

Remote- and Ground-Based Sensor Techniques to Map Soil Properties

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Abstract

Farm managers are becoming increasingly aware of the spatial variability in crop production with the growing availability of yield monitors. Often this variability can be related to differences in soil properties (e.g., texture, organic matter, salinity levels, and nutrient status) within the field. To develop management approaches to address this variability, high spatial resolution soil property maps are often needed. Some soil properties have been related directly to a soil spectral response, or inferred based on remotely sensed measurements of crop canopies, including soil texture, nitrogen level, organic matter content, and salinity status. While many studies have obtained promising results, several interfering factors can limit approaches solely based on spectral response, including tillage conditions and crop residue. A number of different ground-based sensors have been used to rapidly assess soil properties "on the go" (e.g., sensor mounted on a tractor and data mapped with coincident position information) and the data from these sensors complement image-based data. On-the-go sensors have been developed to rapidly map soil organic matter content, electrical conductivity, nitrate content, and compaction. Model and statistical methods show promise to integrate these ground- and image-based data sources to maximize the information from each source for soil property mapping.

Introduction

The processes of soil formation over landscapes, along with management-induced soil changes (e.g., accelerated erosion with tillage, compaction, etc.), have created soil

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variations within cropped fields that impact crop production. Yield monitoring has demonstrated to farmers that much of the yield variability within fields is associated with soil and landscape properties. Numerous soil properties influence the suitability of the soil as a medium for rooting. Some of these important properties include soil water holding capacity, water infiltration rate, texture, structure, bulk density, organic matter, pH, fertility, soil depth, landscape features (e.g., slope and aspect), the presence of restrictive soil layers, and the quantity and distribution of crop residues. These properties are complex and vary spatially and temporally within fields. The emergence of variable-rate application technology has generated a need to quantify these variations at relatively fine spatial resolutions. Statistically interpolating between sample points taken over a fixed grid has been used in the past; however, this approach is not always feasible due to the time and cost associated with sample collection. Thus, more emphasis is now being placed on the use of remotely sensed data to quantify differences in soil physical properties. The objective of this paper is to review the current state of knowledge in the application of sensor-based data for rapidly mapping soil properties, with an emphasis on work done by the USDA, Agricultural Research Service (ARS). Additionally, challenges to the current techniques and areas requiring additional research are identified.

Relationships to Soil Spectral Responses

Characterization of soil properties is one of the earliest applications of remotely sensed data in agriculture. Bushnell (1932) described efforts in the 1920s to use aerial photos to map boundaries of different soil series. Aerial photographs have been used as a mapping aid in most of the soil surveys in the United States since the late 1950s. A majority of the studies examining quantitative relationships between remotely sensed data and soil properties have focused on the reflective region of the spectrum (0.3 to 2.8 μm), with some relationships established from data in the thermal and microwave regions. Most of the spectral responses in the reflective spectrum can be related to differences in organic matter content, iron content, and texture (Stoner and Baumgardner, 1981). The soil property that is most directly correlated to reflectance-based data is soil albedo (Post *et al.*, 2000). Additional soil properties have been inferred from reflectance measurements under laboratory conditions such as moisture, organic carbon, total nitrogen, and other chemical properties (Baumgardner *et al.*, 1985; Dalal and Henry, 1986; Shonk *et al.*, 1991; Sudduth and Hummel,

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1993b; Ben-Dor and Banin, 1994). Some of the relationships have also been established for data acquired over tilled or fallow fields, as described in the following paragraphs.

Surface Texture

Reflectance measurements over tilled fields have been used to develop predictive equations for the fraction of sand, silt, and/or clay at the soil surface with varying levels of success (Suliman and Post, 1988; Coleman *et al.*, 1991). Dependable relationships are only possible when imagery is acquired over fields with uniform tillage conditions, and often the response is only strong enough to identify textural class at the surface (Barnes and Baker, 2000). To minimize the effects of soil properties other than texture (e.g., soil moisture, organic matter, and minerals other than quartz), Salisbury and D'Aria (1992) used a combination of visible, near-infrared (NIR) and thermal-infrared data. Directed sampling approaches can also be useful for interpreting bare soil imagery in terms of soil texture (more detail on the concept of "directed sampling" is provided in following sections of this review).

Organic Matter

Soil organic matter (SOM) has been related to reflectance data collected over agricultural fields in several studies (Coleman *et al.*, 1991; Henderson *et al.*, 1992; Chen *et al.*, 2000). Henderson *et al.* (1992) found that visible wavelengths (0.425 to 0.695 μm) had a strong correlation with soil organic matter for soils with the same parent material; however, the relationship was sensitive to Fe and Mn-oxides for soils from different parent materials. Use of middle infrared bands improved predictions of organic carbon content when the soils were from different parent materials. Chen *et al.* (2000) were able to accurately predict soil organic carbon using true color imagery of a 115-ha field with the use of locally developed regression relationships.

Salinity

Many salt-affected soils can be identified by a white salt crust that will form on the soil surface; thus, these soils tend to have higher visible and NIR reflectance (Rao *et al.*, 1995). This spectral response cannot always be used to identify saline soils, because soils with high sand contents will have visible and NIR spectral properties similar to salt-crusted soils (Verma *et al.*, 1994). The ability to discriminate salt-affected soils has been improved through the inclusion of thermal data (Verma *et al.*, 1994) and L-band microwave data (Sreenivas *et al.*, 1995).

Moisture

Microwave data (both passive and active) have been related to surface soil moisture (Jackson, 1993; Moran *et al.*, 1998). The approach is limited when vegetation is present and is often only sensitive to conditions at the surface (~5 to 20 cm depth); however, use of different bands and integrating the data with soil-water balance models have shown that microwave data can be useful in mapping soil moisture conditions. Soil moisture has been correlated to visible and NIR reflectance of bare-soil fields if the data are taken a few days after rainfall (Milfred and Kiefer, 1976). Similarly, thermal imagery has also been related to differences in surface soil moisture content (Davidoff and Selim, 1988).

