Chapter 6
Delineating Site-Specific Management Units with Proximal Sensors

D.L. Corwin and S.M. Lesch

Abstract Conventional farming manages fields uniformly with no consideration for spatial variation. This causes reduced productivity, misuse of finite resources (e.g. water and fertilizers) and detrimental impacts on the environment. Site-specific management units (SSMUs) have been proposed as a way of resolving the spatial variation of various factors (i.e. soil, climate, management, pests, etc.) that affect variation in crop yield. Mobile proximal sensors, such as those used to measure apparent soil electrical conductivity (EC_a), can be used to characterize the spatial variation of soil properties that affect crop yield. This Chapter provides an overview of the work by the authors that has led to the delineation of SSMUs based on edaphic and anthropogenic properties, with particular emphasis given to the geostatistical techniques needed to direct soil sampling to characterize the spatial variation. The approach uses geospatial proximal sensor measurements to locate the positions of soil samples to characterize the variation in soil properties that affect crop yield within a field. A crop yield response model is developed and maps of SSMUs based on soil and crop yield information are produced. The methodology for delineating SSMUs can be used whenever the proximal sensor measurements correlate with yield. Maps of SSMUs provide the vital information for variable-rate technology (e.g. site-specific fertilizer and irrigation water application).

Keywords Soil salinity · Apparent electrical conductivity (ECa) · ECa-directed sampling · Response surface sampling design · Electromagnetic induction · Electrical resistivity

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6.1 Introduction

6.1.1 The Need for Site-Specific Management

Tremendous strides have been made to expand the world's supply of food. Even though the world population has doubled over this time period, food production has risen even faster with per capita food supplies increasing from less than 2000 calories per day in 1962 to more than 2500 calories in 1995 (World Resources Institute 1998). The rise in global food production has been credited to better seeds, expanded irrigation, and greater fertilizer and pesticide use, commonly referred to as the Green Revolution. However, the prospect of feeding a projected additional 3 billion people over the next 30 years poses more challenges than have been encountered in the past 30 years. In the short term, global resource experts predict that there will be adequate global food supplies, but the distribution of those supplies to malnourished people will be the primary problem. Longer term, however, the obstacles become more formidable, though not insurmountable. Although total yields continue to rise on a global basis, there is a disturbing decline in the growth of yield with some major crops such as wheat and maize reaching a 'yield plateau' (World Resources Institute 1998).

Sustainable agriculture is viewed as the most viable means of meeting the food demands of the projected world's population, barring unexpected technological breakthroughs. The concept of sustainable agriculture is predicated on a delicate balance of maximizing crop productivity to keep pace with population growth and maintaining economic stability while minimizing the use of finite natural resources (e.g. water, fertilizers and pesticides) and the detrimental environmental impacts of associated agrichemical pollutants. Arguably, the most promising approach for attaining sustainable agriculture is precision agriculture or site-specific crop management.

Site-specific crop management, or more specifically site-specific management (SSM) attempts to manage the soil, pests and crops based upon spatial variation within a field (Larson and Robert 1991), whereas conventional farming treats a field uniformly, ignoring the naturally inherent variability of soil and crop conditions between and within fields. There is well-documented evidence that spatial variation within a field is highly significant and amounts to a factor of 3–4 or more for crops (Birrel et al. 1995; Verhagen et al. 1995) and up to an order of magnitude or more for soil (Corwin et al. 2003a). Specifically, SSM is the management of agricultural crops at a spatial scale smaller than the whole field that takes account of local variation to cost effectively balance crop productivity and quality, detrimental environmental impacts and the use of resources (e.g. water, fertilizer, pesticides, etc.) by applying them when, where and in the amount needed. Spatial variation in crops is the result of a complex interaction of biological (e.g. pests, earthworms, microbes), edaphic (e.g. salinity, organic matter, nutrients, texture), anthropogenic (e.g. leaching efficiency, soil compaction due to farm equipment), topographic (e.g. slope, elevation) and climatic (e.g. relative humidity, temperature, rainfall) factors.

6.1.2 Definition of Site-Specific Management Unit (SSMU)

Site-specific management units (SSMUs) have been proposed as a means of dealing with the spatial variation of edaphic (i.e. soil related) properties that affect crop productivity (or quality) to achieve the goals of SSM. A SSMU is simply a mapped unit within a field that could be based on soil properties, landscape units, past yield, etc. that is managed to achieve the goals of SSM. To manage within-field variation site-specifically, geo-referenced areas (or units) that are similar with respect to a specified characteristic must be identified (van Uffelen et al. 1997). Ideally, a site-specific management unit (SSMU) will account for the spatial variation of all factors that affect variation in crop yield, including edaphic, meteorological, biological, anthropogenic and topographic factors. To achieve this, the delineation of SSMUs would be extremely complicated because all these must be considered. One means of simplifying the complexity is to delineate SSMUs based on a single factor, such as edaphic properties, and determine the extent of variation in yield related to this factor.

The extent and conditions under which these spatial patterns are stable should also be established. Yield maps provide information on the integrated effects of the physical, chemical, and biological processes under certain weather conditions (van Uffelen et al. 1997), and the spatial patterns of crop productivity provide a basis for implementing SSM by indicating where varying crop inputs are needed (Long 1998). However, the inputs required to optimize crop productivity and minimize impacts on the environment can be determined only if the factors that gave rise to the observed spatial crop patterns are known (Long 1998). Yield maps alone cannot provide information to distinguish between the various sources of variation and cannot give clear guidelines for management without information on the effects of variation in weather, pests and diseases, and soil physical and chemical properties on the variability of a crop for a particular year (van Uffelen et al. 1997). Each factor that affects within-field variation in yield needs to be characterized spatially to be able to manage a crop on a site-specific basis. The spatial characterization of these factors can be achieved with spatial measurements from a spectrum of proximal sensors.

6.1.3 Proximal Sensors

Ground-based proximal sensors generally include sensors that take measurements from within a distance of 2 m from the soil surface. They may take measurements of the soil, such as electrical, electromagnetic or radiometric sensors, or of plants, such as crop yield or spectral sensors. Adamchuk et al. (2004) reviewed on-the-go proximal soil sensors for precision agriculture and Barnes et al. (2003) provided a concise review of ground-based sensor techniques as well as remote imagery sensors for mapping soil properties.

According to Adamchuk et al. (2004), proximal sensors fall into six main categories: electrical and electromagnetic, optical and radiometric, mechanical, acoustic,

Table 6.1 Selected recent references using proximal soil sensors to map soil properties for applications in precision agriculture. Modification of tables from Adamchuk et al. (2004)

Category of proximal sensor	Review article	Sensor	Technical reference
Electrical and EMI	Corwin and Lesch (2005a)	ER	Corwin and Lesch (2003)
		EMI	Corwin and Lesch (2005b,c)
		Capacitance	Andrade et al. (2001)
Optical	Ben-Dor et al. (2009)[a]	Single wavelength	Shonk et al. (1991)
		Multi- or Hyperspectral	Maleki et al. (2008), Mouazen et al. (2007)
Radiometric	Huisman et al. (2003)	GPR	Lunt et al. (2005)
		Microwave	Whalley and Bull (1991)
Mechanical	Hemmat and Adamchuk (2008)	Draft	Ehrhardt et al. (2001), Mouazen and Roman (2006)
		Load cells and penetrometers	Chung et al. (2003), Verschoore et al. (2003)
Acoustic and pneumatic		Microphone	Liu et al. (1993)
		Air pressure transducer	Clement and Stombaugh (2000)
Electrochemical		ISFET	Birrell and Hummel (2001), Viscarra Rossel and Walter (2004)
		ISE	Adamchuk et al. (2005), Sethuramasamyraja et al. (2008)

EMI, electromagnetic induction; ER, electrical resistivity; GPR, ground penetrating radar; ISFET, ion-selective field effect transistor; ISE, ion-selective electrode.
[a]Review includes remote and proximal sensors.

pneumatic and electrochemical. Several studies have been conducted using proximal sensors with just a few of the more current ones listed in Table 6.1. The output from each sensor is typically affected by more than one agronomic soil property. Table 6.2 outlines the soil properties influencing each category of proximal sensor.

