Mapping Soil Properties for Soil Survey Using Proximal Diffuse Reflectance Spectroscopy

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Abstract

Proximal sensing using diffuse-reflectance near-infrared spectroscopy has demonstrated substantial potential for rapid and accurate estimation of selected soil properties for various applications. Many of these soil properties are diagnostic for the purpose of soil classification and survey. There is increasing interest in complementing the current methodologies employed in initial mapping and soil survey updating processes using proximal sensing, especially with regard to digital and predictive soil mapping. This study focused on developing an accurate method for estimating *in situ* the estimated value and spatial distribution of selected soil chemical and physical properties within a soil profile. An unaligned sampling grid (120 cm × 20 cm) with a sampling interval of 5 cm (n = 124 sample points) was used to predict the spatial distribution of selected soil properties throughout the profile of one pedon in Allegany County, New York USA. An efficient data processing flow was also developed for estimating the spatial distribution of soil properties using PLS1 regression and ordinary kriging. While the estimated soil property values were generally within acceptable error tolerances, a larger sample size and a more robust prediction model would strengthen prediction accuracy. The results of this study suggest that advanced proximal sensing techniques, both laboratory-based and in situ, are useful for soil survey and serve to complement existing field soil survey methods.

Introduction

Hyperspectral sensing of soil pedons can provide a low-cost alternative to direct measurements of soil chemical and physical properties and improved prediction of nutrients where large numbers of observations are required to accurately characterize an area or where the cost of analysis and field survey are high.

Previous studies using hyperspectral sensing of soils have focused on estimating soil chemical and physical properties, characterizing land degradation processes, and supporting nutrient management programs (Ben-Dor 2002; Ben-Dor and Banin 1995; Baumgardner et al. 1985; Reeves et al. 1999).

Specifically, studies have focused on using laboratory- and field-based sensors to estimate soil organic matter, moisture, and cation exchange capacity (Barrett 2002; Hummel et al. 1996); correlating near-infrared reflectance spectra with soil properties using principal components analysis (Chang et al. 2001); building soil reflectance spectral libraries and using multivariate adaptive regression spline (MARS) and classification trees analyses (Shepherd and Walsh 2002); predicting moisture content with data stratification by landform and soil sodicity while correcting effects of soil moisture (Whiting et al. 2004); and linking crop yield variability with spatial variability in soil properties (Barnes et al. 2003).

Few studies have been focused on *in situ* collection of hyperspectral data for characterizing properties in direct support of soil classification and survey (Waiser et al. 2006). Increased variability of soil spectra acquired *in situ* for soil survey purposes is expected due primarily to variations in soil profile and individual soil horizon moisture and illumination conditions. Field-based experiments should be conducted where these conditions are controlled and quantified to the extent possible. We anticipate these field sampling methods will help determine the feasibility of delineating quantitatively soil horizon extent, boundary conditions and transitions, and differentiating characteristics that are used to classify soil individuals.

Objectives

1. Characterize the hyperspectral response of selected soil chemical and physical properties that are important to soil survey.

2. Assess quality of hyperspectral data collected *in situ* as an aid to field-based soil survey operations and compare the quality and usefulness of hyperspectral data collected using laboratory- and field-based methods for soil classification and survey.

3. Develop an accurate method for estimating the spatial distribution of selected soil chemical and physical properties within a pedon.

Materials & Methods

The methods described by Brown et al. (2006), Shepherd and Walsh (2002) and Reeves et al. (1999) and new methods developed by these authors are being used to acquire laboratory- and field-based hyperspectral data of soil samples in cooperation with the USDA-NRCS New York Soil Survey Program.

Spectra are being measured under field and controlled laboratory conditions using an ASD FieldSpec Pro FR spectrometer (Analytical Spectral Devices Inc, Boulder, Colorado; www.asdi.com). All the soil samples were scanned using a spectral sensing interval of 1 nm between 300 and 2500 nm (Figure 1) (1) by soil horizon as they are defined by soil survey staff in the field, and (2) for one pedon using an unaligned systematic sample to eliminate bias from pre-designating horizon type and extent.

