respect to the application of fertilizer, pesticides, soil amendments, and other inputs. However, soil is spatially heterogeneous, with most soil chemical and physical properties varying significantly within just a meter. Soil spatial heterogeneity is one of several factors that cause within-field variation in crop yield. Other spatially and/or temporally variable factors influencing within-field variation in crop yield include anthropogenic (for example, irrigation management and compaction due to equipment), biological (for example, disease and pests), meteorological (for example, humidity, rainfall, and wind), and topographical (for example, slope and aspect) factors. The inability of conventional farming to address within-field variations in these factors not only has a detrimental economic impact due to reduced yield in certain areas of a field, but also detrimentally impacts the environment due to over applications of agrochemicals and wastes finite resources, such as pesticides, fertilizers, and irrigation water.

Site-specific crop management refers to the application of precision agriculture to crop production. Site-specific crop management has been proposed as a means of managing the spatial variability of edaphic (soil related), anthropogenic, topographical, biological, and meteorological factors that influence crop yield with the aim of increasing profitability, increasing crop productivity, sustaining the soil-plant environment, optimizing inputs, and/or minimizing detrimental environmental impacts. A fundamental aspect of site-specific crop management is the delineation of site-specific management units (SSMUs), which are spatial domains of soil that can be managed similarly to optimize yield by accounting for spatial variability. The spatial variability of edaphic factors is a consequence of pedogenic and anthropogenic influences, which produce variation in soil physical and chemical properties within agricultural fields. A variety of soil physical and chemical properties are known to influence crop productivity, including plant-available water; infiltration; permeability; soil texture and structure; soil depth; restrictive soil layers; organic matter; chemical constituents such as fertilizers, pesticides, trace elements, and toxic ions; meteorology; and landscape features such as microelevation and topography (Black, 1968; Thornley and Johnson, 1990; Hanks and Ritchie, 1991; Tanji, 1996). In the arid southwestern USA the primary soil properties influencing crop yield are salinity, soil texture and structure, plant-available water, trace elements (particularly boron), nutrient deficiency, and ion toxicity from Na^+ and Cl^- (Tanji, 1996).

Bullock and Bullock (2000) indicate that efficient methods for accurately measuring within-field variations in soil physical and chemical properties are important for site-specific crop management. Because apparent soil electrical conductivity (EC_a) is influenced by a variety of soil physical and chemical properties (for example, salinity, water content, texture, bulk density, organic matter, and temperature) often related to yield and is a reliable easy-to-take measurement, geospatial measurements of EC_a have become one of the most frequently used measurements to characterize field variability for agricultural applications (Corwin and Lesch, 2003). Spatial measurements of EC_a have been used to characterize soil salinity, nutrients (for example, NO_3^-), water content, texture, bulk density, leaching, and organic matter (see review paper by Corwin and Lesch, 2005a).

Geo-referenced EC_a measurements have been correlated to associated yield-monitoring data with mixed results (Jaynes and others, 1993; Sudduth and others, 1995; Kitchen and others, 1999; Johnson and others, 2003; Corwin and others, 2003). 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 (for example, salinity and water content) that are being measured by EC_a, which may or may not influence yield within a particular field, and because a temporal component of yield variability is poorly captured by a state variable such as EC_a.

Geospatial measurements of EC_a are a powerful tool in site-specific management when combined with GIS, spatial statistics, and crop-yield monitoring. 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 is to integrate spatial statistics, GIS, EC_a-directed soil sampling, and a crop-yield response model (i) to identify edaphic properties that influence cotton yield and (ii) to use this spatial information to delineate SSMUs with associated management recommendations for irrigated cotton. This article summarizes the previous work conducted and published by Corwin and colleagues (Corwin and Lesch, 2003, 2005b; Corwin and others, 2003).

