HYPERSPECTRAL IMAGERY: VARIABILITY WITHIN AND BETWEEN SOIL MAP PHASES

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ABSTRACT

Hyperspectral imagery allows investigators to identify remote sensing opportunities for farmers and surveyors particularly at narrow regions along the electromagnetic spectrum that have been, until recently, difficult to study. The objectives of this study were to: (1) use statistical techniques to identify spectral bands that relate well with the delineations of a detailed soil survey and (2) determine how accounting for spatial autocorrelation affects the statistical analyses. A detailed first order (1:3,744) soil survey was created for a field in Calloway Co., Kentucky. Hyperspectral imagery was obtained with a Real-time Data Acquisition Camera System (RDACS-3), which had a 2 by 2-m pixel resolution and 120 spectral bands (471 to 828 nm in 3-nm increments). For each band, a one-way analysis of variance (did not account for spatial autocorrelation) and two random field analyses (accounted for spatial autocorrelation) were used to determine the extent to which variability was greater between than within map units (F-ratio). The analyses were greatly affected by the degree to which spatial variability was taken into account. Regions of the spectrum with larger F-values included 537 to 573, 723 to 744 and 816 to 822 nm. Slope and erosion classes were related to spectral radiant intensity; however, the relationships may or may not be band specific.

Keywords: First order soil survey, remote sensing, soil classification

INTRODUCTION

Accurate soil information is crucial for soil use and management decisions. Unfortunately, routine soil surveys are not developed at an adequate scale for many applications (Moore et al., 1993; Robert, 1993; Bell et al., 1995; Pierce and Nowak, 1999). Precision agriculture technologies may add to the value of soil survey information by improving soil survey accuracy and the efficiency of survey development. Our interest was with remote sensing as a tool for enhancing the quality of soils information available to land managers and surveyors.

Soil reflectance is strongly affected by soil organic matter (Henderson et al., 1989; Schulze, 1993; Chen et al., 2000), soil moisture (Schulze, 1993), texture (Schulze, 1993), iron oxides (Schwetmann, 1993), mineral composition, and the presence of vegetation. Spatial variation of these soil properties at the soil surface can be indicative of major soil differences in drainage, erosion, soil moisture, the presence or absence of soil horizons, slope, texture, parent materials, vegetation, soil depth, fertility, and others. Drainage, erosion, soil horizons, slope and parent material are also basic criteria for classification of soil across landscapes.

In this study, we used hyperspectral imagery to identify bands that would correlate well with mapped soil phases of a detailed soil survey for a field in Calloway Co., Kentucky. The fundamental premise was that if a band could be useful in delineating soil types, then the variability of the radiant intensity would be greater *between* rather than *within* soil phase boundaries (F-ratio). Our secondary interest was to determine how different methods of analysis would affect statistical tests. Specifically, we were interested in determining how accounting for the spatial autocorrelation of the residuals affects the interpretations. Typically, these autocorrelations are ignored, but some argue that they should be included in the statistical model (Schabenberger and Pierce, 2002).

MATERIALS AND METHODS

A first order soil survey was created for a 15-ha field in Calloway Co. (36°32’37”N, 88°27’7”W) at a scale of 1:3,744 (Fig. 1). Two experienced Natural Resource and Conservation Service soil scientists obtained soil cores (1.1 m in depth and 5 cm diameter) on a 61-m regular grid with a truck mounted hydraulic soil probe. Six soil series were identified and 17 delineations were made in 11 man hours. The locations of some of the map unit boundaries were fine tuned with additional observations made with a hand probe (2.5-cm diameter). A grass waterway in the middle of the field (north-south direction) was not mapped.

The soils in this field included the Calloway, Grenada, Henry, and Purchase series, developed from loess, and Falaya and Kurk series, developed from silty alluvium derived from loess (Table 1). Many of the series have fragipans within the upper 1 m including the Grenada (51 to 76 cm), Calloway

Fig. 1. First order soil survey.