Challenges

There are several challenges that emerge as one tries to infer soil properties for application to agricultural management from bare-soil imagery. First, if a soil property map for use in agricultural management decisions is derived from reflectance or emitted thermal data, an implicit assumption

is that the soil property at the surface also correlates to changes throughout the root zone. Second, changes in surface tillage condition (e.g., bedded versus flat, fine disking versus coarse plow), rain compaction, moisture, and plant residue all may induce changes in apparent soil reflectance that approach or exceed spectral responses due to soil physical properties such as texture and organic matter (Courault *et al.*, 1993; Barnes and Baker, 2000). The impact of tillage on the ability to detect differences in surface soil texture is illustrated in Plate 1. Plate 1a is a surface texture map generated by kriging from sand, silt, and clay fractions measured in the top 30 cm of the soil profile at an approximate grid spacing of 120 m (adapted from Barnes and Baker (2000)). The resulting maps were used to form a three-band composite "image" by assigning fractions of sand, silt, and clay to the red, blue, and green bands, respectively (e.g., increased red levels in Plate 1a represent areas with high sand content). Plate 1b is a SPOT-1 HRV false-color composite of the same area. Within areas of similar tillage, areas of high sand content appear to be relatively brighter in the image; however, it can be seen that any attempt to apply a single relationship between the image brightness level and sand content would not yield accurate results. Therefore, there is a definite need to integrate other data sources and approaches before robust methods can be developed to translate bare soil imagery into maps of soil properties such as textural percentage, or plant nutrient availability.

Crop Residue Cover Assessment

One approach to improving remote sensing techniques that relies on the spectral response to infer soil properties is to develop methods that can identify inferring factors so that they can be removed during later analysis. One example where progress is being made in this area is in the detection of crop residue. In addition to improving soil-mapping techniques, quantifying crop residue cover on the soil surface is important for improving estimates of surface energy balance, net primary productivity, nutrient cycling, and carbon sequestration. Quantifying crop residue cover is also an important factor in controlling soil erosion and evaluating the effectiveness of conservation tillage practices. By reducing the movement of eroded soil into streams and rivers, the movement of nutrients and pesticides is also reduced.

Current Techniques

The standard technique for measuring crop residue cover used by the USDA, Natural Resources Conservation Service (NRCS) is visual estimation along a line transect (Morrison *et al.*, 1993). In this method, a cable is stretched over the soil surface and the presence or absence of residue at selected points along the cable is determined. Accuracy of the line-point transect depends on the length of the line and the number of points used per line (Lafren *et al.*, 1981). Reviews of crop residue measurement techniques document recent modifications and illustrate the unresolved problems of current techniques (Morrison *et al.*, 1993; Morrison *et al.*, 1995; Morrison *et al.*, 1998).

Photographs and digital images have been analyzed using either manual or computer-aided methods to identify and classify residues and soils. Errors occur when the spectral differences between classes (i.e., soil and residue) are not sufficiently large for discrimination (Meyer *et al.*, 1988; Morrison and Chichester, 1991). The reflectance of both soils and crop residue lack the unique spectral signature of green vegetation in the 400- to 1000-nm wavelength region (Gausman *et al.*, 1975; Gausman *et al.*, 1977; Wanjura

and Bilbro, 1986; Aase and Tanaka, 1991). Crop residues and soils are often spectrally similar and differ only in amplitude at a given wavelength (Figure 1). This makes discrimination between crop residues and soil difficult or nearly impossible using reflectance techniques in the visible and NIR portions of the spectrum.

Improved Remote Sensing Approaches

Two promising approaches have been identified for discriminating crop residues from soil — one based on blue fluorescence emissions and another based on shortwave infrared reflectance. The fluorescence approach is based on research first reported by McMurtrey *et al.* (1993), that crop residues fluoresce more than soils when illuminated with ultraviolet radiation. Chappelle *et al.* (1995) made considerable progress in developing a portable agricultural residue sensor based on the fluorescence of soils and residues and have a patent on the technique.

Advances in low-light imaging technology make it possible to capture fluorescence images. Albers *et al.* (1995) described a broadband fluorescence imaging system for detection, characterization, and monitoring of contaminants in the environment. Multispectral fluorescence images have been used to detect the spatial variability in the fluorescence of plant leaves associated with various physiological stresses (Kim *et al.*, 2001) and to determine the fraction of the soil surface covered by crop residue (Daughtry *et al.*, 1997). Although considerable progress has been made in developing a portable agricultural residue sensor based on the fluorescence of soil and residues, several problems must be addressed, including (1) the excitation energy must be supplied to induce fluorescence and (2) the fluorescence signal is small relative to normal, ambient sunlight.

Three broad absorption features (near 1730 nm, 2100 nm, and 2300 nm) in the reflectance spectra of crop residues

are not evident in reflectance spectra of soils (Figure 1). Band-depth analysis of these absorption features using simulated mixed residue-soil scenes indicated that quantitative assessment of crop residue cover is possible (Nagler *et al.*, 2000; Daughtry *et al.*, 2001). A three-band spectral variable, cellulose absorption index (CAI), which measured the depth of the absorption feature at 2100 nm, separated crop residues from soils (Daughtry, 2001). In a preliminary study with AVIRIS (Airborne Visible InfraRed Imaging Spectrometer) data, fields with vegetation, crop residue, and plowed soil were correctly identified using CAI and the Normalized Difference Vegetative Index (NDVI; Daughtry *et al.*, 2001). Pairs of vegetation indices were useful in discriminating most, but not all, cover types. A multiband radiometer with 3 to 5 bands could be used as a replacement for the manual line-transect method of measuring field crop residue cover. Regional surveys and maps of crop residue cover and conservation tillage practices may be feasible using hyperspectral imaging systems.

Challenges

One of the challenges facing the application of these newer technologies for residue assessment is data availability. Only a limited number of sensor systems provide data in the wavelength range needed to determine CAI. Fluorescence techniques require an excitation source, and the fluorescence signal is small relative to ambient sunlight. More work is also needed to determine how crop residue maps can be used to improve interpretation of soil properties from multispectral data.

