Reflectance Measurements of Soil Variability

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Abstract: Variations in soil physical and chemical properties can affect agricultural productivity and the environmental implications of crop production. These variations are present and may be important at regional, field, and sub-field (precision agriculture) scales. Because traditional measurements are time-consuming and expensive, reflectance-based estimates of soil properties such as texture, organic matter content, water content, and nutrient status are attractive. Soil properties have been related to reflectance measured with laboratory, in-field, airborne, and satellite sensors. Both multispectral and hyperspectral instruments have been used, with both natural and artificial illumination. Varying levels of accuracy have been obtained, with the best results ($r > 0.95$) using hyperspectral reflectance data to estimate soil organic matter and water content.

Keywords: precision agriculture, hyperspectral, organic matter, texture, fertility, soil water content

1. Introduction

Soil variability is a factor in agricultural productivity and the environmental implications of crop production. Soil variability at regional and local scales has long been recognized, and soil scientists have developed soil surveys and other approaches to characterizing soil differences. In recent years, sub-field soil variability has been studied extensively as a key part of the precision agriculture approach to crop management. In precision agriculture, spatiotemporal within-field variability is measured and agricultural practices are adjusted to optimize production, and/or environmental stewardship with respect to this variability. Even at the sub-field precision agriculture scale, soil variability can have a large effect on crop production. For example, we have related up to 74% of within-field variability in crop yield to variations in soil properties [1]. Soil variability within fields can also have an effect on environmental factors, such as herbicide concentrations in the soil [2].

In order to account for soil variability in agricultural management systems, cost- and time-efficient ways to quantify such variability are needed. The objective of this paper is to discuss several approaches to reflectance-based sensing of soil properties such as texture, organic matter, water content, and nutrient levels.

2. Reflectance Sensing Methods

1) Reflectance Characteristics of Soils

The spectral reflectance of soils has been studied extensively as a function of soil chemical and physical properties [3]. Soil reflectance is generally low, but increases monotonically with wavelength through the visible and near-infrared (NIR) regions of the spectrum. Soil reflectance is influenced by mineral composition of the soil parent material, organic matter, water content, physical surface conditions (e.g., surface roughness, aggregation), soil constituents (e.g., particle size, iron oxide, soluble salts), and observation conditions (e.g., illumination, view direction) [3, 4].

2) Remote Sensing

A variety of aircraft- and satellite-based remote sensing data sources, such as photographs, videographs, and multispectral and hyperspectral images, are available for use in agricultural applications. Interpretation of these images is often complicated by a lack of timeliness (i.e., delays due to clouds obscuring the area of interest in the optimum sensing window), variable signal attenuation in the atmosphere, and complex interactions of sun/sensor/ target geometry [5].

Although satellite remote sensing has the ability to cover larger areas at a potentially lower cost, much of the current work in agricultural remote sensing is accomplished with airborne data. For example, in a study described elsewhere in this volume [6], we related aircraft hyperspectral bare-soil images of a field to variations in soil properties. Challenges encountered in, and not unique to, this study included distortion of images due to aircraft attitude changes, and the need for image-specific radiometric calibration. These practical issues, coupled with only a slight increase in accuracy over more conventional multispectral data [6], led us to conclude that hyperspectral remote sensing of soil properties is currently of limited utility.

3) Close-Range Sensing

In addition to data collected by aerial or satellite sensors, reflectance data can be obtained with sensors operating near the soil surface. Depending on configuration, these sensors may be in contact with the soil, or may operate at distances from a few mm to a few m away from the surface. The close-range approach has several potential advantages over the remote sensing approach – spatial resolution can be higher; georeferencing is generally less of an issue, and problems caused by variations in illumination intensity and/or geometry can be eliminated through the use of artificial lighting.

The close-range approach has been implemented both with commercial radiometers and with prototype sensors developed for particular applications. Both commercial and prototype systems have been applied in two ways – direct within-field sensing and laboratory reflectance sensing of soil samples collected in the field. Commercial radiometers used to estimate soil parameters have acquired data at either several [7] or many [8] wavelengths in the visible and/or NIR regions. Prototype soil sensors have ranged in complexity from those that measure reflectance at a single visible wavelength [9] to those that obtained data at >300 wavelengths in the visible and NIR [10]. Most prototype soil sensors have been developed to incorporate artificial illumination and to exclude ambient sunlight for improved accuracy. For example, we developed [11] and later improved [12] a portable NIR spectrophotometer with self-contained illumination. This device worked well for quantifying soil properties in the laboratory, but was less accurate in the field, where movement of soil past the sensor during the data collection process increased measurement noise.

