18 Geospatial Measurements of Apparent Soil Electrical Conductivity for Characterizing Soil Spatial Variability

Dennis L. Corwin
USDA-ARS, George E. Brown, Jr. Salinity Laboratory, Riverside, California, U.S.A.

CONTENTS

18.1 Introduction...................................................................................... 640
  18.1.1 Justification for Characterizing Spatial Variability with Geospatial $EC_a$ Measurements........................................................................ 640
  18.1.2 Edaphic Factors Influencing $EC_a$ Measurements .................. 642
  18.1.3 Mobile $EC_a$ Measurement Equipment ................................ 644
18.2 Guidelines for Conducting an $EC_a$-Directed Soil Sampling Survey ............................................................................. 646
18.3 Strengths and Limitations................................................................. 647
18.4 Characterizing Spatial Variability with $EC_a$-Directed Soil Sampling: Case Studies ................................................................. 650
  18.4.1 Landscape-Scale Solute Transport in the Vadose Zone...... 652
  18.4.2 Assessing Soil Quality and Spatio-Temporal Changes in Soil Quality................................................................. 658
  18.4.3 Delineating Site-Specific Management Units for Precision Agriculture................................................................. 660
18.5 Future Directions.............................................................................. 662
Acknowledgments ....................................................................................... 664
References ................................................................................................... 664
18.1 INTRODUCTION

Ever since the classic paper by Nielsen et al. (1973) concerning the variability of field-measured soil water properties, the significance of within-field spatial variability of soil properties has been scientifically acknowledged and documented. Spatial variability of soil has been the focus of books (Bouma and Bregt, 1989; Mausbach and Wilding, 1991) and numerous comprehensive review articles (Warrick and Nielsen, 1980; Jury, 1985, 1986; White, 1988). The significance of soil spatial variability lies in the fact that it is a key component of any landscape-scale soil-related issue including solute transport in the vadose zone, site-specific crop management, and soil quality assessment, to mention a few.

There are a variety of methods for potentially characterizing soil spatial variability, including ground penetrating radar (GPR), aerial photography, multi- and hyperspectral imagery, time domain reflectometry (TDR), and apparent soil electrical conductivity ($EC_a$). However, none of these approaches has been as extensively investigated as the use of $EC_a$ (Corwin and Lesch, 2004a).

Since its early agricultural use for measuring soil salinity, the application of $EC_a$ has evolved into a widely accepted means of establishing the spatial variability of several soil physicochemical properties that influence the $EC_a$ measurement (Corwin and Lesch, 2003, 2004a). Geospatial measurements of $EC_a$ are well suited for characterizing spatial variability for several reasons. Geospatial measurements of $EC_a$ are reliable, quick, and easy to take. The mobilization of $EC_a$ measurement equipment is easy and can be accomplished at a reasonable cost. Finally, and most importantly, $EC_a$ is influenced by a variety of soil properties for which the spatial variability of each could be potentially established. Corwin and Lesch (2004a) provide a compilation of literature pertaining to the soil physicochemical properties that are either directly or indirectly measured by $EC_a$.

It is the goal of this chapter to provide an overview of the characterization of soil spatial variability using $EC_a$-directed soil sampling for three different landscape-scale applications: (1) solute transport modeling in the vadose zone, (2) site-specific crop management, and (3) soil quality assessment. Guidelines, methodology, and strengths and limitations are presented for characterizing spatial and temporal variation in soil physicochemical properties using $EC_a$-directed soil sampling.

18.1.1 JUSTIFICATION FOR CHARACTERIZING SPATIAL VARIABILITY WITH GEOSPATIAL $EC_a$ MEASUREMENTS

The prospect of feeding a projected additional 3 billion people over the next 30 years poses formidable, but not insurmountable, challenges. Feeding the ever-increasing world population will require a sustainable agricultural system that can keep pace with population growth. The concept of sustainable agriculture is predicated on maximizing crop productivity and
maintaining economic stability while minimizing utilization of finite natural resources and detrimental environmental impacts of associated agrichemical pollutants. To sustain agriculture, a balance must be attained between profitability, resource utilization, crop yield, and environmental stewardship.

Conventional farming currently treats a field uniformly, ignoring the naturally inherent variability of soil and crop conditions between and within fields. However, until recently, with the introduction of global positioning systems (GPS) and yield-monitoring equipment, documentation of crop yield and soil variability at field scale was difficult to establish. Now there is well-documented evidence that spatial variability within a field is highly significant and amounts to a factor of 2–4 or more for crops (Birrel et al., 1995; Verhagen et al., 1995; Kaffka et al., 2004) and up to an order of magnitude or more for soils (Jury, 1986; Corwin et al., 2003a).

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. To a varying extent from one field to the next, crop patterns are influenced by edaphic (i.e., soil-related) properties. Bullock and Bullock (2000) pointed out the imminent need for efficient methods to accurately measure within-field variation in soil physical and chemical properties as a key component for precision agriculture.

A fundamental component of assessing field-scale soil quality is establishing the spatial distribution of the soil properties affecting the soil’s intended management goal (e.g., maximize agricultural productivity, minimize environmental impact, and/or maximize waste recycling) and its intended function (e.g., biodiversity, filtering and buffering, nutrient cycling, physical stability and structural support, resistance and resilience, and water and solute flow). It is not sufficient to take a single measurement within a field to characterize its soil quality. Rather, a sufficient number of measurements must be taken and at specific locations to representatively characterize the spatial distribution of the existing soil conditions that influence the soil’s intended use. Therefore, assessing soil quality requires quantitative knowledge of each indicator property associated with a soil’s quality and the spatial variability of those indicator properties.

Furthermore, spatial variability has a profound influence on solute transport, particularly of non–point source pollutants. In fact, it has become clear that the real constraint on modeling solute transport is not the detail of the model structures, but defining the characteristics of individual places (Beven, 2002). Jury (1986) provides an excellent fundamental discussion of the spatial variability of soil properties and its impact on solute transport in the vadose zone. As Jury points out, “any hope of estimating a continuous spatial pattern of chemical emissions at
each point in space within a field must be abandoned due to field-scale variability of soils.”

The characterization of spatial variability is without question one of the most significant areas of concern in soil science because of its broad reaching influence on all field- and landscape-scale processes. The geospatial measurement of $EC_a$ is a sensor technology that has played, and continues to play, a major role in addressing the issue of characterizing spatial variability. Geospatial measurements of $EC_a$ have been successfully used for (1) identifying the soil physicochemical properties influencing crop yield patterns and soil condition, (2) establishing the spatial variation of these soil properties, and (3) characterizing the spatial distribution of soil properties influencing solute transport through the vadose zone (Corwin et al., 1999, 2003a, 2003b, 2004; Kaffka et al., 2004).