Inferring Soil Properties from Crop Spectral Responses

A crop's response to differences in soil conditions can also be used as an aide in soil mapping. An advantage of this approach over those discussed in the previous section is that the crop response integrates conditions throughout the root zone. Soil properties that have been inferred from crop response include salinity (Wiegand *et al.*, 1996), soil nutrient deficiencies (McMurtrey *et al.*, 1994; Bausch and Duke, 1996), and soil moisture availability (Colaizzi *et al.*, 2003). In the following paragraphs, brief examples are given where crop response can be related to soil properties. Pinter *et al.* (2003; p. xxx this issue) provide a more detailed review of examples related to crop nutrient and water status.

Salinity

Wiegand *et al.* (1996) used airborne digital videography and SPOT HRV imagery in conjunction with soil and plant samples to quantify and map the variations in electrical conductivity of the root zone in a salt-affected sugarcane field. They found that crop spectral response based on either videography or SPOT data provided good estimates of soil salinity. Regression equations between the weighted electrical conductivity and the spectral data were then used to generate a salinity map for the field.

Nutrients

The nutrient status of a crop provides an integrated measure of soil nutrient availability in the root zone when there are no other factors limiting the crop's nutrient uptake (e.g., pest infestations and salinity). Several studies have shown good relationships between spectral reflectance, chlorophyll content, and nitrogen status in green vegetation (Bausch and Duke, 1996; Stone *et al.*, 1996; Blackmer *et al.*, 1996). Stone *et al.* (1996) developed a Plant Nitrogen Spectral Index (PNSI) for correcting in-season wheat N deficiencies from canopy radiance data measured in the red (671 ± 6 nm) and NIR (780 ± 6 nm) portions of the electromagnetic spec-

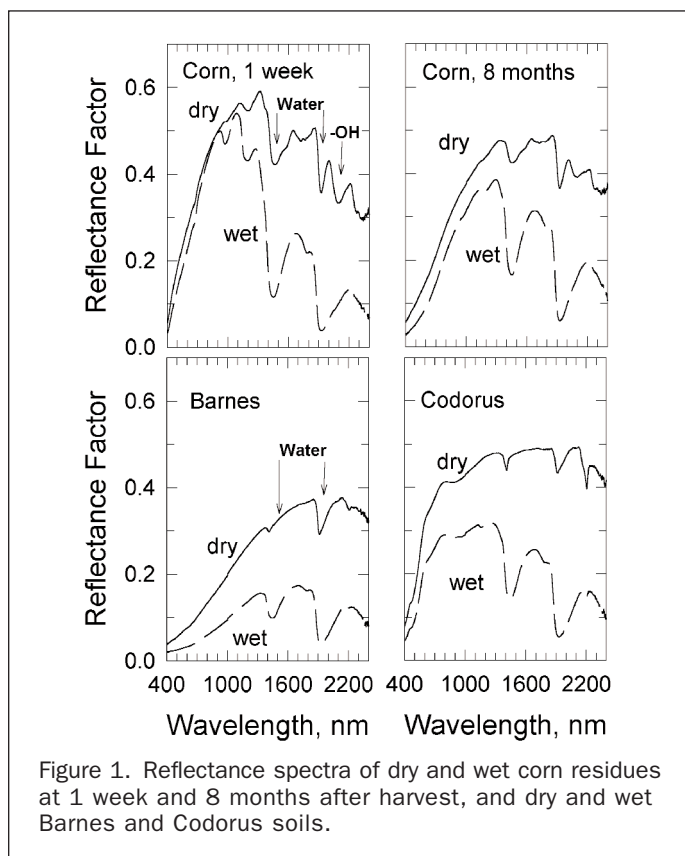


Figure 1. Reflectance spectra of dry and wet corn residues at 1 week and 8 months after harvest, and dry and wet Barnes and Codorus soils.

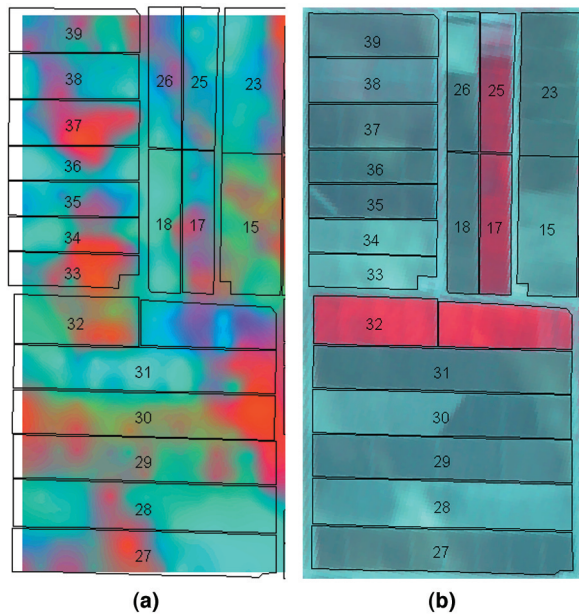


Plate 1. (a) Statistically interpolated map of surface soil texture represented as a false-color composite using fraction sand, silt, and clay for red, green, and blue, respectively. (b) SPOT1-HRV false-color composite (NIR, green, red bands) of the Maricopa Agricultural Center in Arizona (adapted from Barnes and Baker (2000)).

trum. Blackmer *et al.* (1996) used spectroradiometer-measured reflected radiation of corn at the dent growth stage and showed that canopy radiance near 550 nm and 710 nm was superior to canopy radiance near 450 nm or 650 nm for detecting N deficiencies. Their results also showed that the ratio of canopy radiance in the 550- to 600-nm interval to the 800- to 900-nm interval provided sensitive detection of N stress. Bausch and Duke (1996) developed an N Reflectance Index (NRI) to monitor plant N status of irrigated corn from green (520 to 600 nm) and NIR (760 to 900 nm) canopy reflectance. The NRI was defined as a ratio of the NIR/green for an area of interest to the NIR/green for a well N-fertilized reference area. Comparison of the NRI and the PNSI produced a near 1:1 relationship for corn growth stages between V11 and R4. Data plots of the NRI versus plant tissue total N concentration and the PNSI versus plant tissue total N concentration produced very similar slopes and intercepts. Relationships developed between the NRI-nadir view and the Nitrogen Sufficiency Index (NSI) and the NRI-75° view and the NSI from data representing the V9 through V16 corn growth stages had nearly identical coefficients of determination (Bausch and Diker, 2001). However, the 75°-view NRI data had less scatter, as shown in Figure 2. Based on these relationships and the accepted NSI threshold of 0.95 to indicate an N deficiency, an NRI less than 0.95 also indicates an N deficiency that needs correcting by applying additional N. Visible and NIR leaf reflectance data have also been related to plant micronutrients; however, the responses between nutrients were not unique with the possible exception of iron (Masoni *et al.*, 1996).