Oven-dried soil samples of various particle and aggregate size classes were placed in Petri dishes (Figure 2) and then placed on a specially constructed sensing platform as shown in Figure 1.

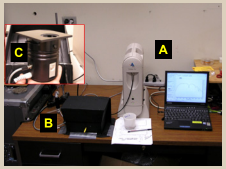

Figure 1. Laboratory spectrometer set-up used for reflectance measurements. A) Field Spec Pro and portable computer, B) box to shield light source and sample from ambient light, C) mount to hold 50-mm diameter Petri dishes a fixed distance from optic fiber sensor.

Figure 2. Size fractions, in 50mm diameter Petri dishes, that were scanned for several experiments related to aggregate stability and other soil properties including the 2 mm fraction for soil survey purposes.

Laboratory- and field-based spectra are being analyzed using numerical and analytical methods described by Chang, et al. (2001), Demetriades-Shah et al. (1990), Shepherd and Walsh (2002), and Tsai and Philpot (1998).

1nm resolution spectral data are used for statistical analyses and modeling, although previous studies have indicated that full resolution data (@ 1nm) does not significantly improve the ability of spectrally-based models to predict soil properties (Ben-Dor and Banin, 1995; Shepherd and Walsh, 2002).

The spectral data are processed and first derivatives computed using the Savitsky-Golay transformation procedure (Savitsky and Golay, 1964) in Unscrambler v9.2 (http://www.camo.com/rt/Products/Unscrambler/unscrambler.html). First-derivative spectra are used to amplify the absorption features that may be indicative of soil properties important to soil survey.

All field samples are submitted to both NRCS-NSSL and Cornell CNAL analytical laboratory prior to laboratory scanning.

Results are presented here for both raw and first derivative spectra. Partial least squares 1 (PLS1) regression results are reported. With regard to field, or *in situ*, reflectance measurements, five pedons were measured as part of the Allegany County soil survey. Additionally, two pedons were measured as part of the Ontario/Yates soil survey. We took three readings per horizon (10 scans/reading) as shown in Figure 3 and Figure 4.

We also scanned one pedon using an unaligned systematic sample at 5 cm x 5 cm spacing for an array 120 cm x 20 cm (n= 124 readings; 5 scans/reading); spatial interpolation methods will be used to investigate the feasibility of delineating soil horizons and associated properties from these spectral measurements.

Raw spectral data processed using Unscrambler were averaged by a factor of five, yielding one spectrum for each sample point. Partial Least Squares 1 (PLS1)-based regression prediction equations were developed for % C, % N, % organic matter (loss on ignition) and % clay using field-acquired (previously by horizon) spectral and laboratory characterization data.

Using these prediction equations, estimates for each property at all 124 sample points were generated using their corresponding field-acquired (by grid) spectra as a set of independent variables. These predictions were tabulated, along with the coordinates (in cm) for each point, for use in spatial modeling. A prediction map was created for each property of interest [% C, % N, % Organic Matter (loss on ignition) and % Clay] using ordinary kriging, blocked by horizon, to produce interpolated property value averages by horizon.

Figure 3. Pedon *in situ* measurement of hyperspectral reflectance by horizon.

Figure 4. Illustration of contact probe, light source, and sensor proximity to soil horizon surface.

Results & Discussion

A. Assessing Hyperspectral Sensing for Soil Survey

Table 1 illustrates an example of PLS1 results computed using field-acquired DRS NIR spectra in Allegany County used in conjunction with NSSC laboratory data. The model performance results demonstrate the efficacy of field-based hyperspectral sensing for estimating soil properties critical for discriminating soil horizons due to the high performance of PLS1 regression models as determined by calibration and validation R^2 values (defined here as 0.85 and greater) and comparison of these values with literature values. Previous research with diffuse reflectance spectroscopy has been conducted using spectra acquired under laboratory conditions. As a result, it is difficult to assess the quality and interpret the significance of *in situ* measurements within the context of most literature values. Nevertheless, the calibration R^2 values for both the selected soil properties in the PLS1 R^2 values table are generally consistent with literature values. As expected, the validation R^2 values are substantially lower for several properties and, in a few cases, indicate that none of the variance is explained by the PLS1 regression model. Since the validation procedure uses a subset of the samples, the effect of the relatively small sample size and narrow range of soil property values (eg. soil pH) are exacerbated further and results in a degradation of model performance. Figure 5 indicates some similarity in the variance structures of lab-based DRS spectra among Ap, E and Btx horizons.