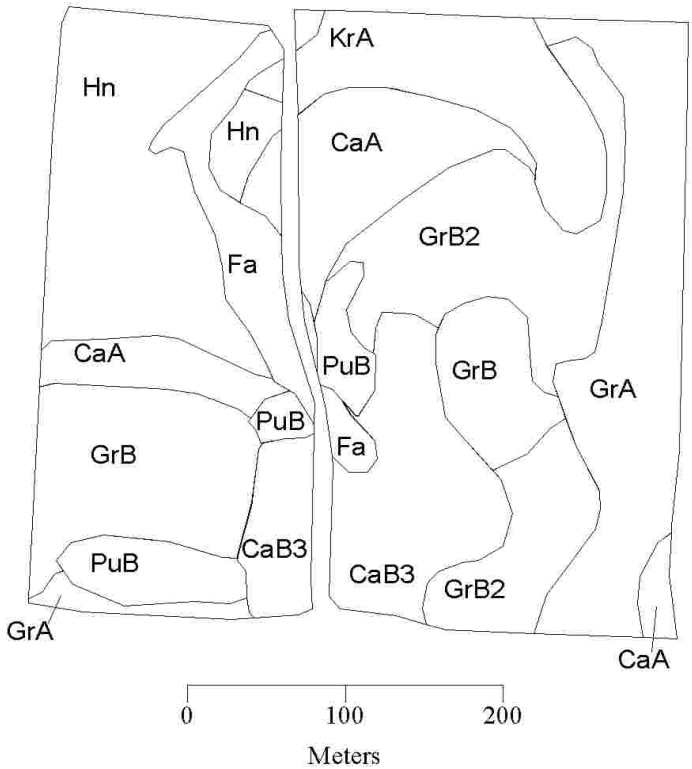


Table 1. Soils information.

Series	Symbol	Slopes	Classification
Calloway silt loam	CaA	0 to 2%	fine-silty, mixed, active, thermic Aquic Fragiudalfs
Calloway silt loam, severely eroded	CaB3	2 to 5%	fine-silty, mixed, active, thermic Aquic Fragiudalfs, severly eroded
Falaya silt loam	Fa	0 to 2%	coarse-silty, mixed, active, acid, thermic Aeric Fluvaquents
Grenada silt loam	GrA	0 to 2%	fine-silty, mixed, active, thermic Oxyaquic Fraglossudalfs
Grenada silt loam	GrB	2 to 5%	fine-silty, mixed, active, thermic Oxyaquic Fraglossudalfs
Grenada silt loam, eroded	GrB2	2 to 5%	fine-silty, mixed, active, thermic Oxyaquic Fraglossud alfs
Henry silt loam	Hn	0 to 2%	coarse-silty, mixed, active, thermic Typic Fragiaqualfs
Kurk silt loam	KrA	0 to 2%	fine-silty, mixed, thermic Aeric Epiaqualfs
Purchase Silt loam	PuB	2 to 5%	coarse-silty, mixed, thermic Ochreptic Fragiudalfs

(51 to 91 cm), Henry (61 to 91 cm), and Purchase (30 to 43 cm) soils. The Grenada (moderately well drained), Calloway (somewhat poorly drained), and Henry (poorly drained) series are members of the Memphis hydrosequence. The Purchase series range from moderately well to well drained. The Falaya is a somewhat poorly drained member of the Vicksburg hydrosequence. The GrB2 phases were moderately eroded and the CaB3 phase was severely eroded (Table 1). The newly established Purchase series replaced the excessively eroded phases of Grenada and Loring soils found in older soil surveys. The Kurk is also a somewhat poorly drained soil that is similar to the Calloway soil but does not have a fragipan.

Elevation measurements were collected along a 7-m transects using Trimble ® 4600 (Trimble, Ltd., Sunnyvale, CA) GPS receivers. Digital elevation models (DEM) were generated on 4-m grids using ANUDEM (Australian National University, Australia). The DEMs were used to calculate percent slope.