Plant Available Soil Moisture

While covered in more detail by Pinter *et al.* (2003; p. xxx this issue), it should be noted that plant available soil moisture can be related to crop canopy temperature in some cir-

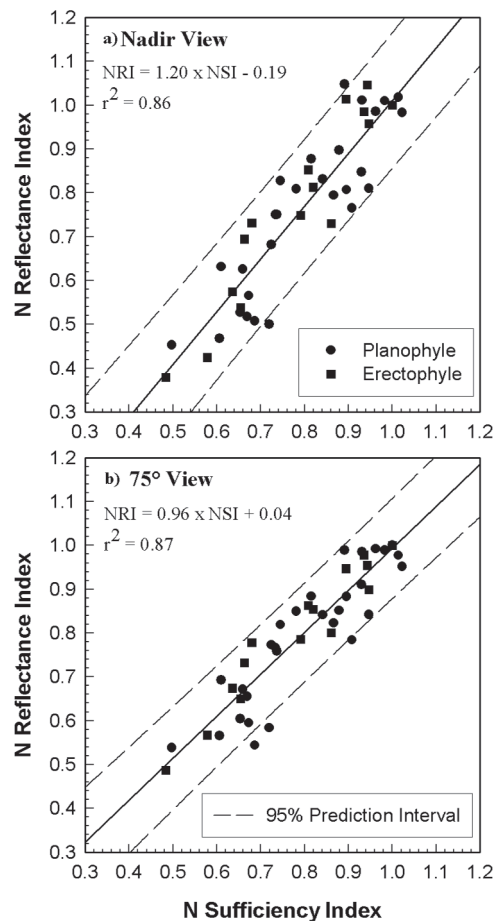


Figure 2. Relationship between the N reflectance index (NRI) and N sufficiency index. (a) NRI calculated from nadir view. (b) NRI calculated from 75°-view radiometer data for the V9 through V16 corn growth stages.

cumstances (Jackson, 1982). Colazzi *et al.* (2003) found that the crop water stress index (CWSI) could be related to the level of soil water depletion determined from neutron probe readings. Wildman (1982) illustrates how crop patterns in color-infrared (CIR) photos can be related to soil type in irrigated fields.

Management Zones

Although crop reflectance data have also been related to moisture stress and nutrient deficiencies in soils, there have been relatively few additional examples in which crop reflectance data have been used to infer soil properties. This is because it is difficult to separate the effect of the desired soil property from other factors in the environment. For example, a crop can be simultaneously deficient in nutrients and experiencing chronic water stress, both of which result in similar spectral features. While it may not always be possible to determine the source of crop variability from remotely sensed data alone, remote sensing research has reinforced the conclusion that crop plants integrate the growing conditions they have experienced and express their response through the canopies produced. Spectral responses in the visible and NIR wavelengths, and vegetation indices calculated from the spectral values, are a measure of the amount of photosynthetically active tissue in plant canopies (Wiegand and Richardson, 1990). Therefore, the best ap-

proach may be to use crop spectral response to identify spatial variability in the field and then use direct sampling in selected areas to diagnose the source of the variability.

Management zones, developed by statistically clustering image pixels into categories of similar spectral response, should reduce both the variance within each zone and the number of soil samples required to characterize each zone. The concept of management zones has practical implications in sampling design and variable rate application for precision farming. Johannsen *et al.* (2000) suggested that management zones might be used to guide soil sampling and form the basis for adjusting nutrient application rates using variable rate technology. Successful development of meaningful management zones from remote observations will reduce the amount of time and resources spent on systematic or grid ground sampling and thus improve the economic viability of precision farming (Lu *et al.*, 1997).

Yang and Anderson (1996; 1999) used airborne multi-spectral digital videography and unsupervised classification techniques to determine within-field management zones for two grain sorghum fields with multiple stresses. Two of the zones identified were soil related: one represented areas with insufficient soil moisture, and the second depicted areas where plants suffered severe chlorosis due to iron deficiency. The remaining zones represented areas with different production levels due to a combination of soil and environmental factors. In another study, grain yields differed significantly among the spectral zones, and the low yield in one of the zones was predominately due to a very sandy soil texture (Yang *et al.*, 2000).

Aerial imagery and grain yield monitor data often show a high degree of spatial correlation, although the patterns may change for wet, dry, and normal years (Lu *et al.*, 1997). Soil chemical and physical properties generally cannot explain the variability observed in crop yield responses (Colvin *et al.*, 1997; Timlin *et al.*, 2001). Dulaney *et al.* (2001) analyzed ground penetrating radar (GPR) image profile data and determined that the orientation and depth of subsurface clay layers governed the movement and direction of groundwater movement. Spatial patterns in the aerial imagery and corn grain yields showed a high degree of correlation with the subsurface flow pathways, suggesting that the movement of ground water along the clay layers may act as a subsurface irrigation system, increasing crop growth and yields in drought years.

Challenges

One of the challenges in using crop spectral response to infer a specific soil property is how to separate the effects caused by other soil physical and chemical properties and biological conditions such as plant growth and pest infestations. Only if the effect of the desired soil property is large enough to cause a change in canopy color or severely alter the crop growth can it be detected reliably by remotely sensed imagery. One problem associated with image-based management zones is their consistency or stability over consecutive seasons. New imagery should be used annually, if necessary, to revise the management zones to accommodate any unexpected changes, such as pest infestations.