Property	R^2 – Field		R^2 – Lab		Range	
	CAL	VAL	CAL	VAL	Field	Lab
% C	1.00 0.86’	0.95 -0.11’	0.99 1.00’	0.98 0.85’	0.1 4.2	0.1 4.2
% OM LOI	1.00 0.98’	0.93 0.25’	0.98 1.00’	0.94 0.86’	1.5 10.0	1.3 10.0
pH	0.99 1.00’	0.41 0.39’	0.92 0.80’	0.72 0.57’	4.7 7.7	4.7 7.8
% Clay	0.99 0.79’	0.72 -0.42’	0.88 1.00’	0.72 0.58’	23.7 40.8	23.8 40.8

Table 1. Example PLS1 R^2 values for Allegany County.

Figure 5. PCA plot for Napoli pedon (lab-based DRS).

B. Mapping Soil Profile Properties Using Proximal DRS

Figure 6 illustrates a spatial process developed to map soil profile properties using proximal diffuse reflectance spectroscopy. Figure 7 displays a soil profile mapping product for % clay. Figure 8 provides a visual comparison of laboratory values and spatially interpolated hyperspectral measurements for % clay.

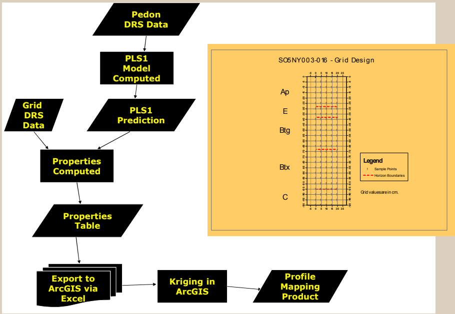

Figure 5. Spatial modeling flow diagram.

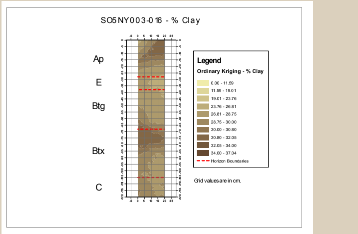

Figure 7. Spatial interpolation of % clay using an unaligned, systematic sample of hyperspectral reflectance measured *in situ* for a Napoli soil profile, Allegany County, New York.

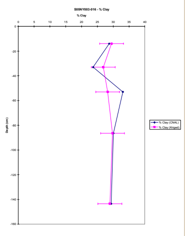

Figure 8. Comparison of laboratory estimate for % clay (CNAL) and spatially interpolated hyperspectral reflectance measured *in situ* for a Napoli profile, Allegany County, New York.

Research Findings

Our findings suggest that advanced proximal sensing techniques are worthy of additional study to assess the full potential of this technology. Before this diffuse-reflectance near-infrared spectroscopy is deployed for field operations, it is critical that potential users have the information they need to use it intelligently, if at all. Hopefully, this study represents the start of efforts to enhance our understanding of which field conditions are conducive to the effective use of this proximal sensing technology for soil survey operations.

Planned Activities

1. Assess the potential of integrating DRS NIR spectra with Digital Soil Mapping (DSM) to enhance prediction of selected soil properties and create soil pedon visualization products;
2. Develop a comprehensive DRS NIR spectra library and robust prediction model set for some of Connecticut's benchmark soils and archived soil survey samples;
3. Support subaqueous soil mapping efforts in Southern New England estuaries and selected salt ponds in Rhode Island;
4. Determine the utility of using DRS NIR for measuring sulfidic materials in soils.

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