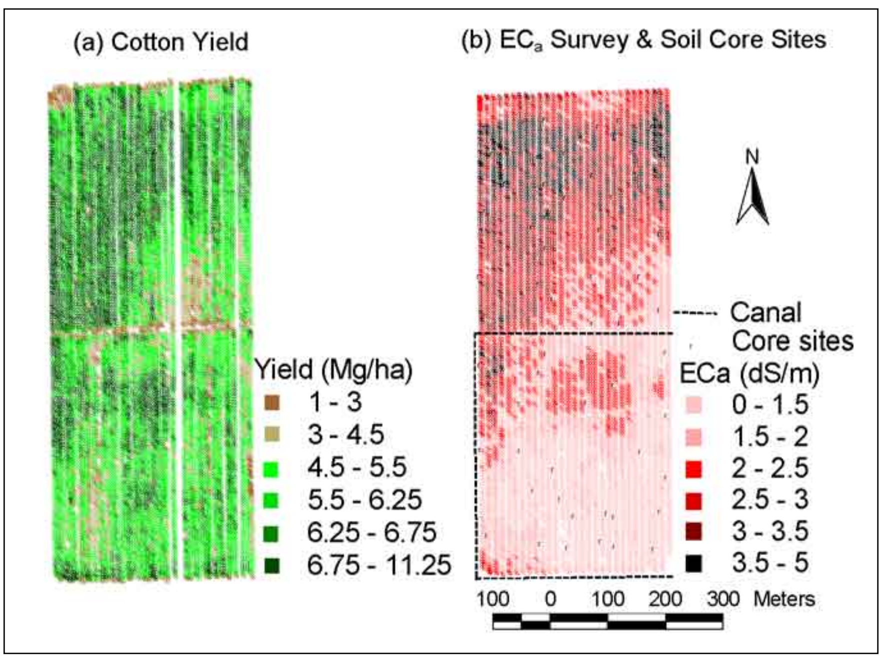

Figure 1. Maps of (a) cotton yield and (b) EC_a measurements including the locations of the 60 soil core sites. Modified from Corwin and others (2003), with permission.

Approach

A 32.4-ha field located in the Broadview Water District on the west side of California's San Joaquin Valley was used as the study site. Broadview Water District is located approximately 100 km west of Fresno, California. The soil at the site is slightly alkaline and has good surface and subsurface drainage (Harradine, 1950). The subsoil is thick, friable, calcareous, and easily penetrated by roots and water.

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). A total of 7706 cotton yield readings were collected (Figure 1a). Each yield observation represented a total area of approximately 42 m^2. From August 1999 to April 2000 the field was fallow.

In March 2000 an intensive EC_a survey (Figure 1b) was collected using mobile fixed-array electrical resistivity (ER, Figure 2) and mobile electromagnetic induction (EMI, Figure 3) equipment developed by Rhoades and colleagues at the U. S. Salinity Laboratory (Rhoades, 1992a, 1992b; Carter and others, 1993).

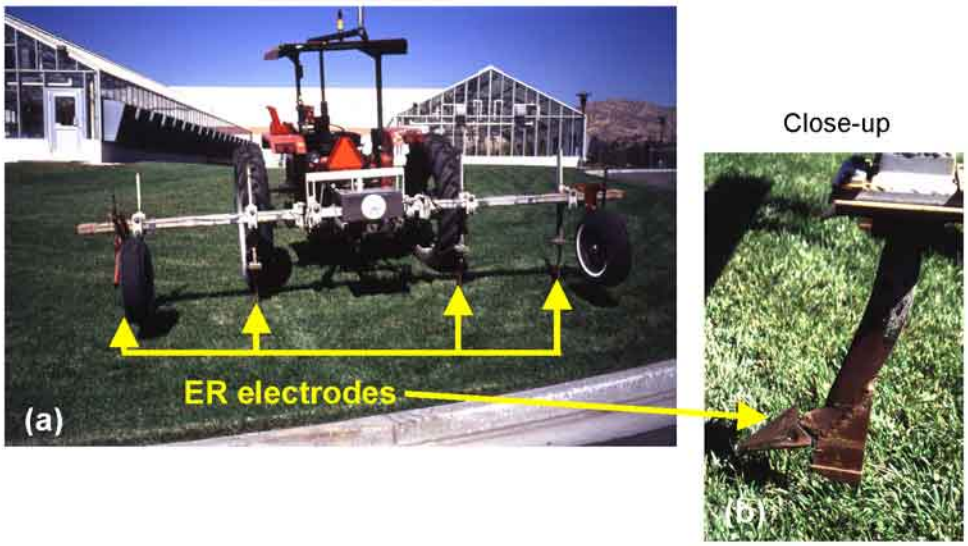

Figure 2. Mobile GPS-based electrical resistivity (ER) equipment showing (a) fixed-array tool bar holding four ER electrodes and (b) a close-up of one of the ER electrodes.