Electrical and electromagnetic sensors include electrical resistivity (ER), electromagnetic induction (EMI), time domain reflectometry (TDR) and capacitance sensors. The most commonly used for field-scale on-the-go measurements are ER and EMI (Corwin and Lesch 2005a). Electrical resistivity and EMI measure the electrical conductivity of the bulk soil, which is referred to as the apparent soil electrical conductivity (EC_a). Corwin and Lesch (2005a) have provided a review of EC_a measurements in agriculture. Apparent soil electrical conductivity is affected by a variety of soil properties including salinity, texture, water content, organic matter, cation exchange capacity (CEC) and bulk density (Corwin and Lesch

Table 6.2 Soil properties that influence proximal sensors. Modified from Adamchuk et al. (2004)

Category of proximal sensor	Agronomic soil property									
	Texture (sand, silt, clay content)	OM	θ	EC or Na	Cp or ρ_b	Depth of topsoil or hard pan	pH	Residual NO_3 or total N	Other macro-nutrients	CEC
Electrical and EMI	X	X	X	X	X	X		X		X
Optical and radiometric	X	X	X				X	X		X
Mechanical					X	X				
Acoustic and pneumatic	X				X	X				
Electrochemical				X			X	X	X	

EMI, electromagnetic induction; OM, soil organic matter; θ, water content; EC, electrical conductivity (salinity); Na, sodium content; Cp, compaction; ρ_b, bulk density; CEC, cation exchange capacity.

2005a). Capacitance sensors and TDR use the dielectric constant or relative permittivity to infer the volumetric water content. There are commercially available on-the-go ER (e.g. Veris 3100) and EMI units (e.g. Geonics EM38-MK2).

Optical sensors comprise single wavelength and hyperspectral reflectance sensors, whereas radiometric sensors include microwave sensors and ground penetrating radar (GPR). Like electrical and electromagnetic sensors, optical and radiometric sensors are frequently influenced by a variety of soil properties (see Table 6.2). However, there is a potential advantage of optical and radiometric measurements in that the response in different parts of the spectral range may be affected to varying degrees by different soil properties, enabling the separation of effects (Adamchuk et al. 2004). As indicated by Baumgardner et al. (1985), soil reflectance is influenced by a variety of properties including parent material, salts, iron oxides, organic matter, particle size, moisture and mineral composition. Radiometric sensors have been widely used to establish the spatial distribution of soil water content.

Mechanical sensors such as a strain gauge, load cell, or horizontal cone and wedge penetrometer are used to measure soil mechanical resistance or soil compaction, which in turn provides information on soil moisture, texture and bulk density. Similarly, acoustic and pneumatic sensors have been correlated to soil texture (Liu et al. 1993) and compaction (Clement and Stombaugh 2000).

Electrochemical sensors use either an ion-selective electrode (ISE) or ion-selective field effect transistor (ISFET) to provide a direct means of measuring pH or nutrient content (e.g. K^+ or NO_3^-) to evaluate soil fertility. Electrochemical sensors have the distinct disadvantage of requiring a significant amount of time for equilibrium between the sensor and the soil or soil solution.

To a varying extent from one field to the next, crop patterns are affected by edaphic properties. Bullock and Bullock (2000) indicated that efficient methods for measuring within-field variation accurately in soil physical and chemical properties are important for precision agriculture. No single sensor will measure all the soil properties that affect crop yield variation; therefore, combinations of sensors are recommended, resulting in a mobile multi-sensor platform. Of all of the proximal sensors, EMI and ER sensors are arguably the most thoroughly researched and commonly used for measuring the edaphic properties that affect crop yield (Corwin and Lesch 2003, 2005a).

6.1.4 Objective

This chapter aims to provide the general knowledge and understanding to delineate SSMUs based on edaphic and anthropogenic factors influencing crop yield that have been identified and spatially defined using geo-referenced proximal sensor data. Because the measurement of EC_a is one of the most widely used and well-understood soil measurements (Corwin and Lesch 2003, 2005a), it has been singled out in this chapter to represent ground-based proximal sensors. However, the methodology that is described in this chapter for delineating SSMUs can be applied to any of the sensors. In addition, this chapter illustrates the use of spatial and geostatistical analysis to calibrate and interpret geo-referenced proximal sensor data.

6.2 Directed Sampling with a Proximal Sensor

6.2.1 Complexity of Proximal Sensor Measurements and the Role of Geostatistics

Numerous studies have related proximal sensors to crop yield (or quality) in a precision agriculture context. A short list of some recent proximal sensor studies associated directly with SSM includes Adamchuk et al. (2007), Yan et al. (2007a, b), Corwin et al. (2008), Vitharana et al. (2008), Morari et al. (2009), as well as those listed in Table 6.1.

Corwin and Lesch (2003) warned of the complexity of proximal sensor measurements, specifically spatial measurements of EC_a, and provided guidance for the application of EC_a to precision agriculture. However, even now some of the most recent proximal sensor studies demonstrate a lack of understanding of the complexity of proximal sensor measurements. For example, the work by Yan et al. (2007a, b) relates yield to EC_a rather than to the edaphic properties affecting the EC_a measurement that concomitantly influence crop yield (or crop quality). By basing SSMUs directly on EC_a, rather than on the properties affecting its measurement at a field site, SSMUs can be defined erroneously, in particular where more than one soil property dominates the EC_a measurement and affects crop yield or quality. In addition, basing SSMUs on EC_a rather than on the properties that affect it does not enable associated management recommendations because increases or decreases in EC_a involve changes in all the properties affecting it at a particular site.

Because proximal sensors are typically affected by more than one agronomic property (i.e. soil- or plant-related properties), spatial measurements with proximal sensors are best used to develop a sampling plan to characterize the spatial distribution of those properties that affect the sensor and that, in turn, influence crop yield (or quality). The proximal sensor directed sampling approach aims to identify sample locations that reflect the range and variability of agronomic properties that affect the sensor measurement. Apparent soil electrical conductivity is not the property that affects crop yield (or quality); rather it is the edaphic properties influencing EC_a (i.e. salinity, water content, texture, organic matter, bulk density) that directly affect crop yield (or quality). Nevertheless, information from the proximal sensor can be used to direct soil (or plant) sampling. Spatial statistics plays a crucial role in establishing the sampling locations from geo-referenced proximal sensor data from which soil (or plant) properties that directly affect yield are determined. It is these latter data that enable the delineation of SSMUs with their associated management recommendations to maximize yield (or quality).