The field had been planted to corn in 19 April 2001. On 16 May 2001, Hyperspectral imagery was obtained with a Real-time Data Acquisition Camera System (RDACS-3), which had a 2x2 meter pixel resolution and 120 spectral bands (471 to 828 nm in 3-nm increments). A linear spectral unmixing technique with end-member spectra was used to remove vegetation effects from the data. Each pixel in the image was classified as belonging to one of the nine soil phases (Table 1) using feature extraction techniques.

For each of the 120 spectral bands, a one-way analysis of variance (AOV) and two random field approaches (RF1 and RF2) (Schabenberger and Pierce, 2002) were used. For the AOV approach, 5000 of the pixels were randomly chosen and analyzed using SAS® procedure GLM. This assumes that the variance-covariance matrix for the error terms is diagonal with homogeneous variance. Note that this assumption implies a constant variance on the diagonal and that all correlations between pixels are zero.

For the random field analyses, the residuals were considered to be spatially autocorrelated. In the RF1 approach, all spatial autocorrelation (for pairs of pixels in the same soil phase and for pairs of pixels in different soil phases) was taken into account. Because the manipulation (e.g., inversion) of these matrices was so computationally demanding, only a smaller subset of randomly selected pixels could be used. We used 900.

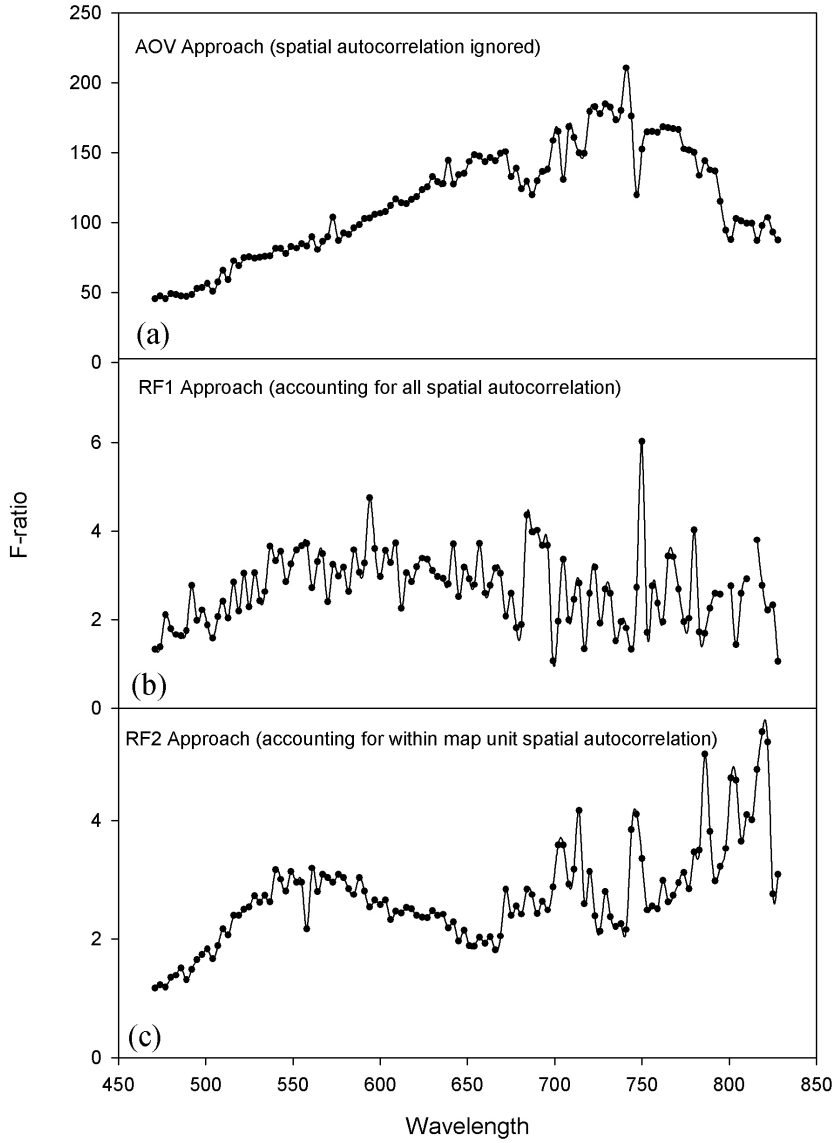
The RF2 approach accounted only for spatial autocorrelation of the residuals within soil phases, thus ignoring autocorrelation between phases. A larger dataset (n = 5000) was used because the RF2 approach was less computationally demanding than RF1. The resulting variance-covariance matrix became block diagonal which could be manipulated more easily (e.g., the inverse of a block diagonal matrix is block diagonal).