Complimentary Ground-Based Sensors to Map Spatial Variability in Soil Properties

One of the major challenges identified in the previous sections on the use of remotely sensed data to accurately map soil properties is the number of interfering factors that can impact the soil or crop's spectral signal. Developments in ground-based sensors show promise to provide data sources

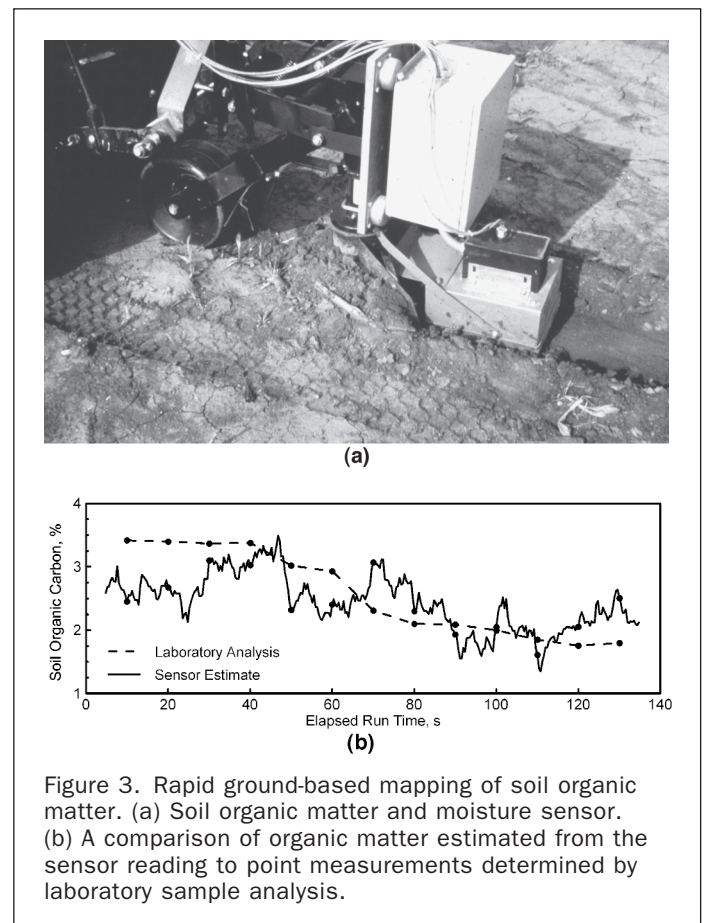
complimentary to image-based information when trying to develop detailed soil property maps. Progress in sensor development for a number of ground-based sensor systems was reviewed by Hummel *et al.* (1996) and Sudduth *et al.* (1997). An overview of several ground-based technologies developed to rapidly assess and map soil properties follows.

NIR Reflectance Sensors

Soil organic matter (SOM) has been correlated with visible and NIR reflectance in many studies (e.g., Krishnan *et al.*, 1980; Stoner and Baumgardner, 1981). Sudduth and Hummel (1993a) developed a portable spectrophotometer designed to acquire NIR soil reflectance data at a number of narrow-band wavelengths and successfully predicted SOM across a range of soil types and moisture contents. However, in field tests, the movement of soil past the sensor during scanning introduced considerable errors and produced unacceptable results (Sudduth and Hummel, 1993b). Figure 3a shows an updated prototype sensor with faster data collection capabilities. The sensors have been used to estimate SOM, soil moisture, and CEC in soils from a wide geographic area (Sudduth and Hummel, 1993c; Sudduth and Hummel, 1996; Hummel *et al.*, 2001). Figure 3b provides a comparison between the estimate of SOM from the sensor to point measurements in the field. Other approaches to SOM and moisture sensing are reviewed by Sudduth *et al.* (1997).

Soil Electrical Conductivity Sensors

Bulk soil electrical conductivity (EC) can serve as an indirect indicator of important soil physical properties. Factors that influence EC include soil salinity, clay content, CEC,