6.2.2 Practical Consideration of Differences in Support

Differences in support are important when using proximal sensors to direct soil (or plant) sampling for site-specific management. First there is a difference in support between the proximal sensor (few m^2 or less) and yield (generally tens of m^2) measurements, and between the soil (or plant) sample volume ($0.075\,m^3$) and the proximal sensor's volume of measurement (e.g. Geonics EM38 measures roughly 1–1.5 m^3). In many respects differences in support are strongly influenced by practical considerations of resources (i.e. time, labor and cost). As a rule-of-thumb, a minimum number of samples needs to be taken at each scale to enable a comparison of local (a few metres) and field-scale variation (tens to hundreds of metres). For example, where local-scale variation is significantly less than field-scale variation sampling directed by a proximal sensor will be viable, but as the scale of local variation approaches the observed field-scale variation, the approach becomes less tenable. In other words, the proximal sensor can resolve local variation because of its support and intensity of measurement, whereas the yield monitor can resolve only the larger scale variation that occurs within fields. For the soil and plant samples, regardless of support, the variation that they resolve will depend on the intensity of sampling, which cannot be as intensive as the sensor because of practical considerations.

6.3 Delineation of SSMUs with a Proximal Sensor

6.3.1 Geostatistical Mixed Linear Model

In a typical field survey where proximal sensor readings such as EC_a are recorded, the sensor data are often used to help predict a specific, unobserved soil property. For instance, assume a dense grid of proximal sensor data has been acquired across a field and soil samples have been taken at some locations so that the data from both sources can be used to estimate a model that can predict the detailed spatial pattern of the soil property measured by or correlated with the proximal sensor measurement. Assume that the relationship between the soil property measurement and sensor data can be approximated adequately using the following geostatistical mixed linear model (Haskard et al. 2007):

$$\mathbf{y} = \mathbf{X}\beta + \eta(\mathbf{s}) + \varepsilon(\mathbf{s}), \tag{6.1}$$

where $\mathbf{y}$ represents an $(n \times 1)$ vector of observed soil property data, $\mathbf{s}$ is the corresponding vector of paired (s_x, s_y) survey location coordinates, $\mathbf{X}$ represents an $(n \times p)$ fixed data matrix that includes observed functions of sensor readings and possibly also the coordinates, $\boldsymbol{\beta}$ is a $(p \times 1)$ vector of unknown parameter estimates, $\eta(\mathbf{s})$ represents a zero mean, second-order stationary spatial Gaussian error process and $\boldsymbol{\varepsilon}(\mathbf{s})$ is a vector of jointly independent normal $(0, \sigma_n^2)$ random variables. Typical stationary spatial structures for $\eta(\mathbf{s})$ are well documented in the spatial statistical and geostatistical literature; examples in two dimensions include the isotropic and anisotropic exponential and spherical covariance structures, as well as the Matérn class of covariance functions (Cressie 1993; Wackernagel 1998; Schabenberger and Gotway 2005; Webster and Oliver 2007). Note also that the second $\boldsymbol{\varepsilon}(\mathbf{s})$ error component is usually referred to as the 'nugget' effect in geostatistics (Webster and Oliver 2007).

Equation 6.1 represents a versatile spatial linear prediction model that can incorporate various types of modelling assumptions. The deterministic component of the model ($\mathbf{X}\boldsymbol{\beta}$) can be defined to include trend surface parameters and or additional collocated soil-property measurements, in addition to various hypothesized target property and sensor relationships. As noted above, the stochastic error terms ($\eta(\mathbf{s}) + \boldsymbol{\varepsilon}(\mathbf{s})$) can be parameterized to match the geostatistical covariance functions commonly used in kriging. Indeed, Eq. 6.1 is identical to universal kriging when ($\mathbf{X}\boldsymbol{\beta}$) contains only trend surface parameters, and kriging with external drift when ($\mathbf{X}\boldsymbol{\beta}$) contains only sensor readings. In addition, both ordinary kriging and regression kriging models can also be derived as special cases of Eq. 6.1 (Schabenberger and Gotway 2005; Haskard et al. 2007).

In the most general case, ($\mathbf{X}\boldsymbol{\beta}$) may contain multiple fixed effects and the residual errors are assumed to be spatially autocorrelated. Assume that the corresponding residual errors follow a Gaussian (e.g. multivariate normal) distribution defined as

$$
\begin{aligned}
&\eta(\mathbf{s}) \approx G(\mathbf{0}, \sigma_s^2\mathbf{C}(\theta)),\\
&\varepsilon(\mathbf{s}) \approx G(\mathbf{0}, \sigma_n^2\mathbf{I}),\\
&\operatorname{cov}\{\eta(\mathbf{s}), \boldsymbol{\varepsilon}(\mathbf{s})\} = \mathbf{0} \qquad (6.2)\\
&\Rightarrow\\
&\operatorname{var}\{\eta(\mathbf{s}) + \boldsymbol{\varepsilon}(\mathbf{s})\} = \sigma_s^2\mathbf{C}(\theta) + \sigma^2 n\mathbf{I} = \Sigma,
\end{aligned}
$$

where Σ is assumed to be positive definite and $\mathbf{C}(\theta)$ represents the correlation function of a second-order stationary error process (for example, $\mathbf{C}(\theta)$ could represent an isotropic exponential correlation function with range parameter θ). When the covariance structure is known up to a proportionality constant in the geostatistical mixed linear model (i.e. $\Sigma = \tau^2\mathbf{V}$, where $\mathbf{V}$ is assumed to be known a priori), $\boldsymbol{\beta}$ of Eq. 6.1 can be estimated by generalized least squares (Rao and Toutenburg 1995). However, the specific Σ hyper-parameter values are rarely known a priori. In practice, $\boldsymbol{\beta}$ and the variance structure $\boldsymbol{\Sigma}$ are jointly estimated from the sample data, typically by maximum likelihood (ML) or residual maximum likelihood (REML) estimation (Littell et al. 1996; Lark et al. 2006). The ML or REML Σ hyper-parameter estimates are then returned to the model to compute the fixed effect parameter estimates, $\boldsymbol{\beta}$, and model predictions.

Conditional on a known covariance structure, standard mixed linear modelling theory (Cressie 1993) can be used to show that the best linear unbiased estimator for β is

$$\hat{\boldsymbol{\beta}} = (\mathbf{X}^{\mathrm{T}}\Sigma^{-1}\mathbf{X})^{-1}\mathbf{X}^{\mathrm{T}}\Sigma^{-1}\mathbf{y}, \qquad (6.3)$$

with a corresponding variance of

$$\mathrm{var}(\hat{\boldsymbol{\beta}}) = (\mathbf{X}^{\mathrm{T}}\Sigma^{-1}\mathbf{X})^{-1}. \tag{6.4}$$

Likewise, one can show that the best linear unbiased prediction for $\mathbf{y}_z$ (where $\mathbf{y}_z$ represents the remaining (non-sampled) survey locations can be expressed as

$$\hat{\mathbf{y}}_z = (\mathbf{X}_z\boldsymbol{\beta} + \Sigma_{yz}\Sigma^{-1}(\mathbf{y} - \mathbf{X}), \tag{6.5}$$

where $\mathbf{X}_z$ represents the design matrix associated with $\mathbf{y}_z$ and Σ_{yz} represents the model-based covariance matrix between $\mathbf{y}_z$ and the observed sample data $\mathbf{y}$. In addition, the corresponding variance estimate associated with this prediction vector is

$$\begin{aligned}\mathrm{var}(\mathbf{y}_z - \hat{\mathbf{y}}_z) = {} & \boldsymbol{\Sigma}_z - \boldsymbol{\Sigma}_{yz}\boldsymbol{\Sigma}^{-1}\boldsymbol{\Sigma}_{yz}^{\mathrm{T}} \\ & + \left[\mathbf{X}_z - \boldsymbol{\Sigma}_{yz}\boldsymbol{\Sigma}^{-1}\mathbf{X}\right]\left(\mathbf{X}^{\mathrm{T}}\boldsymbol{\Sigma}^{-1}\mathbf{X}\right)^{-1}\left[\mathbf{X}_z - \boldsymbol{\Sigma}_{yz}\boldsymbol{\Sigma}^{-1}\mathbf{X}\right]^{\mathrm{T}},\end{aligned} \tag{6.6}$$

where Σ_z represents the model-based variance matrix of $\mathbf{y}_z$ (Cressie 1993). Once again, these predictions and variance estimates are identical to those obtained from universal kriging and or kriging with external drift models (when the design matrix is specified appropriately to give such models).