### 18.1.2 Edaphic Factors Influencing $EC_a$ Measurements

The earliest field applications of geophysical measurements of $EC_a$ in soil science involved the determination of salinity within the soil profile of arid zone soils (Halvorson and Rhoades, 1976; Rhoades and Halvorson, 1977; de Jong et al., 1979; Cameron et al., 1981; Rhoades and Corwin, 1981; Corwin and Rhoades, 1982, 1984; Williams and Baker, 1982). However, it became apparent that the measurement of $EC_a$ in the field to infer soil salinity was more complicated than initially anticipated due to the complexity of current flow pathways arising from the spatial heterogeneity of properties influencing current flow in soil.

Three pathways of current flow contribute to the $EC_a$ of soil: (1) a liquid phase pathway via dissolved solids contained in the soil water occupying the large pores, (2) a solid-liquid phase pathway primarily via exchangeable cations associated with clay minerals, and (3) a solid pathway via soil particles that are in direct and continuous contact with one another (Rhoades et al., 1999a). Of these three pathways, the solid pathway in soil is usually negligible resulting in a dual parallel pathway system.

Rhoades et al. (1989) formulated an electrical conductance model that describes the three conductance pathways of $EC_a$. This model is often referred to as the dual pathway parallel conductance model:

$$EC_a = \left( \frac{(0_s + 0_{ws})^2 \cdot EC_{ws} \cdot EC_s}{0_s \cdot EC_{ws} + 0_{ws} \cdot EC_s} \right) + (0_{wc} \cdot EC_{wc}) \quad (18.1)$$

where $0_{wc}$ and $0_{wc}$ are the volumetric soil water contents in the soil-water pathway (cm$^3$ cm$^{-3}$) and in the continuous liquid pathway (cm$^3$ cm$^{-3}$), respectively; $0_s$ is the volumetric content of the solid phase of soil (cm$^3$ cm$^{-3}$); $EC_{ws}$ and $EC_{wc}$ are the specific electrical conductivities of the soil-water pathway (dS m$^{-1}$) and continuous-liquid pathway (dS m$^{-1}$); and $EC_s$ is the electrical conductivity of the solid soil particles (dS m$^{-1}$). Equation (18.1)
Electrical Conductivity for Characterizing Soil Spatial Variability

was reformulated by Rhoades et al. (1989) into Eq. (18.2):  

\[ EC_a = \left( \frac{(\theta_s + 0.5\theta_{ws})^2 \cdot EC_w \cdot EC_s}{(\theta_s \cdot EC_w) + (\theta_{ws} \cdot EC_s)} \right) + (\theta_w - \theta_s) \cdot EC_w \]  

(18.2)

where \( \theta_w = \theta_{ws} + \theta_{wc} = \) total volumetric water content (cm\(^3\) cm\(^{-3}\)), and \( EC_w \) is the average electrical conductivity of the soil water assuming equilibrium (i.e., \( EC_w = EC_{sw} = EC_{wc} \)). The following simplifying approximations are also known:

\[ \theta_w = \frac{(PW \cdot \rho_b)}{100} \]  

(18.3)

\[ \theta_{ws} = 0.639\theta_w + 0.011 \]  

(18.4)

\[ \theta_{ss} = \frac{\rho_b}{2.65} \]  

(18.5)

\[ EC_{ss} = 0.019(SP) - 0.434 \]  

(18.6)

\[ EC_w = \left[ \frac{EC_e \cdot \rho_b \cdot SP}{100 \cdot \theta_w} \right] \]  

(18.7)

where \( PW \) is the per cent water on a gravimetric basis, \( \rho_b \) is the bulk density (Mg m\(^{-3}\)), \( SP \) is the saturation percentage, and \( EC_e \) is the electrical conductivity of the saturation extract (dS m\(^{-1}\)).

The reliability of Eqs. (18.2)–(18.7) has been evaluated by Corwin and Lesch (2003). These equations are reliable except under extremely dry soil conditions. However, Lesch and Corwin (2003) developed a means of extending equations for extremely dry soil conditions by dynamically adjusting the assumed water content function. By measuring \( EC_a, SP, PW, \) and \( \rho_b \), and using Eqs. (18.3)–(18.7), the \( EC_e \) can be estimated. The determination of \( EC_e \) is of agricultural importance because traditionally \( EC_e \) has been the standard measure of soil salinity used in all salt-tolerance plant studies. Alternatively, \( EC_a \) can be estimated by knowing \( EC_e, SP, PW, \) and \( \rho_b \).

Because of the pathways of conductance, \( EC_a \) is influenced by a complex interaction of soil properties including salinity, \( SP \), water content, and \( \rho_b \). The \( SP \) and \( \rho_b \) are both directly influenced by clay content (or texture) and organic matter (OM). Furthermore, the exchange surfaces on clays and OM provide a solid-liquid phase pathway primarily via exchangeable cations; consequently, clay type and content (or texture), cation exchange capacity (CEC), and OM are recognized as additional factors influencing \( EC_a \).
measurements. Measurements of $EC_a$ must be interpreted with these influencing factors in mind. Table 18.1 from Corwin and Lesch (2004a) is a compilation of work related to the influence of various edaphic properties on the $EC_a$ measurement.

Another factor influencing $EC_a$ is temperature. Electrolytic conductivity increases at a rate of approximately 1.9% per degree centigrade increase in temperature. Customarily, $EC$ is expressed at a reference temperature of 25°C for purposes of comparison. The $EC$ (i.e., $EC_a$, $EC_e$, or $EC_w$) measured at a particular temperature $t$ (in degrees centigrade), $EC_t$, can be adjusted to a reference $EC$ at 25°C, $EC_{25}$, using equations from Handbook 60 (U.S. Salinity Laboratory, 1954):

$$EC_{25} = f_t = EC_t$$  \hspace{1cm} (18.8)

where $f_t$ is a temperature conversion factor. Approximations for the temperature conversion factor are available in polynomial form (Stogryn, 1971; Rhoades et al., 1999b; Wraith and Or, 1999) or other equations such as Eq. (18.9) by Sheets and Hendrickx (1995):

$$f_t = 0.4470 + 1.4034e^{-t/26.815}$$  \hspace{1cm} (18.9)

### 18.1.3 Mobile $EC_a$ Measurement Equipment

The characterization of soil spatial variability using $EC_a$ involves the use of mobile electrical resistivity (ER) or electromagnetic induction (EMI) equipment that geo-references each $EC_a$ measurement using a global positioning system (GPS). Mobile $EC_a$ equipment has been developed by a variety of researchers (McNeill, 1992; Carter et al., 1993; Rhoades, 1993; Jaynes et al., 1993; Cannon et al., 1994; Kitchen et al., 1996; Freeland et al., 2002). The development of mobile $EC_a$ measurement equipment has made it possible to produce $EC_a$ maps with measurements taken every few meters.