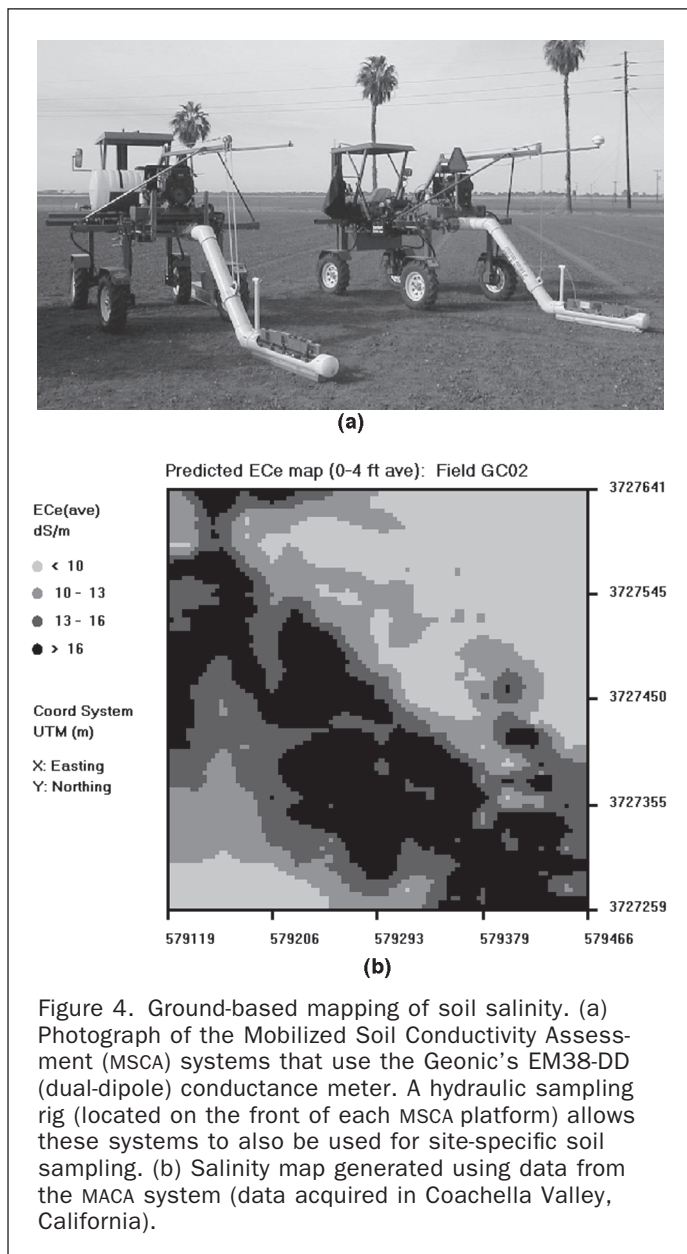


clay mineralogy, soil pore size and distribution, soil moisture content, and temperature (McNeill, 1992; Rhoades *et al.*, 1999). Rhoades and his colleagues pioneered research on adapting insertion electrode and electromagnetic (EM) induction sensors for *in situ* soil appraisal (Rhoades and Ingvalson, 1971; Rhoades and Corwin, 1981; Corwin and Rhoades, 1982; Rhoades and Corwin, 1984; Rhoades *et al.*, 1989; Rhoades *et al.*, 1990) and developed techniques for assessing irrigation, drainage, and salinity management using conductivity survey data (Rhoades, 1992; Rhoades *et al.*, 1997). Two basic designs of EC sensors are now commercially available — an electrode-based sensor requiring soil contact, and a non-invasive EM sensor. These two sensors provided similar results on claypan soils and led to the development of guidelines for reliable and accurate EC data collection using commercially available sensors (Sudduth *et al.*, 1999; Sudduth *et al.*, 2001). Figure 4a is a photograph of a commercially available, mobilized soil conductivity assessment (MSCA) system designed by the ARS George E. Brown Jr. Salinity Laboratory. This system uses

the recently developed EM38-DD (dual-dipole) conductance meter, which allows for the on-the-go simultaneous collection of GPS referenced horizontal and vertical EM38 signal data. Figure 4b provides an example of a bulk average (0 to 1.2 m) soil salinity map generated using this system.

In areas of salt-affected soils, most of the EC signal is related to concentration of soluble salts. However, in non-saline soils, EC variations are primarily a function of soil texture, organic matter, moisture content, and cation exchange capacity (Rhoades *et al.*, 1976; Rhoades *et al.*, 1999). In a model that provided a theoretical basis for the relationship between EC and soil physical properties, EC was described as a function of soil water content (both the mobile and immobile fractions), the electrical conductivity of the soil water, the soil bulk density, and the electrical conductivity of the soil solid phase (Rhoades *et al.*, 1989). This model, referred to as the dual pathway parallel conductance (DPPC) equation by Lesch *et al.* (2000), described the conductivity of the soil as a multi-pathway parallel electrical conductance equation.

In some situations, the contribution of within-field changes in one factor will be large enough with respect to variation in the other factors such that EC can be calibrated as a direct measurement of that dominant factor. Lesch *et al.* (1995a; 1995b; 1998) used this direct calibration approach to quantify within-field variations in soil salinity under uniform management and where water content, bulk density, and other soil properties were “reasonably homogeneous.” Direct, within-field calibrations have also been established between EC and the depth of topsoil above a subsoil claypan horizon (Doolittle *et al.*, 1994; Kitchen *et al.*, 1999; Sudduth *et al.*, 2001). Because soil EC integrates texture and moisture availability, two characteristics that both vary over the landscape and also affect productivity. EC sensing also shows promise in interpreting crop yield variations, at least in certain soils (Jaynes *et al.*, 1993; Kitchen *et al.*, 1999). Jaynes *et al.* (1995) used EC as an estimator of herbicide partition coefficients, theorizing that both were responding to changes in soil drainage class.



Soil Compaction Sensors

Soil compaction caused by wheel traffic or tillage operations can cause yield depression within fields. Soil compaction has traditionally been measured with the cone penetrometer (Perumpal, 1987; ASAE, 1999). Standard penetrometers exhibit variability due to clods and cracks, operating parameters, and soil wedge formation in front of the tip (Gill, 1968). Automated penetrometers have been developed to control operating parameters and speed collection of the amount of data required to characterize a field (e.g., Sudduth *et al.*, 1989). Speed of data collection with a standard single-shaft vertical penetrometer is inadequate for collecting site-specific data in large fields. A multiple-shaft penetrometer has been developed that could collect data from five row positions simultaneously (Raper *et al.*, 1999). Sudduth *et al.* (2000) showed that data collected with a commercial penetrometer that simultaneously measured EC and soil strength differed significantly from that collected with an ASAE-standard tip, due to differences in tip geometry. Nevertheless, simultaneous measurement of EC and penetration force in a claypan soil provided a better soil characterization. Other modifications to a standard soil cone penetrometer have allowed the simultaneous measurement of soil moisture content (Newman *et al.*, 1999) and soil organic matter/soil moisture sensing (Sudduth and Hummel, 1993a; Sudduth and Hummel, 1993b). Laboratory tests indicated that soil moisture effects could be removed from the penetration resistance values through use of a force prediction relationship.

Soil Nitrate Sensors

A dramatic advance in the miniaturization of ion-selective membrane technology occurred when Bergveld reported on ion selective field effect transistors (Bergveld, 1970; Bergveld, 1972). Ion Selective Field Effect Transistors (ISFETs), which are based on the same chemical principles as ion selective electrodes, have several advantages such as small dimensions, low output impedance, high signal-to-noise ratio, fast response, and the ability to integrate several sensors on a single electronic chip. Birrell and Hummel (1997) investigated the use of a multi-ISFET sensor chip to measure soil nitrate in a flow injection analysis (FIA) system using low flow rates, short injection times, and rapid washout. The multi-ISFET/FIA system was successfully used to measure soil nitrates in manually extracted soil extracts ($r^2 > 0.9$) under these conditions. A prototype automated extraction system was tested; however, the extraction system did not consistently provide soil extracts that could be analyzed by the FIA/ISFET system, and it required considerable improvement (Birrell and Hummel, 2001). The rapid response of the system allowed samples to be analyzed within 1.25 s, and the low sample volumes required by the multi-sensor ISFET/FIA system make it a likely candidate for use in a real-time soil nutrient sensing system. The potential of several PVC matrix membranes for use as ISFET membranes was investigated (Birrell and Hummel, 2000). More recently, research on rapid extraction of nitrate (Price *et al.*, 2000) demonstrated that judicious selection of data analysis techniques could result in nitrate analysis results in 2 to 5 seconds after injection of the extracting solution into the soil core.