Figure 3. Mobile GPS-based electromagnetic induction (EMI) equipment showing (a) a side view of the entire rig and (b) a close-up of the sled holding the EMI unit.

The methods and materials used in the EC_a survey were those subsequently published as a set of guidelines and protocols by Corwin and Lesch (2003, 2005b). The fixed-array ER electrodes were spaced to measure EC_a to a depth of 1.5 m. Over 4000 EC_a measurements were collected (Figure 2b).

Following the EC_a survey, soil samples were collected at 60 locations. The data from the EC_a survey were used to direct the selection of soil sample sites. The ESAP-95 version 2.01 software package developed by Lesch and others (1995a, 1995b, 2000) at the U. S. Salinity Laboratory was used to establish the locations where soil cores were taken based on the EC_a survey data. The software used a model-based response-surface sampling strategy to locate the 60 sites. These sites reflected the observed spatial variability in EC_a while simultaneously maximizing the spatial uniformity of the sampling design across the study area. Figure 1b visually displays the distribution of EC_a survey data in relation to the locations of the 60 core sites. Soil core samples were taken at each site at 0.3-m increments to a depth of 1.8 m: 0-0.3, 0.3-0.6, 0.6-0.9, 0.9-1.2, 1.2-1.5, and 1.5-1.8 m. The soil samples were analyzed for pH, boron (B), nitrate nitrogen (NO_3-N), Cl^-, salinity (EC_e), leaching fraction (LF; defined as the fraction of applied water at the soil surface that drains beyond the root zone), gravimetric water content (θ_g), bulk density (ρ_b), % clay, and saturation percentage (SP). All samples were stored and analyzed for physical and chemical properties following the methods outlined in Agronomy Monograph No. 9 Part 1 (Blake and Hartage, 1986) and Part 2 (Page and others, 1982).

Statistical analyses were conducted using SAS software (SAS Institute, 1999). The statistical analyses consisted of three stages: (i) determination of the correlation between EC_a and cotton yield using data from the 60 sites, (ii) exploratory statistical analysis to identify the significant soil properties influencing cotton yield, and (iii) development of a crop-yield response model based on ordinary least squares regression adjusted for spatial autocorrelation with restricted maximum likelihood.

Because the location of EC_a and cotton yield measurements did not exactly overlap, ordinary kriging was used to determine the expected cotton yield at the 60 sites. The spatial correlation structure of yield was modeled with an isotropic variogram. The following fitted exponential variogram was used to describe the spatial structure at the study site:

$$v(\delta) = (0.76)^2 + (1.08)^2 [1 - \exp(-D/109.3)] \quad [1]$$

where D is the lag distance.

All spatial data were compiled, organized, manipulated, and displayed within a geographic information system (GIS). Kriging was selected as the preferred method of interpolation because in all cases it outperformed inverse distance weighting based on comparisons using jackknifing.

Correlation between Cotton Yield and EC_a

The fitted variogram model (Eq. [1]) was used in an ordinary kriging approach to estimate cotton yield at the 60 sites. The correlation of EC_a to yield at the 60 sites was 0.51. The moderate correlation between yield and EC_a suggests that some soil property(ies) influencing EC_a measurements also influence cotton yield making an EC_a-directed soil sampling strategy a viable approach at this site. The similarity of the spatial distributions of EC_a measurements and cotton yield in Figure 1 visually confirms the reasonably close relationship of EC_a to yield (R^2=0.51).