6.3.2 Soil Sampling Strategies Based on Geo-Referenced Proximal Sensor Data

A minimum number of sites for soil (or plants) must be sampled to calibrate the geostatistical mixed linear model following the proximal sensor survey. In general, the most common strategies currently used can be classified as either probability-based (design-based) or prediction-based (model-based) sampling approaches. A brief description of each of these approaches is given below.

Probability sampling includes techniques such as simple random, stratified random and cluster sampling. Thompson (1992) provides a review of these. Probability sampling has a well developed underlying theory (Thompson 1992; Brus and de Gruijter 1993), but it was not designed specifically for estimating models. Indeed, most probability sampling strategies explicitly avoid incorporating any parametric modelling assumptions; they rely instead on the principles of randomization that are built into the design for drawing statistical inference.

Prediction-based sampling strategies, which are adopted in geostatistics and time-series analysis, are focused explicitly towards model estimation. The underlying theory behind this approach for finite population sampling and inference is discussed in detail in Valliant et al. (2000). More generally, response surface and optimal experimental design theory are closely related areas of statistical research in which sampling designs are studied specifically from the viewpoint of model estimation (Myers and Montgomery 2002). Techniques from these two subject areas have been applied to the optimal collection of spatial data by Müller (2001), the specification of optimal designs for variogram estimation by Müller and Zimmerman (1999), the estimation of spatially referenced regression models by Lesch et al. (1995) and Lesch (2005), and the estimation of geostatistical linear models by Zhu and Stein (2006) and Brus and Heuvelink (2007). Conceptually similar types of non-random sampling designs for variogram estimation have been introduced by Russo (1984) and Warrick and Myers (1987).

Sampling on a grid has been used for many years in soil science; however, it is not strictly randomized even when a random starting point is used. As a consequence there is no direct way of estimating the standard errors of the mean from a design-based viewpoint. Grid sampling has generally been favored in model-based sampling designs and has also been commonly used in precision agriculture because it is easy to implement and results in an even distribution of sample sites. Grid sampling is often used when kriging is to be used for analysis and mapping because it is an effective way to minimize the average interpolation error (Burgess et al. 1981; Burgess and Webster 1984).

Theoretically, any of the above sampling approaches can be used to estimate a spatial or geostatistical model, although each approach has various strengths and weaknesses. Lesch (2005) compares and contrasts probability- and prediction-based sampling strategies in more detail, and highlights some of the strengths of the prediction-based sampling approach.

The prediction-based sampling approach discussed by Lesch (2005) was designed specifically for use with ground-based EC_a sensor readings. A minimum number of samples for calibration is selected based on the observed magnitudes and spatial locations of the EC_a data. These sites are chosen in an iterative, non-random way to (i) optimize the estimation of a regression model (i.e. minimize the mean square prediction errors produced by the calibration function) and (ii) maximize simultaneously the average separation between adjacent sampling locations to reduce the possibility of spatially correlated residual errors. Intuitively, this sampling approach represents a hybrid of a response surface sampling technique (Myers and Montgomery 2002) with a space-filling algorithm (Müller 2001). Lesch (2005) demonstrated that such a sampling approach can substantially outperform probability-based sampling with respect to several important model-based prediction criteria, particularly optimal estimation of the fixed-effect part of a spatial (or geostatistical) linear model. Response surface sampling design software, known as ESAP, has been developed specifically for use with EC_a measurements and other proximal sensors (Lesch et al. 2000). See http://www.ars.usda.gov/services/software/software.htm for this open access software.

There are two main advantages of the response surface approach. First, the number of samples required for estimating a calibration function can be reduced substantially in comparison to more traditional design-based sampling. Response surface designs are commonly used to minimize the estimation variance of linear statistical models in the non-spatial setting. Second, this approach lends itself naturally to the analysis of proximal sensor data. Indeed, many types of ground-, airborne- and satellite-based remotely sensed data are often collected specifically because one expects them to correlate strongly with some property of interest (e.g. crop stress, soil type, soil salinity, etc.). Nevertheless, the exact parameter estimates associated with the calibration model may still need to be determined by some type of site-specific sampling design. The response surface approach explicitly optimizes this site selection process.

6.3.3 Applications of Geostatistical Mixed Linear Models to Proximal Sensor Directed Surveys

Geostatistical mixed linear models can be used effectively to delineate SSMUs using one of two approaches. In the first (and more common) approach, the model is used directly to map one or more specific soil (or plant) properties. Such an approach is useful when the SSMU can be defined effectively by only a few properties, and each of these properties correlates reasonably well with the sensor readings. Some well-known examples of application include the mapping of field-scale soil salinity and or soil texture patterns, typically for leaching or reclamation of the soil using EC_a measurements. Corwin and Lesch (2005b, c) and Lesch (2005) discuss the survey protocols associated with this approach in detail, together with various case studies.

When a geostatistical mixed linear model is used to produce detailed maps of just one or two primary soil (or plant) properties by direct prediction using proximal sensor data, the delineation of SSMUs is straightforward. For a single property, the resulting map defines the SSMU boundaries. Likewise, if two or three properties are considered, a GIS overlay (or similar operation) of the predicted values can usually be used to define and determine the SSMUs. Note that the 'optimal' boundaries and or size of the units are nearly always application specific and subject to the operational constraints of the associated farming management practices.

In the second approach, proximal sensor data are again used to direct soil (or plant) sampling. Soil (or plant tissue) from the selected sampling locations is then analysed for several secondary soil chemical and physical properties (or plant properties), and it is these measurements that are used for prediction in the geostatistical model. This approach was originally suggested by Corwin and Lesch (2003); it is well suited for determining the primary SSMUs influencing a crop response function. Note that in this case the proximal sensor data are not used directly in the geostatistical model as explicit predictor variables. Rather, the model relates the collocated soil chemical and physical properties (or plant properties) to the crop response levels, which enables us to relate the SSMUs better to these individual properties. It is the secondary soil properties that affect EC_a (i.e. salinity, water content, etc.) that are used as the predictor variables, rather than the sensor data themselves.

If the geostatistical model is used to estimate a crop response equation, which in turn is a function of measured soil chemical and physical properties, the delineation of the SSMUs can become more complex. Crop response equations can often include many different soil chemical and physical property effects, and these individual effects may not all be spatially well defined or easily predicted from the sensor data. In addition, the overlaying of many soil properties tends to produce overly complex mosaic maps that are not easily interpreted or delineated into contiguous SSMUs (see Chapter 8). In such a situation, considerable subjective intuition may be needed to define a useful set of SSMUs.