Mobile $EC_a$ measurement equipment has been developed for both ER and EMI geophysical approaches. In the case of ER, four stainless-steel electrodes are inserted into the soil generally at equal distances and connected to a resistivity meter. Current is applied to the two outer electrodes with the two inner electrodes serving as the potential electrodes. By mounting the electrodes to "fix" their spacing, considerable time for a measurement is saved. The "fixed-electrode array" has been mounted on a vehicle and coupled to a datalogger and GPS, which geo-references the $EC_a$ measurement (Rhoades, 1992, 1993; Carter et al., 1993). Veris Technologies* (Salinas, KS; www.veristech.com) has developed a commercial mobile system for measuring $EC_a$ using the principles of ER. In the case of EMI, an EM-38 unit*

*Product identification is provided solely for the benefit of the reader and does not imply the endorsement of the USDA.
### TABLE 18.1
Compilation of Literature Measuring $EC_a$ Categorized According to the Physicochemical and Soil-Related Properties Either Directly or Indirectly Measured by $EC_a$.

<table>
<thead>
<tr>
<th>Soil property</th>
<th>Ref.</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Directly Measured Soil Properties</strong></td>
<td></td>
</tr>
<tr>
<td>Salinity (and nutrients, e.g., NO$_3^-$)</td>
<td>Halvorson and Rhoades (1976); Rhoades et al. (1976); Rhoades and Halvorson (1977); de Jong et al. (1979); Cameron et al. (1981); Rhoades and Corwin (1981, 1990); Corwin and Rhoades (1982, 1984); Williams and Baker (1982); Greenhouse and Slaine (1983); van der Leij (1983); Wollenhaupt et al. (1986); Williams and Hoey (1987); Corwin and Rhoades (1990); Rhoades et al. (1989, 1990, 1999a, 1999b); Slavich and Petterson (1990); Díaz and Herrera (1992); Hendrickx et al. (1992); Lesch et al. (1992, 1995a, 1995b, 1998); Rhoades (1992, 1993); Cannon et al. (1994); Nettleton et al. (1994); Bennett and George (1995); Drommerhausen et al. (1995); Ranjan et al. (1995); Hanson and Kaia (1997); Johnston et al. (1997); Mankin et al. (1997); Eigenberg et al. (1998, 2002); Eigenberg and Nienaber (1998, 1999, 2001); Mankin and Karthikeyan (2002); Herrero et al. (2003); Paine (2003); Kaffka et al. (2004).</td>
</tr>
<tr>
<td>Water content</td>
<td>Fitterman and Stewart (1986); Kean et al. (1987); Kachanoski et al. (1988, 1990); Vaughan et al. (1995); Sheets and Hendrickx (1995); Hanson and Kaia (1997); Khakural et al. (1998); Morgan et al. (2000); Freeland et al. (2001); Brevik and Fenton (2002); Wilson et al. (2002); Farahani et al. (2004); Kaffka et al. (2004).</td>
</tr>
<tr>
<td>Texture-related (e.g., sand, clay, depth to claypans or sand layers)</td>
<td>Williams and Hoey (1987); Brus et al. (1992); Jaynes et al. (1993); Stroh et al. (1993); Sudduh and Kitchen (1993); Doolittle et al. (1994, 2002); Kitchen et al. (1996); Banton et al. (1997); Boettiger et al. (1997); Rhoades et al. (1999b); Scanlon et al. (1999); Inman et al. (2001); Triantafilis et al. (2001); Anderson-Cook et al. (2002); Brevik and Fenton (2002); Farahani et al. (2004).</td>
</tr>
<tr>
<td>Bulk density related (e.g., compaction)</td>
<td>Rhoades et al. (1999b); Gorucu et al. (2001).</td>
</tr>
<tr>
<td><strong>Indirectly Measured Soil Properties</strong></td>
<td></td>
</tr>
<tr>
<td>Organic matter related (including soil organic carbon, and organic chemical plumes)</td>
<td>Greenhouse and Slaine (1983, 1986); Brune and Doolittle, 1990; Nyquist and Blair (1991); Jaynes (1996); Benson et al. (1997); Bowling et al. (1997); Brune et al. (1999); Nobes et al. (2000); Farahani et al. (2004).</td>
</tr>
<tr>
<td>Cation exchange capacity</td>
<td>McBride et al. (1990); Triantafilis et al. (2002); Farahani et al. (2004).</td>
</tr>
<tr>
<td>Leaching</td>
<td>Slavich and Yang (1990); Corwin et al. (1999); Rhoades et al. (1999b).</td>
</tr>
<tr>
<td>Groundwater recharge</td>
<td>Cook and Kilty (1992); Cook et al. (1992); Salama et al. (1994).</td>
</tr>
<tr>
<td>Soil map unit boundaries</td>
<td>Fenton and Lauterbach (1999); Stroh et al. (2001).</td>
</tr>
<tr>
<td>Corn rootworm distributions</td>
<td>Elsberry et al. (1999).</td>
</tr>
<tr>
<td>Soil drainage classes</td>
<td>Kravchenko et al. (2002).</td>
</tr>
</tbody>
</table>

*Source: Corwin and Lesch, 2004a.*
(Geonics Ltd., Mississauga, Ontario, Canada) has been mounted in a cylindrical nonmetallic housing in the front of a mobile spray rig that has adequate clearance to traverse fields with a crop cover (Rhoades, 1992, 1993; Carter et al., 1993). The housing can be raised and lowered to take measurements at the soil surface or at various heights above the soil or to lock into a travel position to go from one measurement site to the next. The housing can also be rotated 90° to take EMI readings at each site with the transmitter and receiver coils oriented to the soil surface in two configurations ($EM_{h}$, electromagnetic induction measurement in the horizontal coil-mode configuration; $EM_{v}$, electromagnetic induction measurement in the vertical coil-mode configuration). Recently, mobile EMI equipment developed at the Salinity Laboratory was modified by the addition of a dual-dipole EM-38 unit in place of the single EM-38 unit (Corwin and Lesch, 2004a). The dual-dipole EM-38 unit permits continuous, simultaneous $EC_{a}$ measurements in both the horizontal ($EM_{h}$) and vertical ($EM_{v}$) dipole configurations at time intervals of just a few seconds between readings. Other less costly mobile EMI equipment has been developed that carry the EM-38 unit on a nonmetallic cart or sled pulled by an all-terrain vehicle or tractor (Jaynes et al., 1993; Cannon et al., 1994; Kitchen et al., 1996; Freeland et al., 2002). These sleds or carts allow continuous $EC_{a}$ measurements, but in only one dipole position. No commercial mobile system has been developed with EMI. The mobile “fixed-electrode array” ER and EMI equipment are both well suited for collecting detailed maps of the spatial variability at field scales and larger.