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: (i) a preliminary multiple linear regression (MLR) analysis, (ii) a correlation analysis, and (iii) scatter plots of yield versus potentially significant soil properties. The preliminary multiple linear regression analysis and correlation analysis were used to establish the significant soil properties influencing cotton yield, while the scatter plots were used to formulate the general form of the cotton yield response model. Both preliminary MLR and correlation analysis showed that the 0-1.5 m depth increment resulted in the best correlations and best fit of the data; consequently, the 0-1.5 depth increment was considered to correspond to the active root zone.

The preliminary MLR analysis indicated that the following soil properties were most significantly related to cotton yield: EC_e, LF, pH, % clay, θ_g, and ρ_b. The correlation between cotton yield and soil properties indicated the highest correlation occurred with salinity (EC_e).

A scatter plot of ECe and yield indicates a quadratic relationship where yield increases up to a salinity of 7.17 dS/m and then decreases (Figure 4a). The scatter plot of LF and yield shows a negative, curvilinear relationship (Figure 4b). Yield shows a minimal response to LF below 0.4 and falls off rapidly for LF > 0.4. Clay percentage, pH, θ_g, and ρ_b appear to be linearly related to yield to various degrees (Figures 4c, 4d, 4e, and 4f, respectively). Even though there was clearly no correlation between yield and pH (r = -0.01; Figure 4d), pH became significant in the presence of the other variables, which became apparent in both the preliminary multiple linear regression analysis and in the final yield response model.

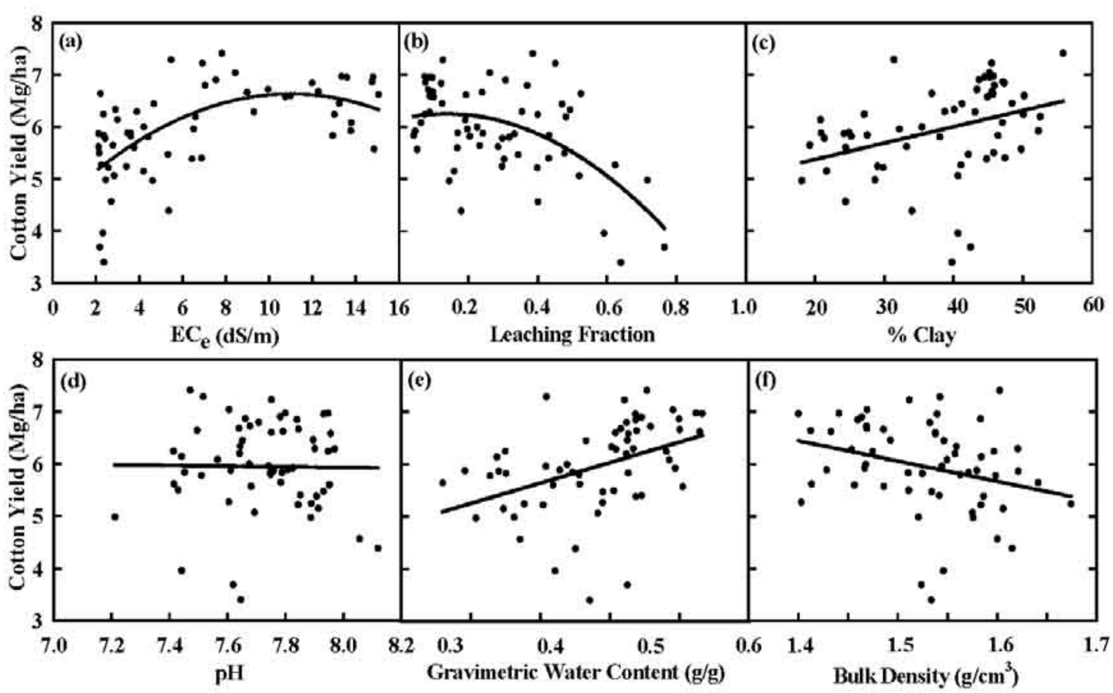

Figure 4. Scatter plots of soil properties and cotton yield: (a) electrical conductivity of the saturation extract (EC_e, dS/m), (b) leaching fraction, (c) percentage clay, (d) pH, (e) gravimetric water content, and (f) bulk density (Mg/m^3). From Corwin and others (2003), with permission.