6.4 Case Study Using Apparent Soil Electrical Conductivity (EC_a) – San Joaquin Valley, CA

The objective of this case study is (i) to use an intensive EC_a survey to direct soil sampling and to identify edaphic properties that affect cotton yield and (ii) to use this spatial information to make recommendations for SSM of cotton by delineating SSMUs based solely on the edaphic and anthropogenic properties that affect cotton yield. This paper draws from previous more detailed work conducted and published by Corwin and colleagues (Corwin and Lesch 2003, 2005b; Corwin and Lesch 2003).

6.4.1 Materials and Methods

6.4.1.1 Study Site

The study site is a 32.4 ha field in the Broadview Water District on the west side of the San Joaquin Valley in central California. 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. In the arid southwestern USA 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^+ and Cl^- (Tanji 1996).

6.4.1.2 EC_a-Directed Soil Sampling Protocols for Site-Specific Management

General survey protocols for EC_a-directed soil sampling developed by Corwin and Lesch (2005b, c) were followed to characterize soil spatial variation. The basic elements of a field-scale EC_a survey applied specifically to precision agriculture include: (i) site description and EC_a survey design, (ii) geo-referenced EC_a data collection, (iii) soil sampling strategies based on geo-referenced EC_a data, (iv) soil sample collection, (v) physical and chemical analysis of pertinent soil properties, (vi) statistical and spatial analysis, (vii) geographic information system (GIS) database development and (viii) approaches for delineating SSMUs. The basic steps within each component are outlined in Table 6.3 and discussed in detail in Corwin and Lesch (2005b).

Table 6.3 Outline of steps for an EC_a field survey for precision agriculture applications. (Modified from Corwin and Lesch 2005b)

1. Site description and EC_a survey design
   (a) Record site metadata
   (b) Define project's or survey's objective
   (c) Establish site boundaries
   (d) Select GPS coordinate system
   (e) Establish EC_a measurement intensity
2. EC_a data collection with mobile GPS-based equipment
   (a) Geo-reference site boundaries and significant physical geographic features with GPS
   (b) Measure geo-referenced EC_a data at the pre-determined spatial intensity and record associated metadata
3. Soil sampling strategies based on geo-referenced EC_a data
   (a) Statistically analyse EC_a data using an appropriate statistical sampling design to establish the soil sample site locations
   (b) Establish sampling depth, sample depth increments and number of cores per site
4. Soil core sampling at specified sites designated by the sample design
   (a) Obtain measurements of soil temperature through the profile at selected sites
   (b) At randomly selected locations obtain duplicate soil cores within a 1-m distance of one another to establish local-scale variation of soil properties
   (c) Record soil core observations (e.g. mottling, horizonation, textural discontinuities, etc.)
5. Laboratory analyses of appropriate soil physical and chemical properties defined by project objectives
6. Statistical and spatial analyses to determine the soil properties that affect EC_a and crop yield (provided EC_a correlates with crop yield):
   (a) Perform a basic statistical analysis of physical and chemical data by depth increment and by composite depths
   (b) Determine the correlation between EC_a and physico-chemical soil properties by depth increment and by composite depths
   (c) Determine the correlation between crop yield and physical/chemical soil properties by depth and by composite depths to determine depth of concern (i.e. depth with consistently highest correlation, whether positive or negative, of soil properties to yield) and the soil properties that have a significant effect on crop yield (or crop quality)
   (d) Conduct an exploratory graphical analysis to determine the relationship between the significant physical and chemical properties and crop yield (or crop quality)
   (e) Formulate a spatial linear regression (SLR) model that relates soil properties (independent variables) to crop yield or crop quality (dependent variable)
   (f) Adjust this model for spatial autocorrelation, if necessary, using residual maximum likelihood (REML) or some other technique
   (g) Conduct a sensitivity analysis to establish dominant soil property affecting yield or quality
7. GIS database development and graphic display of spatial distribution of soil properties
8. Approaches for delineating site-specific management units

For the protocols to be applicable to SSM, EC_a must be correlated to crop yield (or quality), which would indicate that EC_a is measuring some edaphic property (or properties) that affect crop yield (or quality). The correlation coefficient (r) for yield and EC_a was $r = 0.51$ ($p < 0.01$).

6.4.1.3 Yield Monitoring and EC_a 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). 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 recorded (Fig. 6.1a). Each yield observation represented an area of approximately 42 m^2. From August 1999 to March 2000 the field was fallow.

On March 2000 an intensive EC_a survey was conducted using mobile fixed-array electrical resistivity equipment developed by Rhoades and colleagues (Rhoades 1992; Carter et al. 1993) that measured EC_a at 9-m intervals (4000 EC_a readings). The fixed-array electrodes were spaced to measure EC_a to a depth of 1.5 m using a Wenner array electrode configuration with an inter-electrode spacing of 1.5 m. A map of the EC_a measurements is shown in Fig. 6.1b.

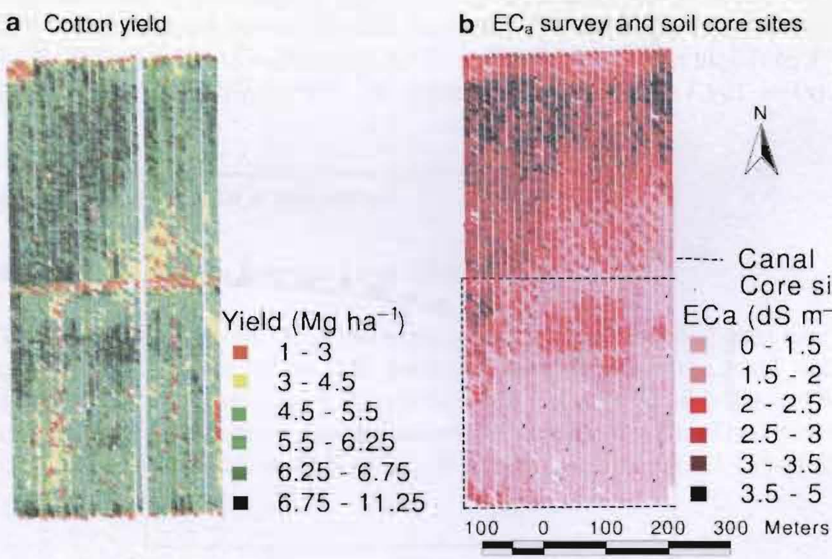

Fig. 6.1 Maps of: (**a**) cotton yield and (**b**) EC_a measurements including 60 soil sampling sites (Modified from Corwin and Lesch (2003) with permission)

6.4.1.4 Sample Site Selection, Soil Sampling and Soil Analyses

Data from the EC_a survey were used to direct the selection of 60 sample sites. The statistics software ESAP-95 version 2.01 (Lesch et al. 2000) was used to determine 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 signal variation in EC_a while simultaneously maximizing the spatial uniformity of the sampling design across the study area. Figure 6.1b shows the spatial EC_a survey data and the locations of the 60 soil sampling sites. Soil samples were taken at 0.3-m increments to a depth of 1.8 m and were analysed for the physical and chemical properties thought to influence cotton yield. They included gravimetric water content (θ_g), bulk density (ρ_b), pH, B, NO_3-N, Cl^-, electrical conductivity of the saturation extract (EC_e), leaching fraction (LF), % clay and saturation percentage (SP). The laboratory analyses followed the methods outlined in Agronomy Monograph No. 9 (Page et al. 1982).