18.2 GUIDELINES FOR CONDUCTING AN $EC_{a}$-DIRECTED SOIL SAMPLING SURVEY

Because of the influence of edaphic properties on $EC_{a}$, the spatial distribution of $EC_{a}$ within a field provides a potential means of mapping the spatial variability of the edaphic properties with an $EC_{a}$-directed soil sampling. Characterizing spatial variability with $EC_{a}$-directed soil sampling is based on the hypothesis that when $EC_{a}$ correlates with a soil property or properties, then spatial $EC_{a}$ information can be used to identify sites that reflect the range and variability of the property or properties. In instances where $EC_{a}$ correlates with a particular soil property, an $EC_{a}$-directed soil sampling approach will establish the spatial distribution of that property with an optimum number of site locations to characterize the variability and keep labor costs minimal (Corwin et al., 2003a). Also, if $EC_{a}$ is correlated with crop yield, then an $EC_{a}$-directed soil sampling approach can be used to identify what soil properties are causing the variability in crop yield (Corwin et al., 2003b). Details for conducting a field-scale $EC_{a}$ survey for the purpose of characterizing the spatial variability of soil properties influencing soil quality or crop yield variation can be found in Corwin and Lesch (2004b). General guidelines appear in Corwin and Lesch (2003) and Corwin et al. (2003a, 2003b).
Electrical Conductivity for Characterizing Soil Spatial Variability

The basic elements of a field-scale ECₐ survey for characterizing spatial variability include (1) ECₐ survey design, (2) geo-referenced ECₐ data collection, (3) soil sample design based on geo-referenced ECₐ data, (4) soil sample collection, (5) physico-chemical analysis of pertinent soil properties, (6) spatial statistical analysis, (7) determination of the dominant soil properties influencing the ECₐ measurements at the study site, and (8) GIS development. The basic steps of an ECₐ-directed soil sampling survey are provided in Table 18.2.

18.3 STRENGTHS AND LIMITATIONS

At present, no other single soil measurement provides a greater level of spatial information than that of geospatial measurements of ECₐ. Even so, there are a variety of strengths and limitations for the use of ECₐ to characterize soil spatial variability. Awareness of these strengths and weaknesses is crucial for the proper use of ECₐ in characterizing spatial variability.

Apparent soil electrical conductivity is a fast, reliable, and scientifically documented approach that is reasonable in cost and can be readily mobilized for geospatial referencing when mounted on a mobile platform and coupled to a GPS. Because of these positive attributes, commercial vendors have developed mobile units using ER to measure ECₐ and numerous researchers have developed EMI-based mobile units (see Sec. 18.13). However, ER requires direct contact between the inserted probe and the soil, which limits its use in dry or stony soils. In contrast, EMI-based units are noninvasive; consequently, contact is not an issue, so ECₐ measurements of dry or stony soils can be made without difficulty. The fact that the ECₐ measurement is influenced by a variety of soil physicochemical properties is both an advantage and a disadvantage to characterizing spatial variability. The advantage is that the spatial variability of each of the soil properties influencing ECₐ can be potentially characterized. The disadvantage is that the relationship between ECₐ and the properties influencing ECₐ is complex and requires ground truth soil samples to unravel. Nevertheless, when used correctly there is no means of characterizing spatial variability that is more dependable, cost-effective, and flexible than geospatial measurements of ECₐ.

Even though an ECₐ survey is a quick, easy, reliable, and cost-effective means of characterizing the spatial variability of a variety of physicochemical properties, there are crucial limitations and weaknesses. A knowledge and understanding of these limitations and weaknesses is imperative for the proper use of ECₐ measurements. The complex spatial heterogeneity of the soil system has subtle influences on geospatial ECₐ measurements that can have significant interpretive impacts. The ability to recognize and interpret these influences can be the difference between the successful or failed application of ECₐ measurements for characterizing spatial variability.
TABLE 18.2
Outline of Steps to Conduct an $EC_a$ Field Survey.

1. Site description and $EC_a$ survey design
   a. record site metadata
   b. define the project’s/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 sample design based on geo-referenced $EC_a$ data
   a. statistically analyze $EC_a$ data using an appropriate statistical sampling design to establish the soil sample site locations
   b. establish site locations, depth of sampling, 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 analysis of appropriate soil physicochemical properties defined by project objectives
6. If needed, stochastic and/or deterministic calibration of $EC_a$ to $EC_e$ or to other soil properties (e.g., water content and texture)
7. Spatial statistical analysis to determine the soil properties influencing $EC_a$ and/or crop yield
   a. soil quality assessment:
      (1) perform a basic statistical analysis of physicochemical data by depth increment and by composite depth over the depth of measurement of $EC_a$
      (2) determine the correlation between $EC_a$ and physicochemical soil properties by composite depth over the depth of measurement of $EC_a$
   b. precision agriculture applications (if $EC_a$ correlates with crop yield, then):
      (1) perform a basic statistical analysis of physicochemical data by depth increment and by composite depths
      (2) determine the correlation between $EC_a$ and physicochemical soil properties by depth increment and by composite depths
      (3) determine the correlation between crop yield and physicochemical 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 significant soil properties influencing crop yield (or crop quality)
      (4) conduct an exploratory graphical analysis to determine the relationship between the significant physicochemical properties and crop yield (or crop quality)
      (5) formulate a spatial linear regression (SLR) model that relates soil properties (independent variables) to crop yield or crop quality (dependent variable)
      (6) adjust this model for spatial auto-correlation, if necessary, using restricted maximum likelihood or some other technique
      (7) Conduct a sensitivity analysis to establish dominant soil property influencing yield or quality
8. GIS database development and graphic display of spatial distribution of soil properties

Source: Corwin and Lesch, 2004b.
First and foremost, geospatial measurements of $EC_a$ by themselves do not directly characterize spatial variability. Actually, $EC_a$ measurements provide limited direct information about the physiochemical properties that influence yield, affect solute transport, or determine soil quality. Rather, $EC_a$-survey measurements provide the spatial information necessary to direct soil sampling. It is as a cost-effective tool for directing soil sampling that $EC_a$-survey measurements are invaluable for characterizing spatial variability. The primary strength of geospatial $EC_a$ measurements lies in their effectiveness as a means to direct soil sampling with a minimum number of sample sites that best characterize the spatial variability of those soil properties influencing $EC_a$ at the site of interest.

Second, $EC_a$-directed soil sampling can only spatially characterize soil properties that correlate with $EC_a$. This correlation may be due to a direct or indirect influence on the $EC_a$ measurement or the correlation may be a complete artifact. For example, salinity and water content will directly influence $EC_a$, and CEC will indirectly influence $EC_a$ through its influence on current flow at the surface of clay particles. In many instances B and salinity distributions are similar; consequently, a correlation of B with $EC_a$ can result. Yet, there is no cause-and-effect relationship between B and $EC_a$.

Consequently, an understanding of the soil properties that influence $EC_a$ and of those properties that are correlated with but may not influence $EC_a$ at a specific site is particularly essential for temporal applications of $EC_a$ because over time the correlation may or may not persist.

Third, as already mentioned there is a complex relationship between $EC_a$ and those properties that influence $EC_a$. Apparent soil electrical conductivity is a complex measurement that requires knowledge and experience to interpret. Ground-truth soil samples are obligatory to be able to understand and interpret spatial measurements of $EC_a$. Without ground-truth soil samples an $EC_a$ survey will be of minimal value. Geospatial measurements of $EC_a$ do not supplant the need for soil sampling, but they do minimize the number of samples necessary to characterize spatial variability. Users of $EC_a$ survey data must exercise caution and be aware of what $EC_a$ is actually measuring at the site of interest. The only way to establish those soil properties that influence $EC_a$ at a site is to take ground truth soil samples and establish the relationship between $EC_a$ and the property(ies) of interest. This requires that every $EC_a$ survey have an associated soil sampling survey based on the spatial distribution of $EC_a$.