3. Applications

1) Soil Texture

Surface soil texture, either represented by textural class (e.g., silt loam, silty clay loam) or by the fractions of sand, silt, and clay present, affects soil reflectance characteristics. Using procedures described elsewhere in this volume [6], we related airborne hyperspectral data to surface texture variations across a field. Using a field-specific calibration and a stepwise multiple linear regression (SMLR) method for spectral band selection, reflectance data from 2-3 visible wavelength bands were predictive of clay fraction ($R^2 \approx 0.6$ to 0.8). In laboratory analyses of soil samples collected from 30 locations across the state of Illinois in the USA, we were able to estimate surface clay fraction ($R^2 = 0.88$) based on reflectance from 6 bands in the wavelength range from 1850 to 2400 nm [12]. Other researchers [e.g., 13] have reported similar results using laboratory reflectance data.

Because many management decisions are based on soil textural class, spectral estimation of this property is a reasonable option. Researchers in Arizona, USA used airborne multispectral and satellite (Landsat and SPOT) images to estimate textural classes across a 350- ha area [7]. Classification accuracy was 81% with the airborne data and 88 to 92% with the satellite data.

2) Organic Matter

Soil organic matter (OM) has a strong influence on soil reflectance [3]. Soils with more OM have a lower reflectance in the visible and NIR regions. If the other soil properties affecting reflectance (e.g., soil water content, parent material) are relatively homogeneous over the area (or soils) of interest, then it is feasible to directly estimate OM using visible reflectance, perhaps from a single band [8, 9]. However, in our research [14] NIR data were more predictive of OM than were visible data, for a range of soils and water contents. Excellent estimations ($R^2 > 0.9$) were possible with as few as 12 reflectance data points from a commercial laboratory spectrophotometer [14], while 24 points from a mobile sensor [11, 12] provided similar levels of accuracy ($R^2 = 0.85$). Other researchers have also used close-range NIR reflectance to estimate OM [e.g., 8, 10, 13] with varying degrees of success.

Remote sensing estimates of within-field variation in OM have generally been calibrated to laboratory analyses of samples obtained from the same field. In our work [6], the relationship of OM to visible reflectance data was not strong ($R^2 \approx 0.4$); however, there was little OM variation within the test field. Other researchers [15] have used true color aerial images, calibrated with in-field sampling, to estimate OM variability in production fields with a classification accuracy of 74 to 77%.

3) Soil Water Content

Reflectance sensing of soil moisture generally relies on the water absorption bands present in the NIR spectrum at approximately 1450 and 1950 nm [3]. For example, we were able to estimate soil water content in the laboratory ($R^2 > 0.95$), using reflectance in 4 bands from 1730 to 2470 nm [12]. Reflectance at 1462 nm was related ($R^2 = 0.68$) to soil water content in field research in Japan [10]. A review of close-range sensing of water content, OM and other soil properties is given in [16].

4) Soil Nutrients

In precision agriculture, variations in soil chemical properties important for plant growth (e.g., phosphorus, potassium, pH) are generally determined by laboratory analysis of soil samples collected on a spatial pattern; most often a uniform grid. We related this type of gridsample data to aerial hyperspectral image data [6] for a 35-ha field. Calibrations developed using SMLR were reasonable (R^2 = 0.4 to 0.65) for cations (Ca, K, Mg), CEC, and pH. Phosphorus levels were not well-represented by the image data (R^2 < 0.2). Other researchers [e.g., 17] have reported variable success when relating reflectance to soil chemical properties.

5) Other Soil Properties

Reflectance-based sensing has been applied to a number of other soil properties, including surface roughness and salinity. In addition, such techniques have been used to assess crop residue cover and to infer soil properties from crop spectral responses. A recent review can be found in [18].

4. Conclusions

Soil reflectance in the visible and NIR regions can provide efficient estimates of variations in such soil properties as texture, organic matter, water content, and nutrients. Generally, the strongest relationships between reflectance and soil properties have been found in controlled laboratory tests on prepared soil samples. In such settings, accurate predictions (R^2 > 0.8) have been obtained for texture (i.e., clay fraction), organic matter, soil water, and some soil nutrients. These accuracies have been possible even when prediction equations are developed for widely varying soil types (i.e., varying in texture and organic matter), and over a range of water contents.

Accuracy has generally been somewhat less for close-range sensing under field conditions. Reasons for this reduction in accuracy may include increased instrumentation noise and, for sensors without artificial light sources, variability in ambient lighting conditions. Compared with remote sensing, close-range sensors allow a higher degree of control over data acquisition and, with incorporation of a soil-opening mechanism, may obtain measurements below the soil surface.

Relationships between remotely sensed images and soil properties have, for the most part, been less accurate. Issues related to radiometric calibration and accurate registration of images with ground-measured data may account for some of this reduction in accuracy. Another factor is that many remote sensing images do not extend past about 1100 nm, rendering many of the important NIR wavelengths unavailable. Although the inherent accuracy of soil property estimates from remote sensing images is lower, images can be a useful tool for densifying soil property estimates when used in conjunction with ground-based data collection.

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