The cotton yield data were not collocated with the EC_a or soil data; therefore, cotton yield was predicted at the 60 soil sampling sites by ordinary kriging. The experimental variogram computed by the usual method of moments on the yield data was fitted by an isotropic exponential function with a large nugget effect (Fig. 6.2). The considerable variation in yield over distances less than the sample spacing was most likely due to large measurement errors caused by the yield-monitoring dynamics (see Chapter 4). Nonlinear least-squares estimation was used to derive the three variogram model parameter estimates (and standard errors): nugget (c_0) = 0.76 (0.02), partial sill (c) = 1.08 (0.02) and distance parameter of the exponential function (r) = 109.3 (6.0) (approximate range, $3r$ = 327.9 m). The mean estimated

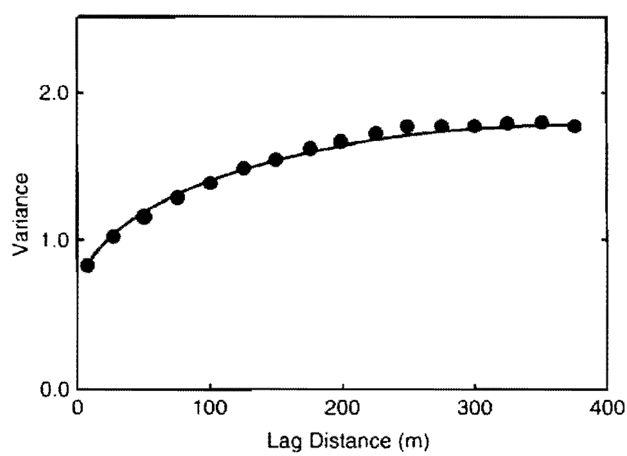

Fig. 6.2 Variogram of cotton yield. The points are the experimental variogram computed on all 7706 yield data and the solid line is the fitted exponential variogram model (see Section 1.3.2) (Taken from Corwin and Lesch (2003) with permission)

yield for the 60 sample sites was 5.95 Mg ha^{-1}, and individual estimates ranged from 3.40 to 7.41 Mg ha^{-1}. The associated kriging standard errors were from 0.93 to 0.96 Mg ha^{-1}.

6.4.1.5 Statistical and Spatial Analyses

The statistical analyses done using SAS software (SAS Institute 1999) were: (i) correlation analysis between EC_a and interpolated cotton yield using data from the 60 sites, (ii) exploratory statistical analysis to identify the significant soil properties that affect cotton yield and (iii) development of a crop yield response model using REML estimation techniques. Exploratory statistical analysis was done to determine the soil properties that have a significant effect on cotton yield and to establish the general form of the cotton yield response model. This required two stages of analysis: (i) a correlation analysis in conjunction with scatter plots of yield versus potentially significant soil properties and (ii) a preliminary multiple linear regression (MLR) analysis.

The commercial GIS software ArcView 3.3 (ESRI 2002) was used to compile, manipulate, organize and display all spatial data. The final delineation of SSMUs was done using the GIS, after exploratory statistical analyses and estimating a crop yield response model adjusted for spatial autocorrelation. A sensitivity analysis of the adjusted crop yield response model was used to identify the most significant property influencing crop yield. This analysis calculated how much the predicted yield decreased when the value for each soil property was shifted up (or down) by 1 standard deviation from its mean (Corwin and Lesch 2003).

6.4.2 Results and Discussion

6.4.2.1 Correlation Between Crop Yield and EC_a

The correlation between EC_a and yield at the 60 soil sampling sites was 0.51 (r coefficient of correlation). The moderate correlation between yield and EC_a suggests that some soil property(ies) affect both EC_a and cotton yield making an EC_a-directed soil sampling strategy potentially viable at this site. The visual similarity in the spatial distributions of EC_a and cotton yield in Fig. 6.1 confirms their close relationship.

6.4.2.2 Exploratory Statistical Analysis

Both preliminary MLR and correlation analysis showed that the 0–1.5 m soil depth resulted in the strongest correlations between yield and soil properties and best fit of the MLR to the data for the various depths considered (i.e. 0–0.3, 0–0.6, 0–0.9,

Table 6.4 Simple correlation coefficients between EC_a and soil properties and between cotton yield and soil properties. Modified from Corwin and Lesch (2003)

Soil property[a]	Fixed-array EC_a[b]	Cotton yield[c]
θ_g	0.79	0.42
EC_e	0.87	0.53
B	0.88	0.50
pH	0.33	−0.01
% clay	0.76	0.36
ρ_b	−0.38	−0.29
NO_3-N	0.22	−0.03
Cl^-	0.61	0.25
LF	−0.50	−0.49
SP	0.77	0.38

[a]Properties averaged over 0–1.5 m.
[b]Pearson correlation coefficients based on 60 observations.
[c]Pearson correlation coefficients based on 59 observations.
θ_g, gravimetric water content; EC_e, electrical conductivity of the saturation extract (dS m^{-1}); LF, leaching fraction; SP, saturation percentage.

0–1.2 and 0–1.5 m); 0–1.5 m was considered to correspond to the active root zone. The correlation analysis indicated that the following soil properties are those most significantly related to cotton yield: EC_e, LF, pH, % clay, θ_g and ρ_b. Table 6.4 shows that the correlation coefficients between EC_a and θ_g, EC_e, B, % clay, ρ_b, Cl^-, LF and SP are significant at the 0.01 level. The strongest correlations are between EC_a and θ_g, EC_e, B, % clay and SP. Note that B is not measured directly by EC_a. The strong correlation between B and EC_a is an artifact due to its close correspondence to salinity (i.e. EC_e) as a consequence of leaching. The strong correlation between EC_a and both % clay and SP is expected because it reflects the effect of texture on the EC_a. In this particular field, EC_a is strongly correlated with salinity, θ_g and texture. Table 6.4 also gives the correlation between cotton yield and the soil properties; the strongest correlation is with salinity (EC_e).

A scatter plot of EC_e and yield indicates a quadratic relationship where yield increases and then decreases (Fig. 6.3a). The scatter plot of LF and yield shows a negative, curvilinear relationship (Fig. 6.3b). Yield shows a minimal response to LF below 0.4 and it declines rapidly for LF > 0.4. Clay percentage, θ_g and ρ_b appear to be linearly related to yield to various degrees (Figs. 6.3c, f, respectively). Although there is clearly no correlation between yield and pH ($r = -0.01$, Table 6.4; Fig. 6.3d); pH became significant in the presence of the other variables, which became apparent in both the preliminary MLR analysis and final yield response model.