For both RF1 and RF2 approaches, SAS® procedure MIXED with the exponential covariance structure [TYPE = SP(EXP)], along with the local option, was used to model the variance-covariance autocorrelation structure (Schabenberger and Pierce, 2002). Differences between soil phase units were included in the model as fixed effects and the analysis was done using the maximum likelihood method (METHOD = ML).

RESULTS AND DISCUSSION

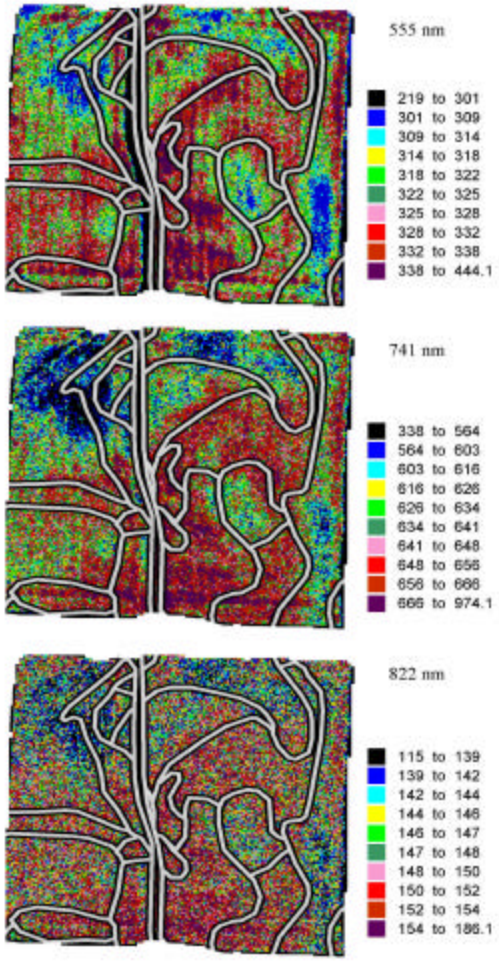
For the AOV approach, the greatest peak in F-value occurred at the beginning of the infrared region at about 741 nm (Fig. 2a). The RF1 approach (accounting for all spatial autocorrelation) (Fig. 2b) produced more noisy results than did the other two approaches, most likely due to the smaller subset of data used in the analysis (n=900) and perhaps also to confounding of between-map-unit differences with effects of spatial autocorrelation (i.e., difficulty in numerically distinguishing whether variation between soil phases is or is not explainable by large scale spatial autocorrelation). Unfortunately, memory problems occurred with the larger dataset (n=5000). Although, there was a peak in the 550 to 650 nm region, it was rather weak. We were reluctant to draw

Fig. 2. F-ratios as a function of wavelength.



conclusions from this data because of the small sample size. The RF2 approach (accounting for only within-soil-phase spatial autocorrelation and using a larger sample size, viz., n = 5000) (Fig. 2c) produced less noisy results and showed several notable peaks, particularly at 555 and 822 nm.

Fig. 3. Hyperspectral imagery (radiance) at three wavelengths.



At 555, 741, and 822 nm (Fig. 3), there was a region of low radiant intensity in the northwest corner of the field coinciding with the most poorly drained soil phase in the field (Hn). However, there was not a consistent relationship between drainage class and radiant intensity. For example, the moderately well drained GrA phase had lower reflectance values than the somewhat poorly drained CaA phases. There were stronger relationships, however, between slope class and spectral radiant intensity values. Soils with A slopes tended to have higher radiant intensity values than soils with B slopes (Fig. 1, 3, and 4). Less sloping regions may be wetter and darker colored. Greater erosion on the steeper slopes may also explain differences in radiant intensity. Areas with the largest radiant intensity values were the most eroded soils in the field: GrB2, CaB3, and PuB phases (Table 1, Fig. 3). This was particularly evident when comparing eroded and uneroded phases of the Grenada soil. Both GrB map units had lower radiant intensity values than the moderately eroded

GrB2 map units. If erosion was a major factor affecting soil reflectance, it was not evident in the differences across the field in surface (0 to 15.2-cm) organic matter (Fig. 5).