Based on the exploratory statistical analysis it became evident that the general form of the cotton yield response model was:

$$Y = \beta_0 + \beta_1(EC_e) + \beta_2(EC_e)^2 + \beta_3(LF)^2 + \beta_4(pH) + \beta_5(\%\ clay) + \beta_6(\theta_g) + \beta_7(\rho_b) + \varepsilon \qquad [2]$$

where, based on the scatter plots of Figure 4, the relationships between cotton yield (Y) and pH, percentage clay, θ_g, and ρ_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; β_0, β_1, β_2, . . . , β_7 are the regression model parameters; and *e* represents the random error component.

Cotton Yield Response Model Development

Ordinary least squares regression based on Eq. [2] resulted in the following response model:

$$Y = 20.90 + 0.38(EC_e) - 0.02(EC_e)^2 - 3.51(LF)^2 - 2.22(pH) + 9.27(\theta_g) + \varepsilon \qquad [3]$$

where the non-significant t test for % clay and ρ_b indicated that these soil properties did not contribute to the yield predictions in a statistically meaningful manner and dropped out of the regression model, while all other parameters were significant near or below the 0.05 level. The R^2 value for Eq. [3] is 0.61, indicating that 61% of the estimated spatial yield variation is successfully described by Eq. [3]. However, the residual variogram plot indicates that the errors are spatially correlated, which implies that Eq. [3] 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 Eq. (4):

$$Y = 19.28 + 0.22(EC_e) - 0.02(EC_e)^2 - 4.42(LF)^2 - 1.99(pH) + 6.93(\theta_g) + \varepsilon \qquad [4]$$

A comparison of measured and simulated cotton yields at the locations where EC_a-directed soil samples were taken showed close agreement, with a slope of 1.13, *y*-intercept of -0.70, and R^2 value of 0.57.

A visual comparison of the measured and simulated spatial yield distributions of cotton shows a spatial association between interpolated measured (Figure 5b) and predicted (Figure 5c) maps.

Sensitivity analysis reveals that LF is the single 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 ECe, LF, pH, and θ_g of 4.6%, 9.6%, 5.8%, and 5.1%, respectively.

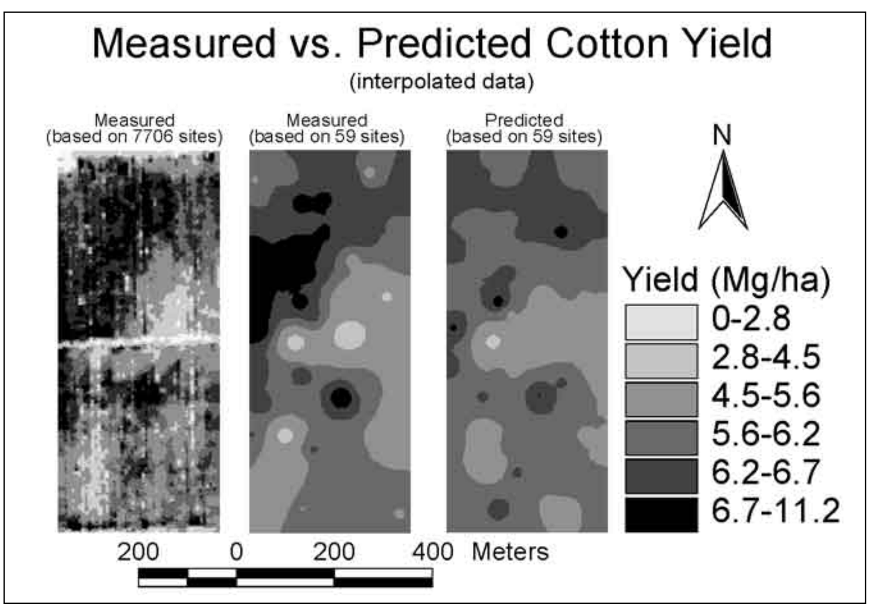

Figure 5. Comparison of (a) measured cotton yield based on 7706 yield measurements, (b) kriged data at 59 sites for measured cotton yield, and (c) kriged data at 59 sites for predicted cotton yields based on Eq. [4]. From Corwin and others (2003), with permission.