This generally requires a minimum of 8–16 soil core sites, where the location and number of sites is dependent on the spatial variability of $EC_a$. The location and number of sites is established from an intensive ECA survey using model-based sample design software such as ESAP (Lesch et al., 2000).

Finally, the temporal stability of $EC_a$ measurements at a site may be of potential concern due to the fact that $EC_a$ is a product of both static and dynamic factors (these static and dynamic factors are discussed in greater detail in the subsequent section). This adds another dimension to the
complexity of understanding and interpreting geospatial $EC_a$ measurements. For this reason, caution must be taken to characterize spatial variability with $EC_a$ when dynamic conditions influencing $EC_a$ are minimal. Apparent soil electrical conductivity surveys are generally conducted (1) within a set time frame to minimize the effects of dynamic properties (e.g., temperature, water content, and salinity), (2) when the soil is at or near field capacity, and (3) with regard for subtle topographic effects (e.g., bed-furrow). Protocols for conducting an $EC_a$ survey that consider all the previously discussed limitations are presented by Corwin and Lesch (2004b, 2004c).

18.4 CHARACTERIZING SPATIAL VARIABILITY WITH $EC_a$-DIRECTED SOIL SAMPLING: CASE STUDIES

Measured $EC_a$ is the product of both static and dynamic factors, which include soil salinity, clay content and mineralogy, water content, $\rho_b$, and temperature. Johnson et al. (2003) astutely described the observed dynamics of the general interaction of these factors. In general, the magnitude and spatial heterogeneity of $EC_a$ in a field are dominated by one or two of these factors, which will vary from one field to the next making the interpretation of $EC_a$ measurements highly site specific. In instances where dynamic soil properties (e.g., salinity, water content, and temperature) dominate the $EC_a$ measurement, temporal changes in spatial patterns exhibit more fluidity than systems that are dominated by static factors (e.g., texture). In texture-driven systems, spatial patterns remain consistent because variations in dynamic soil properties affect only the magnitude of measured $EC_a$ (Johnson et al., 2003). For this reason, Johnson et al. (2003) warn that $EC_a$ maps of static-driven systems convey very different information from those of less stable dynamic-driven systems. Furthermore, the application of manure and commercial fertilizer can influence $EC_a$ to the point where texture-dominated systems can be transformed into salt-dominated systems (Johnson et al., 2003). Although it has not been experimentally evaluated, texture-driven systems will likely be more temporally stable than salinity-driven systems.

Numerous $EC_a$ field studies have been conducted that have revealed the site specificity and complexity of spatial $EC_a$ measurements with respect to the particular property influencing the $EC_a$ measurement at that study site. Table 18.1 is a compilation of various field studies and the associated dominant soil property measured. The range of factors correlated to field measurements of $EC_a$ in Table 18.1 points to the need for ground truth soil samples associated with each $EC_a$ survey to adequately interpret spatial $EC_a$ data.

After the initial, largely observational work compiled in Table 18.1 involving geophysical measurements of $EC_a$ in soil, the direction of research has gradually shifted to mapping within-field variation of $EC_a$ to characterize the spatial distribution and variability of properties that statistically correlate with $EC_a$. The mapping of within-field variation of $EC_a$
to characterize the spatial distribution of properties has its roots in the early salinity mapping work by Rhoades (1992, 1993), who observed the geospatial relationship between maps of $EC_a$ and soil salinity patterns. The earliest work in the soil science literature for the application of geospatial $EC_a$ measurements to direct soil sampling for the purpose of characterizing the spatial variability of a soil property was by Lesch et al. (1992), who used a spatial response surface sampling (SRSS) design. The shift in the emphasis of field-related $EC_a$ research from observation to directed-sampling design has gained momentum resulting in the accepted use of geospatial measurements of $EC_a$ as a reliable directed-sampling tool for characterizing spatial variability at field and landscape scales (Corwin and Lesch, 2003, 2004a, 2004b).

Currently, two $EC_a$-directed soil sampling design approaches are used: (1) design-based sampling and (2) model-based sampling. The former consists of the use of unsupervised classification (Johnson et al., 2001), whereas the latter typically relies on optimized spatial response surface (SRS) sampling designs (Corwin and Lesch, 2004b). Throughout the statistical literature model-based designs are less common, although some statistical research has been performed in this area (Valliant et al., 2000). Nathan (1988) and Valliant et al. (2000) discuss the merits of design (probability) and model (prediction) based sampling strategies in detail. Specific model-based sampling approaches having direct application to agricultural and environmental survey work are described by McBratney and Webster (1981), Lesch et al. (1995a, 1995b) Van Groenigen et al. (1999), and Lesch (2004).

In the past the characterization of soil spatial variability using $EC_a$-directed soil sampling focused on three different landscape-scale applications: (1) solute transport modeling in the vadose zone (Corwin et al., 1999), (2) soil quality assessment (Johnson et al., 2001; Corwin et al., 2003a), and (3) precision agriculture (Corwin et al., 2003b). All three studies by Corwin et al. (1999, 2003a, 2003b) were conducted on irrigated, arid-zone, agricultural land located in California’s Central Valley (Fig. 18.1). Two of the three studies were conducted within the Broadview Water District west of Fresno, CA: (1) a landscape-scale study of salt loading through the vadose zone to tile drains from 1991 to 1996 (Corwin et al., 1999) and (2) a precision agriculture study to identify edaphic properties influencing cotton yield on an irrigated field in 1999 (Corwin et al., 2003a). The third study was a soil quality assessment study on arid zone soil conducted by Corwin et al. (2003b) at a study site located on Westlake Farm near Stratford, CA, as part of a project to assess the sustainability of drainage water reuse to mitigate drainage volumes in the San Joaquin Valley (SJV). The study by Johnson et al. (2001) was conducted on an experimental site in Colorado.

Spatial variability for each of the three studies by Corwin and colleagues was characterized following protocols and guidelines for conducting an $EC_a$ survey to direct soil sampling that were later outlined and published by Corwin and Lesch (2003, 2004b). In each study ESAP software developed by Lesch et al. (1995a, 1995b, 2000) was used to establish the locations
where soil cores were taken based on the geo-referenced \( EC_a \) data that was obtained from \( EC_a \) surveys. The ESAP software uses a spatial response surface sampling (SRSS) design, which is a model-based sampling approach. The SRSS design locates a minimum set of calibration soil sample sites based on the observed magnitudes and spatial locations of geo-referenced \( EC_a \) measurements, with the explicit goal of optimizing the estimation of a regression model by minimizing the mean-square prediction errors produced by the calibration function (Lesch et al., 2000). It is the intention of the SRSS design to characterize the variability in geo-referenced \( EC_a \) measurements with a minimum number of sites. These sites are the locations where soil core samples are taken and appropriate soil physicochemical properties are measured as determined by the intended application (e.g., solute transport properties, site-specific crop management properties, or soil quality properties). A detailed discussion of the SRSS design concept is found in Lesch (2004).