Challenges

A major challenge is keeping abreast of sensing and data processing technological developments. Continuing advancements in data processing speed and data storage capacity, coupled with reduced per-unit costs, make it possible to store, access, and process quantities of data with portable PC-based instrumentation on field equipment that previously had to be relegated to post-processing on desktop or mainframe computers. As advances are made in data processing and storage, sensors requiring these capabilities become candidates for application in agriculture. Cooperation and interaction with industry partners will be needed to ensure that new sensor developments are commercialized. Advances in manufacturing technology, such as micro-electromechanical systems (MEMS), allow mechanical devices as well as electronics to be incorporated through microfabrication to produce fully integrated microsystems, resulting in a sensor having all electronic and mechanical components on a single silicon chip. Significant research will be needed to incorporate this and other developing technology into sensor systems for agriculture. Considerable time and effort will be needed to expand, as appropriate, the adoption of data collection and processing across agriculture. Extension personnel, crop consultants, farm supplier representatives, and producers will need exposure to and training in new sensing technologies and data processing and management techniques so that equipment is properly used, data are correctly interpreted, and timely management decisions are made.

Modeling and Statistical Approaches for Data Integration and Interpretation

A primary difference between image-based data and data collected by ground-based sensors is the spatial distribution of data. Image-based data can be viewed as a spatially continuous grid, averaging the entire response over an area

in a pixel. Ground-based data are typically composed of discrete points, often collected in transects and generally require some type of spatial data analysis to be interpolated to grids of a resolution similar to that of the remotely sensed images. Most of the data analysis and interpretation used to process ground-based data in the examples of the previous section can be classified into either deterministic or empirical modeling categories. In discussing these two categories, electrical conductivity data will be used for the examples; however, these principles could be extended to other data sources.

Deterministic (Theoretical) Modeling Approaches

Deterministic conductivity data modeling and interpretation can be carried out either from a geophysical or (more commonly) a soil science approach. In the geophysical approach, mathematically sophisticated inversion-type algorithms are generally employed. These approaches rely heavily on geophysical theory developed for deep penetrating signal data and have not proved to be especially useful for the interpretation of near-surface soil conductivity data. The soil science approach used in salinity inventorying work is to employ some form of deterministic "conductivity-to-salinity" model; i.e., an equation which converts conductivity to salinity, based on knowledge of additional soil physical properties. Probably the most useful and well-known model of this type is the DPPC model (Rhoades *et al.*, 1989; Rhoades *et al.*, 1990; Rhoades, 1992) noted earlier in the section on ground-based sensors. The model predicts soil salinity levels based on soil conductivity survey data and measured or inferred information about the remaining soil physical properties. The influence that these soil properties have on the acquired soil conductivity data can be assessed using the model (Lesch *et al.*, 2000; Corwin and Lesch, 2003).

Empirical (Statistical) Modeling Approaches

Empirical models are based on objective sampling methodology used in conjunction with various statistical calibration techniques. The most common types of calibration equations are spatially referenced regression models, universal kriging models (sometimes also referred to as spatial random field models), and co-kriging models. Because nearly all empirical modeling approaches depend on site-specific calibration, the use of an efficient, cost-effective statistical sampling design is clearly important. For soil salinity inventory work using ground-based conductivity sensors, the difference between a good and poor sampling design often determines both the economic feasibility and technical success of the survey project.

Design-based sampling includes simple random sampling, stratified random sampling, multistage sampling, cluster sampling, network sampling schemes, and line-transect sampling. An excellent review of these methods (along with extensive references) can be found in Thompson (1992). Model-based sampling designs stem directly from traditional response surface sampling methodology (Box and Draper, 1987). Specific model-based sampling approaches having direct application to agricultural and environmental survey work are described by McBratney and Webster (1983), Russo (1984), and Lesch *et al.* (1995b).

In the model-based sampling approach, a minimum set of calibration soil salinity samples are selected based on the observed magnitudes and spatial locations of conductivity sensor data, with the explicit goal of optimizing the estimation of a regression model (i.e., minimizing the mean-square prediction errors produced by the calibration function). Therefore, fewer samples are needed for the calibration when compared to random or designed-based sampling to

obtain the same level of accuracy in the regression model. The regression model is used to predict salinity at all remaining (i.e., non-sampled) sites.

The main advantage of the model-based approach is a substantial reduction in the number of samples required for calibration compared to design-based sampling. The model-based approach also lends itself naturally to the analysis of remotely sensed data. Ground-, airborne-, and/or satellite-based remotely sensed data are often collected specifically because one expects the data to correlate strongly with some parameter of interest (e.g., crop stress, soil type, and soil salinity), but the exact parameter estimates (associated with the calibration model) may still need to be determined using some type of site-specific sampling design. This approach explicitly optimizes this site selection process.

Data Integration

The idea of combining ground-based data with airborne or satellite remotely sensed data to facilitate the regional assessment of specific soil attributes has considerable merit. For example, non-saline remotely sensed vegetation indices can be combined with ground conductivity data to map residual nitrogen levels in soils. Although site specific, such an approach could still prove to be cost effective, especially if model-based sampling approaches are employed. In saline areas, remotely sensed data could similarly prove to produce more accurate salinity maps.

Most types of remotely sensed spectral observations still require site-specific calibration using ground-sampling techniques. When remotely sensed data are used to infer soil properties which are correlated with soil electrical conductivity data (such as salinity, texture, or water holding capacity), accuracy of ground calibration data could be improved by using ground-based soil electrical conductivity surveying techniques. For example, detailed ground-based soil electrical conductivity surveys (used in conjunction with appropriate soil calibration sampling designs) could be undertaken within selected sub-areas of a much larger remotely sensed survey region. The ground-based electrical conductivity data provide a better estimate of the soil attribute of interest (within the sub-areas) and produce more calibration data for an analysis of the remotely sensed data.