Conclusions

Based on Eq. [4], Figure 4, and knowledge of the interaction of the significant factors influencing cotton yield in the Broadview Water District, four recommendations can be made to improve cotton productivity at the study site:

1. reduce the LF in highly leached areas (areas where LF > 0.5),
2. reduce salinity by increased leaching in areas where the average root zone (0-1.5 m) salinity is > 7.17 dS/m,
3. increase the plant-available water in coarse-texture areas by more frequent irrigation, and
4. reduce the pH where pH > 7.9.

Figure 6 indicates the areas pertaining to the above recommendations. All four recommendations can be accomplished by improving water application scheduling and distribution and by site-specific application of soil amendments. The use of variable-rate irrigation technology at this site would enable the site-specific application of irrigation water at the times and locations needed to optimize yield.

Hypothetically, when crop yield correlates with EC_a, then spatial distributions of EC_a provide a means of determining edaphic properties that influence yield. This hypothesis was evaluated and found to hold true. A yield map could potentially provide the same capability as an EC_a map, but an EC_a map provides information specific to the spatial distribution of edaphic properties, whereas a yield map reflects the influence of numerous additional factors.

Even though EC_a-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 interac-

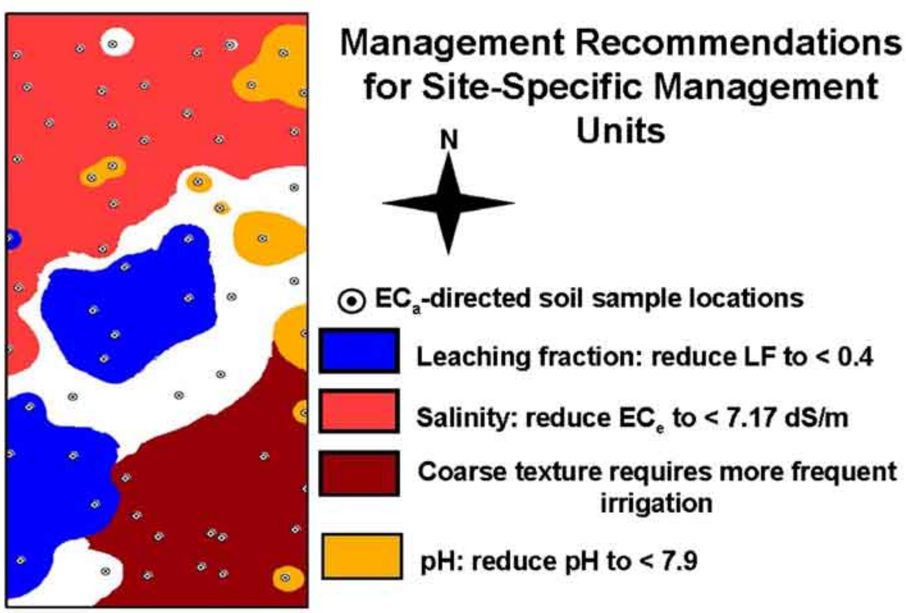

Figure 6. Site-specific management units for a 32.4-ha cotton field in the Broadview Water District of central California's San Joaquin Valley. Recommendations are associated with the SSMUs for (a) leaching fraction, (b) salinity, (c) texture, and (d) pH. From Corwin and Lesch (2005a), with permission.

tions of meteorological (for example, temperature, humidity, and wind), biological (for example, pests and earthworms), anthropogenic (management related), and edaphic (for example, salinity, soil pH, and water content) factors. Furthermore, precision agriculture requires more than just a myopic look at crop productivity. It must balance sustainability, profitability, crop productivity, optimization of inputs, and minimization of environmental impacts. Nevertheless, the presented approach is a step forward that provides valuable spatial information for use in site-specific crop management.

Acknowledgments

The authors acknowledge the assistance of Peter Shouse, Richard Soppe, and Jim Ayars. The authors also acknowledge the exemplary work of Jack Jobes and JoAn Fargerlund, who performed the field soil sample collection and laboratory analyses, respectively.

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