Based on the exploratory statistical analysis, an empirical cotton yield response model was specified as:

$$\begin{aligned} Y = {} & \beta_0 + \beta_1 (EC_e) + \beta_2 (EC_e)^2 + \beta_3 (LF)^2 \\ & + \beta_4 (pH) + \beta_5 (\%\ clay) + \beta_6 (\theta_g) + \beta_7 (\rho_b) + \varepsilon. \end{aligned} \tag{6.7}$$

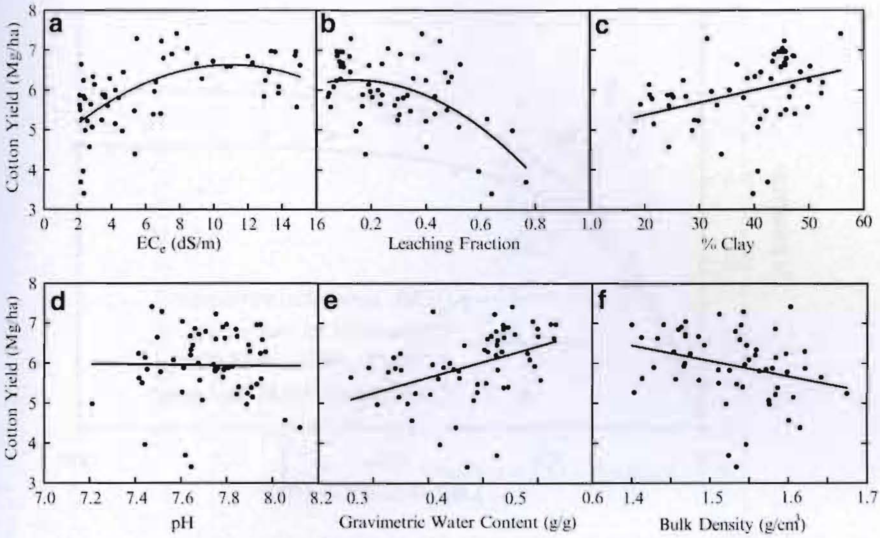

Fig. 6.3 Scatter plots of soil properties and cotton yield: (**a**) electrical conductivity of the saturation extract (ECe, $\mathrm{dS\,m^{-1}}$), (**b**) leaching fraction, (**c**) percentage clay, (**d**) pH, (**e**) gravimetric water content ($\mathrm{g\,g^{-1}}$) and (**f**) bulk density ($\mathrm{g\,cm^{-3}}$) (Taken from Corwin and Lesch (2003) with permission)

In this model, the relationships between cotton yield (Y) and pH, % clay, θ_g and ρ_b are assumed to be linear; the relationship between yield and EC_e is assumed to be quadratic; the relationship between yield and LF is assumed to be curvilinear; $\beta_0, \beta_1, \beta_2, \ldots, \beta_7$ are the regression model parameters and ε represents the random error component.

6.4.2.3 Crop Yield Response Model Development

The initial estimation of Eq. 6.7 by ordinary least squares resulted in the following simplified crop yield response model:

$$Y = 20.90 + 0.38\,(\mathrm{EC_e}) - 0.02\,(\mathrm{EC_e})^2 - 3.15\,(\mathrm{LF})^2 - 2.22\,(\mathrm{pH}) + 9.27\,(\theta_g) + \varepsilon. \tag{6.8}$$

In this initial analysis, the parameter estimates for % clay and ρ_b were not significant in the t-tests and were dropped from the regression model (all other parameters were significant near or below the 0.05 level). The R^2 value for Eq. 6.8 was 0.61 indicating that 61% of the estimated spatial variation in yield could be described successfully by this model. However, a variogram of the residuals from the fitted function (Fig. 6.4) indicates that the errors are clearly spatially correlated, implying that Eq. 6.8 should be refitted using REML to adjust for spatial autocorrelation.

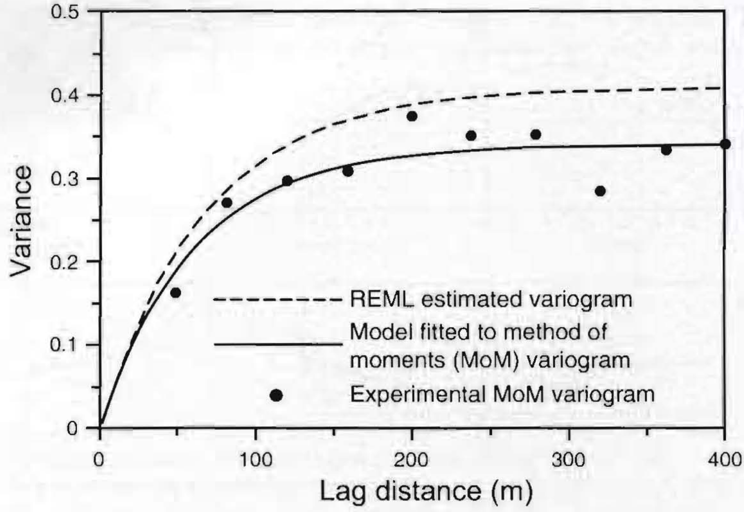

Fig. 6.4 Variograms estimated on the residuals from the ordinary least-squares yield regression model (Eq. 6.8) by residual maximum likelihood (REML) (*dashed line*) and method of moments (MoM). The symbols are the experimental variogram estimated by MoM for the 59 calibration locations and the solid line is the fitted model (Modified from Corwin and Lesch (2003) with permission)

After re-fitting Eq. 6.8 using an isotropic exponential covariance structure without a nugget effect, the following crop yield response model estimated by REML was obtained:

$$Y = 19.28 + 0.22\,(\mathrm{EC_e}) - 0.02\,(\mathrm{EC_e})^2 - 4.42\,(\mathrm{LF})^2 - 1.99\,(\mathrm{pH}) + 6.93\,(\theta_g) + \varepsilon. \tag{6.9}$$

The dashed line in Fig. 6.4 represents the variogram model estimated by REML (sill = 0.39, distance parameter = 66.2 m (working range = 198.6 m)). Note that the sill variance is larger than for the method-of-moments variogram of the residuals because the residuals from the trend are biased and the variogram is underestimated (Rao and Toutenburg 1995). The bias increases with increasing lag distance (Cressie 1993); this occurs in Fig. 6.4 to the distance at which the asymptotic sill of the exponential function is reached.

Figure 6.5 shows the observed versus predicted cotton yield estimates for Eq. 6.9. Figure 6.5 suggests that the estimated regression relationship is reasonably successful at reproducing the predicted yield estimates. A sensitivity analysis showed that LF was the single most significant factor affecting cotton yield; the degree of predicted yield sensitivity to a one standard deviation change in the $\mathrm{EC_e}$, LF, pH and θ_g resulted in % yield reductions of 4.6%, 9.6%, 5.8% and 5.1%, respectively. The point of maximum yield with respect to salinity was calculated by setting the first partial derivative of Eq. 6.9 to zero with respect to $\mathrm{EC_e}$. We note in passing that the value of 7.17 dS m^{-1} obtained is quite similar to the salinity threshold for cotton (7.7 dS m^{-1}) reported by Maas and Hoffman (1977).