18.4.1 LANDSCAPE-SCALE SOLUTE TRANSPORT IN THE VADOSE ZONE

To date, the only landscape-scale study to use \( EC_a \)-directed soil sampling to characterize soil variability for use in the modeling of solute transport in the vadose zone is by Corwin et al. (1999). In a study modeling salt loading to tile drains on a 2396 ha study site in California’s SJV, Corwin et al. (1999) used \( EC_a \)-directed soil sampling to define spatial domains of similar solute

![Map of Broadview Water District and Westlake Farm study sites located in California’s San Joaquin Valley.](image)
transport capacity in the vadose zone. These spatial domains, referred to as stream tubes, are volumes of soil that are assumed to be independent of adjacent stream tubes in the field with minimal lateral interaction (i.e., no solute exchange) so that a one-dimensional, vertical solute transport model can be applied to each stream tube without concern for lateral flow of water and transport of solute. The application of a one-dimensional solute transport model to each stream tube resulted in the prediction of salt loading for a 5-year study period.

An area of 37 contiguous quarter sections (i.e., 2396 ha) within the Broadview Water District was chosen as the experimental site to simulate salt loading to tile drains from May 1991 to May 1996 (Fig. 18.2). The model that was used to simulate salt transport through the vadose zone was a one-dimensional, “tipping bucket,” layer-equilibrium, functional model of solute transport (Corwin et al., 1991). The selection of a functional model, rather than a mechanistic model, to simulate salt transport through the vadose zone at landscape scale is based on organization hierarchy of spatial scales, which indicates that functional models are more appropriately applied at scales ranging from field to global (Corwin et al., 1997), whereas mechanistic models are best suited for molecular to pedon scales.

The single greatest challenge to modeling non–point source (NPS) pollutants, such as salinity, is to obtain sufficient data to characterize the temporal and spatial distribution of model parameter and variable inputs (Corwin et al., 1997). Therefore, a critical aspect of the study was to utilize a sampling strategy that would reflect the spatial heterogeneity of the physicochemical parameters and variables used in the functional solute transport model.
transport model. To meet this end, the statistical routine developed by Lesch et al. (1992, 1995a, 1995b) was utilized for electromagnetic induction (EMI) measurements of $EC_a$ taken with a Geonics EM-38 to determine soil sample locations. This statistical routine selects sample sites that reflect the spatial heterogeneity exhibited for $EC_a$, the supposition being that the EMI measurements of $EC_a$ are reflective of cumulative transport processes for salinity at a given location and can be used to identify spatial domains of similar transport properties for salt. Because $EC_a$ in arid zone soils is primarily a result of salinity, but is also influenced by water content, texture, and bulk density, this supposition relies upon local-scale spatial variation in soil properties that can be characterized and upon uniform irrigation applications within a spatial domain defined as similar in its ability to transport salts through the vadose zone (i.e., stream tube).

Within the 37 quarter sections, EMI measurements (both $EM_h$, electromagnetic induction measurement in the horizontal coil-mode configuration, and $EM_v$, electromagnetic induction measurement in the vertical coil-mode configuration) were acquired in each quarter section on a centric, systematic $8 \times 8$ grid generating 64 survey locations per quarter section (i.e., 2368 total locations for all 2396 hectares). Figure 18.3a and 18.3b show the locations of the EMI measurements for both $EM_h$ and $EM_v$ measurements, respectively. Soil spatial variability and spatial domains of solute transport were based upon the geometric mean and profile ratios calculated from the EMI measurements of $EC_a$. The EMI geometric mean was defined as $\sqrt{EM_h \times EM_v}$. The profile ratio was defined as $EM_h/EM_v$.

![FIGURE 18.3 Maps of Broadview Water District showing the 1991 $EC_a$ survey of the (a) $EM_h$ measurements and (b) $EM_v$ measurements, and the (c) spatial transport domains defined from the $EC_a$ survey data. (From Corwin et al., 1999.)](image-url)
In the horizontal coil configuration, the response of the EM-38 is mainly to $EC_a$ in the top 0.5 m of the soil profile with a volume of measurement occurring within the top 0.75 m. Sensitivity declines continuously with depth. In the vertical orientation, the response of the EM-38 is zero at the soil surface, peaks at roughly 0.4 m, then declines with increasing depth. The depth of penetration of measurement in the vertical orientation is roughly 1.5 m. Therefore, the $EM_h$ represents a shallow measurement of $EC_a$, while $EM_v$ represents a deep measurement of $EC_a$ within the root zone. Due to the response of the EM-38 in different coil orientations, the profile
ratio provides an indication of the \( EC_a \) profile. Profile ratios of 1 indicate a uniform profile, profile ratios of \(<1\) indicate an increasing profile with depth, and profile ratios of \(>1\) indicate an inverted profile (i.e., conductivity decreases with depth). It is assumed that the profile ratio is analogous to the leaching fraction, which is calculated by the electrical conductivity (EC) of the soil water passing below the root zone divided by the EC of the irrigation water. As such, the profile ratio is hypothetically reflective of the hydraulic properties of the soil at that particular location. In contrast, the EMI geometric mean reflects the cumulative salinity level within the root zone.

To minimize soil sampling requirements to a realistic number of locations that could be handled with limited manpower resources, soil cores at 0.3 m increments to a depth of 1.2 m were taken at between 8 to 12 of the 64 locations within each quarter section. From the 2396 sites, a total of 315 locations was selected for soil-core sampling. The selection of the 315 soil sampling sites was based on the observed EMI field pattern utilizing the response-surface technique of Lesch et al. (1992, 1995a, 1995b). Figure 18.3c shows the location of the soil-core sample sites in relation to the quarter section boundary lines.

Thiessen polygons for each quarter section were created from the soil-core sample sites, with each soil-core site serving as the centroid of each resulting Thiessen polygon (Fig. 18.3c). Each Thiessen polygon in Figure 18.3c was assumed to define a stream tube or spatial domain of solute transport properties where the variability of the properties is least (Bouma, 1990; Mayer et al., 1999), and solute transport occurs only in the vertical direction with no influence from adjacent stream tubes (Jury and Roth, 1990). In essence, the first four sample locations of each quarter section were selected so that one location satisfied each of the following four criteria: (1) high EMI geometric mean and high profile ratio, (2) high EMI geometric mean and low profile ratio, (3) low EMI geometric mean and high profile ratio, and (4) low EMI geometric mean and low profile ratio. The next four sample locations were chosen randomly within the quarter section. High and low values for the means and ratios were relative, i.e., the highs and lows were identified in each field or quarter section on a field-by-field basis.