Several methods for regional assessment of soil salinity have been documented using advanced information technologies such as GIS, ground-based soil conductivity data, remote sensing data, and solute transport models (Corwin *et al.*, 1989; Corwin, 1996; Corwin *et al.*, 1997; Corwin *et al.*, 1999a; Corwin *et al.*, 1999b). Corwin (1996) described two different GIS-based prediction approaches for regional salinity assessment. Using a statistical approach, Corwin (1996) estimated the aerial distribution of salinity across 44,000 ha of the Wellton-Mohawk irrigation district (Yuma, Arizona) based on various spatial salinity-development factors. Corwin (1996) also described a deterministic approach which successfully predicted changes in soil salinity conditions using a one-dimensional, transient-state solute transport model across 2,400 ha of the Broadview Water District located on the west side of California's San Joaquin Valley over a 5-year study period.

In both approaches, ground-based and remotely sensed data played important roles. The ground-based soil conductivity data were used to predict baseline soil salinity conditions and monitor the spatial changes in salinity levels over time. Likewise, remotely sensed data were used to estimate crop evapotranspiration and potential leaching fractions (using knowledge of water delivery and cropping patterns). Once these data are combined with additional information (such as soil inventory maps, spatial depth-to-groundwater

information, and DEM information) using a GIS, a comprehensive database system can be developed which offers tremendous potential for accurate, regional-scale salinity assessment.

Integration of these data sources with crop simulation models could also play an important role in determining the impact of soil spatial variability on crop yield. Jones and Barnes (2000) used airborne imagery to calibrate a process-oriented cotton model to differences in soil type. First, bare soil imagery was used to determine the spatial extent of differences in two soil types. Next, leaf area index (LAI) for each soil type was inferred from the NIR and red reflectance data obtained during the season using an empirical relationship. The cotton model parameters related to soil water holding capacity were then adjusted until the model predictions followed the same seasonal trend in remotely sensed estimates of LAI. The outputs from the model were then used to evaluate different irrigation strategies for the two soil types.

Considerable corollary data about soil properties and management zones are contained in crop yield maps. However, extracting and interpreting the information is difficult because there often appears to be a lack of consistency in the yield patterns from year to year (Colvin *et al.*, 1997). In rain-fed agriculture, much of the variation in crop yield maps may be due to soil factors that affect water availability. Simulation models may account for the temporal effects of limiting soil water on crop growth when soil water holding capacity is known (Paz *et al.*, 1998). Timlin *et al.* (2001) used a simple water budget-yield model to back-calculate soil water holding capacity by matching simulated and measured corn grain yields. The information was used to classify a field into areas buffered against drought and areas more susceptible to drought. Crop growth and development were correlated with aerial images of the field. Dulaney *et al.* (1999) used ground-penetrating radar (GPR) mapping of subsurface soil structures to accurately identify preferential subsurface (funnel flow) flow pathways which are critical to determining an accurate chemical flux exiting a watershed. The GPR identified subsurface flow pathways (blue lines in Plate 2) were developed by subtracting the depth to the first continuous restricting layers from the surface topography and then applying flow accumulation and flow direction hydrologic models in a GIS framework to the derived subsurface topography. Yield maps, hyperspectral imaging, and real-time soil moisture monitoring were used to confirm the existence and extent of the subsurface water flow pathways.

Challenges

Only limited investigations have been conducted on methods to integrate various data sources, and most of the investigations that have been conducted rely on location specific, empirical relationships. Few data sets are available that contain both the soil property information and remotely sensed data from diverse regions to determine the feasibility of generic algorithms that are not site specific. Further work is needed to determine more robust algorithms that minimize the need for local calibration and a formal definition of the calibration process.

Summary and Conclusions

The use of remotely sensed data alone has significant limitations in developing robust, quantitative assessments of soil properties that do not require local calibration. However, imagery does show good promise to provide a means for directed sampling and field-specific relationships useful for mapping soil organic matter, texture, salinity, moisture content, and nitrogen levels. Recent developments in

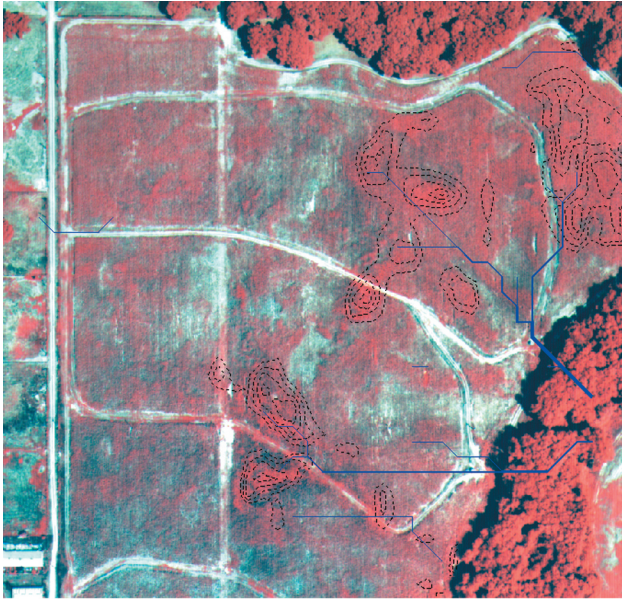


Plate 2. Visual correlation of highest yielding areas in water during drought years (black dashed polygons) with GPR-GIS identified subsurface flow pathways (blue lines), overlaid on a color-infrared image, for two of the watersheds.

ground-based sensors provide new methods to rapidly map soil organic matter, electrical conductivity, compaction, and nitrate levels. With the addition of ground-based sensors, less ambiguous relationships can be established between sensor data and soil properties, and the combination of these two data sources can yield even more accurate soil maps. Ultimately, a combination of multispectral imagery, ground-based sensor data, and other ancillary information integrated through appropriate models could someday yield accurate and detailed soil maps with limited direct sampling. Further incorporation of detailed soil maps with process-oriented crop and soil models will provide a means to determine the environmental and economic impact of different site-specific management approaches.

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