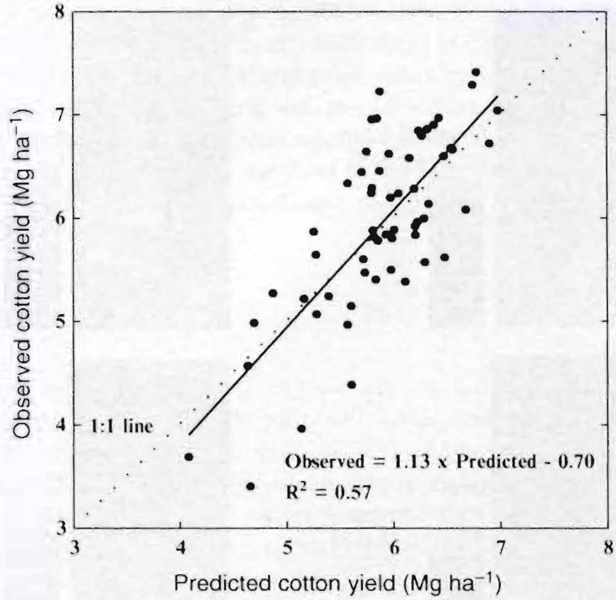

Fig. 6.5 Observed versus predicted estimates of cotton yield using Eq. 6.9. *Dotted line* is a 1:1 relationship (Taken from Corwin and Lesch (2003) with permission)

6.4.2.4 Site-Specific Management Units

Figure 6.6a–d shows the ordinary kriged maps of the four significant soil properties (0–1.5m) that affect cotton yield: (a) soil salinity (EC_e, dS m^{-1}), (b) leaching fraction (LF), (c) gravimetric water content (θ_g, kg kg^{-1}) and (d) soil pH. Ideally, if each of these four soil properties can be suitably adjusted, then in theory an optimal cotton yield could be achieved across the entire field. Based on Eq. 6.9, scatter plots of cotton yield against soil properties (Fig. 6.2) and the corresponding soil property maps (Fig 6.6), management recommendations were made that prescribed spatially what could be done to increase cotton yield in those areas with less than the optimal yield. Four recommendations can be made to improve cotton productivity at the study site: (i) reduce the LF in highly leached areas (i.e. areas where LF > 0.5), (ii) reduce salinity by increased leaching in areas where the average root zone (0–1.5 m) salinity is > 7.17 dS m^{-1}, (iii) increase the plant-available water in coarse-textured areas by more frequent irrigation and (iv) reduce the pH where it is >7.9. The rationale for each recommendation is discussed in Corwin and Lesch (2003).

Corwin and Lesch (2005a) subsequently delineated the SSMUs shown in Fig. 6.7 that indicate those areas that are pertinent to the above recommendations. All four recommendations can be accomplished by improving water application timing and distribution with variable-rate irrigation technology and by the precise application of soil amendments. Strongly leached zones were delineated where the LF needed to be reduced to ≤ 0.5; markedly saline areas were defined where the salinity needed

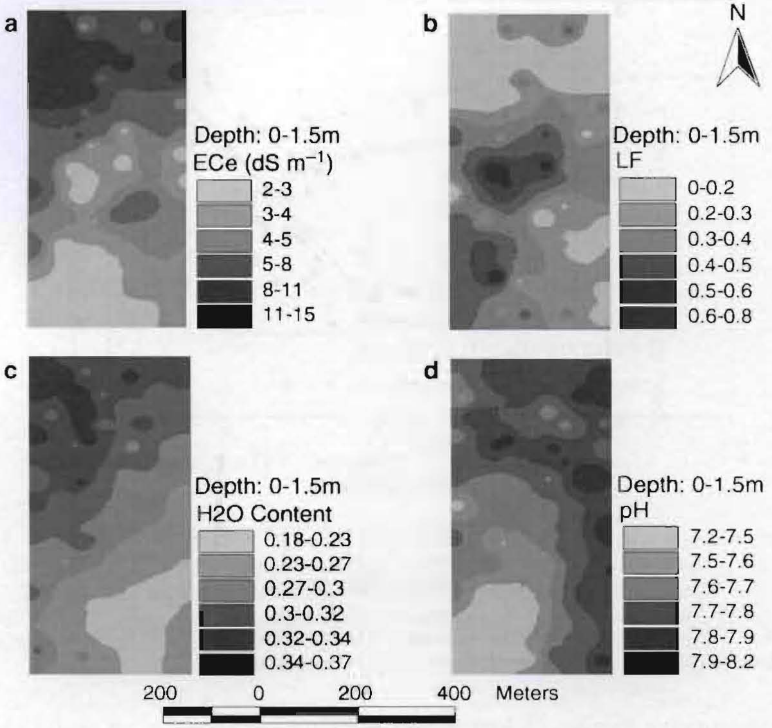

Fig. 6.6 Kriged maps of the four most significant soil properties (0–1.5 m) that affect cotton yield: (**a**) electrical conductivity of the saturation extract (EC_e, dS m^{-1}), (**b**) leaching fraction (LF), (**c**) gravimetric water content (θ_g, kg kg^{-1}) and (**d**) pH (Taken from Corwin and Lesch (2003) with permission)

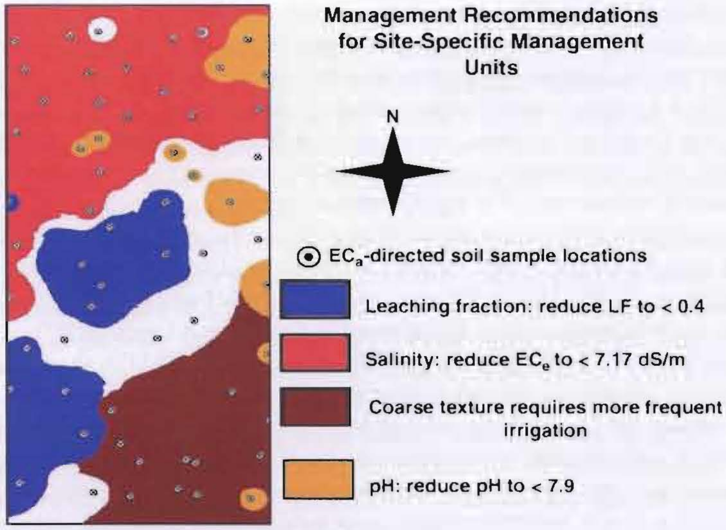

Fig. 6.7 Site-specific management units (SSMUs) for a 32.4-ha cotton field in the Broadview Water District of central California's San Joaquin Valley. Recommendations associated with the SSMUs are for: (**a**) leaching fraction, (**b**) salinity, (**c**) texture and (**d**) pH (Taken from Corwin and Lesch 2005a)

to be reduced below the salinity threshold for cotton, which was established from Eq. 6.9 to be $EC_e = 7.17\,dS\,m^{-1}$ for this field; areas of coarse texture were defined that needed more frequent irrigation and areas were identified where the pH needed to be reduced below a pH 8 with a soil amendment such as OM. Although this work has delineated within-field units where associated site-specific management recommendations would optimize the yield, it still falls short of integrating meteorological, economic and environmental impacts on within-field crop yield variation.

6.5 Conclusion

Since all proximal sensors can be, and generally are, influenced by more than one property that can affect plant yield (or quality), the most appropriate use of georeferenced proximal sensor data is to direct soil (or plant) sampling to determine the spatial distribution of properties affecting crop yield (or quality). Directed soil (or plant) sampling with proximal sensor data provides a means of establishing the properties that have most effect in crop yield (or quality) and of mapping the distribution of these properties. In addition, it provides sufficient information to develop a crop yield (or quality) response model that relates yield to edaphic or other properties affecting yield. The spatial distribution of the properties that have most effect on yield (or quality) together with a crop yield (or quality) response model provide sufficient information to delineate SSMUs with associated recommendations to increase yield (or improve quality).

Even though EC_a-directed soil sampling provides a viable means of identifying some soil properties that affect within-field variation of yield, it is only one piece of a complicated puzzle of interacting factors that result in the observed within-field variation in crops. Crop yield is affected 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.

Mobile platforms containing multiple proximal sensors are currently being developed and tested to provide the full complement of spatial data needed to identify and spatially characterize not only edaphic but anthropogenic, topographic, meteorological and biological properties that influence plant growth. These platforms will provide multiple layers of spatial information enabling the delineation of SSMUs well beyond the capability of single proximal sensor platforms.

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