To evaluate the validity of the stream-tube approach, measured and simulated salt loads were compared for a core area of 16 quarters where water mass balance showed no lateral flow influences. Table 18.3 shows the compared results for simulated and measured salt loads to 7 drainage sumps, which drained the 16 quarter sections as depicted in Figure 18.2. Figure 18.4 shows the spatial distribution of the salt loads after 5 years for the 16 quarter sections. Except for the drainage sump associated with quarter sections 9-3 and 9-4, the simulated salt loads show excellent agreement to within 30% of the measured salt loads. The significant difference between the measured and simulated salt loads for the 9-3/9-4 drainage sump was attributed to lateral water flows that occurred from
TABLE 18.3

<table>
<thead>
<tr>
<th>Quarter section(s) (Mg/ha)</th>
<th>Measured(^a) (Mg/ha)</th>
<th>Simulated(^b)</th>
</tr>
</thead>
<tbody>
<tr>
<td>3-1, 3-2, 3-3, &amp; 3-4</td>
<td>14.33</td>
<td>16.97</td>
</tr>
<tr>
<td>4-1 &amp; 4-3</td>
<td>39.22</td>
<td>31.84</td>
</tr>
<tr>
<td>4-2 &amp; 4-4</td>
<td>46.23</td>
<td>33.00</td>
</tr>
<tr>
<td>9-1 &amp; 9-2</td>
<td>11.48</td>
<td>13.22</td>
</tr>
<tr>
<td>9-3 &amp; 9-4</td>
<td>2.1</td>
<td>10.45</td>
</tr>
<tr>
<td>10-1 &amp; 10-2</td>
<td>16.53</td>
<td>16.56</td>
</tr>
<tr>
<td>10-3 &amp; 10-4</td>
<td>16.05</td>
<td>15.91</td>
</tr>
</tbody>
</table>

\(^a\)Measured at drainage sump.
\(^b\)Area-weighted average of 8–16 simulated Thiessen polygons within each quarter section.

Source: Corwin et al. (1999).

FIGURE 18.4 Map showing the spatial distribution of salt loading for the 16 quarter sections comprising the validation data set. (From Corwin et al., 1999.)

southwest to northeast from the designated buffer zone area in the south (see Fig. 18.4). The general close agreement between measured and simulated results in Table 18.3 validates the delineation of stream tubes with EC\(_a\)-directed soil sampling survey data as a viable means of modeling NPS pollutant loads to tile drains or groundwater at field and landscape scales.
18.4.2 Assessing Soil Quality and Spatio-Temporal Changes in Soil Quality

The application of \( EC_a \)-directed soil sampling to characterize soil condition has been restricted to the Great Plains area and the southwestern United States. Using \( EC_a \) maps to direct soil sampling, Johnson et al. (2001) and Corwin et al. (2003a) spatially characterized the overall soil quality of physicochemical properties thought to affect yield potential.

To characterize soil quality, Johnson et al. (2001) used a stratified soil sampling design (i.e., unsupervised classification) with allocation into four geo-referenced \( EC_a \) ranges. Correlations were performed between \( EC_a \) and the minimum data set of physical, chemical, and biological soil attributes proposed by Doran and Parkin (1996). Their results showed a positive correlation of \( EC_a \) with percentage clay, \( \rho_b \), pH, and \( EC_{1:1} \) over a soil depth of 0–30 cm, and a negative correlation with soil moisture, total and particulate organic matter, total C and N, microbial biomass C, and microbial biomass N. Johnson et al. (2001) concluded that “\( EC_a \) classification effectively delimits distinct zones of soil condition, making it an excellent basis for soil sampling to reflect spatial variability.”

Corwin et al. (2003a) characterized the soil quality of a saline-sodic soil using a SRSS design. A positive correlation (significant at the 0.01 level) was found between \( EC_a \) and the properties of volumetric water content; electrical conductivity of the saturation extract (\( EC_e \)); Cl\(^-\), NO\(_3\), SO\(_4\), Na\(^+\), K\(^+\), and Mg\(^{2+}\) in the saturation extract; SAR (sodium adsorption ratio), exchangeable sodium percentage (ESP); B; Se; and Mo. A negative correlation (significant at the 0.01 level) was found for CaCO\(_3\), inorganic C, and organic C. Most of these properties are associated with soil quality for arid zone soils. The high positive and negative correlations indicated that the spatial variability of these soil properties were accurately characterized by the SRS sampling design and predictable from the \( EC_a \) survey data. However, a number of other soil properties (i.e., \( \rho_b \); percentage clay; pH; SP; HCO\(_3\) and Ca\(^{2+}\) in the saturation extract; exchangeable Na\(^+\), K\(^+\), and Mg\(^{2+}\); As; CEC; gypsum; and total N) did not correlate well with \( EC_a \) measurements. To accurately quantify these properties in this particular field, a complementary design-based sampling scheme is needed.

Neither Johnson et al. (2001) nor Corwin et al. (2003a) actually related the spatial variation in the measured soil physicochemical properties to crop yield variations. Nevertheless, both studies show the practicality and utility of using \( EC_a \)-directed soil sampling to spatially characterize soil quality for a variety of indicator properties.

Spatio-temporal variations in soil quality using \( EC_a \)-directed soil sampling have been studied by Lesch et al. (1998) and Corwin et al. (2004). In both instances, statistically significant temporal changes were identified. Corwin et al. (2004) showed that average salinity levels were reduced roughly 13% in the top 0.6 m. Sodium, B, and Mo levels were also found
to be reduced from 1999 to 2002 in the top 0.6 m, with leaching the most probable cause.

In the study by Corwin et al. (2004), changes in spatial patterns were extremely complex and reflected a preferential pattern of change that was difficult to explain, except for potential microtopographic effects caused by leaching in the near surface (i.e., 0–0.3 m). Nevertheless, the ability to monitor temporal change at field scale was shown. In particular, it was clearly shown that leaching of salts had occurred for the top 0.6 m of soil. Figure 18.5 shows the initial spatial distribution of salinity in 1999, as measured by the electrical conductivity of the saturation extract ($EC_e$), at a saline-sodic study site where a field study was conducted to determine the sustainability of drainage water reuse on a salt-tolerant forage crop as a viable alternative to drainage water disposal on the west side of the San Joaquin Valley. Associated with the 1999 salinity levels in Figure 18.5 are the changes in salinity that have occurred up to 2002 over the 0–0.3 and 0.3–0.6 m depth increments where leaching occurred as a consequence of the application of drainage water that ranged from 5 to 10 dS m$^{-1}$. The preliminary 2002 results showed that salinity, sodium, B, and Mo had been leached in the top 0.6 m of soil, indicating a general improvement in soil quality (Corwin et al., 2004). Another $EC_a$-directed soil sampling survey was to be conducted at the end of the 5-year study.

**FIGURE 18.5** Maps of (a) $EC_e$ for 1999 at depth increments of 0–0.3, 0.3–0.6, 0.6–0.9, and 0.9–1.2 m and (b) change in $EC_e$ from 1999 to 2002 at depth increments of 0–0.3 and 0.3–0.6 m. (From Corwin et al., 2004.)
18.4.3 Delineating Site-Specific Management Units for Precision Agriculture

Corwin et al. (2003b) carried the $EC_a$-directed soil sampling approach to the next level by integrating crop yield to arrive at site-specific crop management recommendations. Through spatial statistical analysis, Corwin et al. (2003b) were able to identify those edaphic (i.e., salinity, water content, and pH) and anthropogenic (i.e., leaching fraction) properties (Fig. 18.6) influencing the within-field spatial variation of cotton yield (Fig. 18.7a) on a 32.4 ha field in the Broadview Water District of central California. A cotton yield response model was formulated that related cotton yield ($Y$) to leaching fraction ($LF$), salinity ($EC_e$), gravimetric water content ($\theta_g$), and pH:

$$Y = 19.277 + 0.218(EC_e) - 0.015(EC_e)^2 - 4.420(LF)^2 - 1.997(pH) + 6.927(\theta_g) + \epsilon \quad (18.10)$$

**FIGURE 18.6** Maps of the four most significant factors (0–1.5 m) influencing cotton yield: (a) $EC_e$ (dS m$^{-1}$), (b) LF, (c) $H_2O$ (kg kg$^{-1}$), and (d) pH. (From Corwin et al., 2003b.)
A comparison of the measured and the simulated cotton yields at the locations where directed soil samples were taken showed close agreement, and Eq. (18.10) successfully described slightly more than 60% of the estimated spatial yield variation. A visual comparison of the measured and simulated spatial yield distributions of cotton shows a reasonably close spatial association between interpolated measured (Fig. 18.7b) and predicted (Fig. 18.7c) maps.

From Eq. (18.10) and scatter plots of cotton yield vs. properties, management recommendations were made that spatially prescribed what could be done to increase cotton yield at those locations with less than optimal yield. Subsequently, Corwin and Lesch (2004a) delineated site-specific management units (SSMUs), which are depicted in Figure 18.8. Highly leached zones were delineated where the $LF$ needed to be reduced to $\leq 0.5$; high-salinity areas were defined where the salinity needed to be reduced below the salinity threshold for cotton, which was established at $EC_e = 7.17 \, dS \, m^{-1}$ 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 to 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 increase yield.

**FIGURE 18.7** 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. (18.10). (From Corwin et al., 2003b.)
18.5 FUTURE DIRECTIONS

Because of the heterogeneous nature of soils, characterization of soil spatial variability is a fundamental component of any landscape-scale process that cannot be overlooked or superficially addressed. Significant technological advances have occurred over the past two decades, particularly in the area of sensor technology and in precisely locating geographic position with GPS. These advances have helped the progress of research in characterizing spatial variability at field and landscape scales.

Geospatial measurements of $EC_a$ are among the ground-based sensor technologies contributing to an improved ability to characterize spatial variability. Numerous soil samples are required for representative estimates of field-scale spatial variability using traditional grid sampling, making grid sampling impractical due to labor and cost intensiveness. Soil sampling directed by geospatial $EC_a$ measurements provides a viable alternative for characterizing spatial variability of a variety of soil-related physicochemical properties. Geospatial $EC_a$ measurements provide a means of significantly reducing the number of soil samples needed to characterize spatial variability, provided that the target soil properties are well correlated with the conductivity survey data. The reliability of $EC_a$-directed soil sampling for characterizing spatial variability has been shown for applications in a variety of areas including (1) solute transport in the vadose zone (Corwin et al., 1999), (2) precision agriculture (Corwin et al., 2003b), and (3) soil quality assessment (Johnson et al., 2001; Corwin et al., 2003a, 2004).
Even though geospatial measurements of $EC_a$ provide one of the most cost-effective means of characterizing spatial variability, associated ground truth soil sampling must accompany $EC_a$ surveys because of the complexity of the $EC_a$ measurement and the need for ground truth samples to interpret $EC_a$ measurements. Without associated soil samples, the interpretation of $EC_a$ measurements is questionable and is not advised. Laboratory analyses of associated ground-truth soil samples impose the greatest cost and labor for characterizing spatial variability with geospatial $EC_a$ measurements. Model-based sampling designs are the most efficient at reducing the number of soil sample sites to a minimum without compromising the characterization of variability, but only when a property correlates with $EC_a$. For those instances where a property does not correlate with $EC_a$, a random or stratified random sampling design should be used to spatially characterize the property to minimize error resulting from sampling design bias.

When geospatial measurements of $EC_a$ are spatially correlated with georeferenced yield data, their combined use provides an excellent tool for identifying edaphic factors that influence crop yield, which can, in turn, be used to delineate site-specific management units (Corwin et al., 2003; Corwin and Lesch, 2004a). The delineation of productivity zones from geospatial measurements of $EC_a$ provides another approach to site-specific management (Kitchen et al., 2004; Jaynes et al., 2004). Even so, an understanding of the soil-related factors influencing yield or the identification of productivity zones does not provide the whole picture for site-specific crop management because yield is influenced by a complex interaction of topographical (elevation, aspect, etc.), meteorological (humidity, temperature etc.), biological (e.g., pests), anthropogenic (management-related), and edaphic (soil-related) factors. Moreover, the precise manner in which these factors influence the dynamic process of plant growth and reproduction is not always well understood. To be able to manage within-field variation in yield, it is necessary to have an understanding within a spatial context of the relationship of all dominant factors causing the variation.

Directed soil sampling with geospatial $EC_a$ measurements has its limitations in characterizing spatial variability because many soil properties are not measured, directly or indirectly, by $EC_a$; therefore, the biased sampling of a model-based sampling design approach will not be representative. Even a design-based approach (e.g., stratified random sampling) directed by $EC_a$ may not be sufficient to characterize those properties not correlated with $EC_a$. In these instances, additional spatial information is needed to fill the gaps necessary to spatially characterize the variability of those properties that are not directly or indirectly measured with $EC_a$. The information from additional sensors is needed to either directly measure or to direct soil sampling of those soil properties not correlated with $EC_a$.

The integrated use of multiple remote and ground-based sensors is the future direction that research will likely take to obtain the extensive spatial
data needed to characterize spatial variability. Integration of multi- and hyperspectral imagery, TDR, GPR, aerial photography, and EC sensors is needed to provide redundant and supplemental data necessary to unravel the spatial complexity of soil. Network-centric multisensor systems will likely provide the broad spectrum of overlapping and supplementary information needed to spatially characterize the compositional and structural complexity of soil.

ACKNOWLEDGMENTS

The author wishes to acknowledge the efforts and contributions of all those colleagues who collaborated with him on past projects involving the characterization of spatial variability with geospatial EC measurements, including Scott Lesch, Stephen Kaffka, Jim Rhoades, Jim Oster, and Pete Shouse. In particular, the author acknowledges the statistical support and collaboration provided by Scott Lesch, who has been a cornerstone to the success of this research. The author also appreciates the numerous hours of diligent technical work performed in the field and in the laboratory by several technicians whose efforts and conscientiousness were crucial to the success of the projects, including Clay Wilkinson, Nahid Vishteh, Harry Forster, Jack Jobes, JoAn Fargerlund, Derrick Lai, and Lena Ting.

REFERENCES


Bouma, J., Using morphometric expressions for macropores to improve soil physical analyses of field soils, Geoderma, 46, 3–11, 1990.

Electrical Conductivity for Characterizing Soil Spatial Variability


Soil-Water Solute Process Characterization