Many of the relationships between spectral radiant intensity and map phases were more general and not specifically related to one region of the spectrum. Of the wavelengths examined, the lower wavelengths (555 and 741) had greater signal to noise ratios than the higher wavelength (822). The 741 band generally had better relationships with slope class and erosion classes, but whether this reflects actual correlations or is a random occurrence is not known. The 741 band is in the near infrared region of the spectrum and generally is not considered an important region for soils.

Fig. 4. Slope (%) Map.

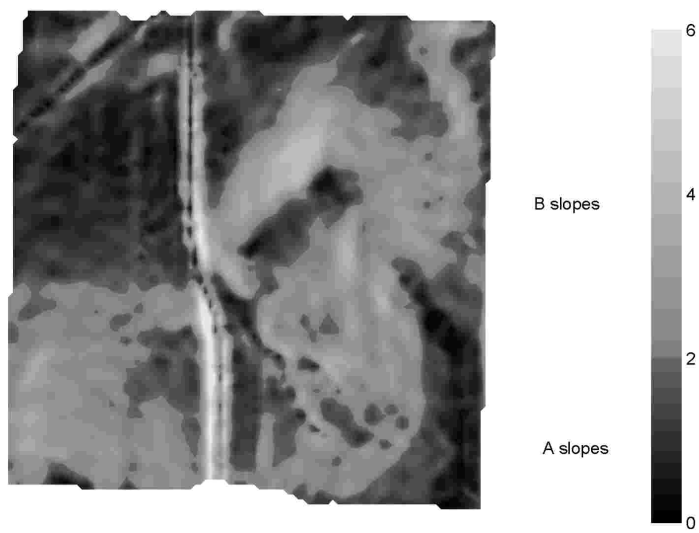
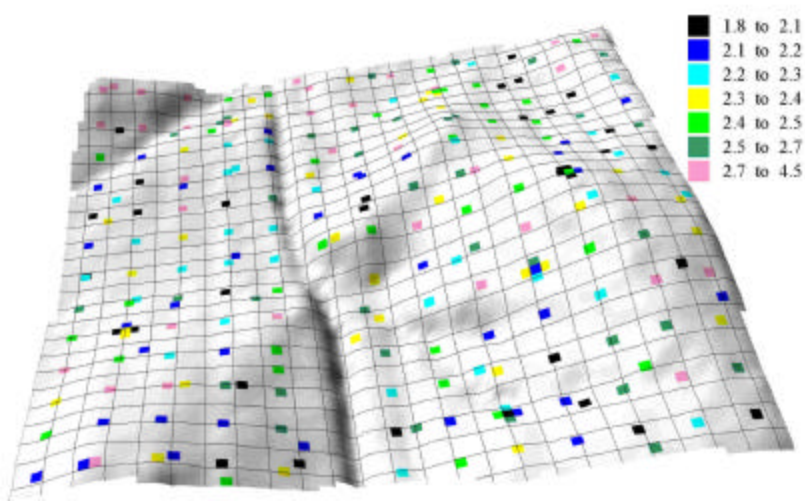


Fig. 5. Organic matter (%) on digital elevation model surface.



SUMMARY AND CONCLUSIONS

The analyses were greatly affected by the degree to which spatial variability of the residuals was taken into account. When spatial variability was not taken into account (AOV), there was a peak between 723 and 744 nm. This range appeared to provide the most information about slope and erosion phases. When all the spatial variability of the residuals (RF1) was taken into account, the peaks were much less abrupt. The dataset for this analysis was truncated because of the large computational resources required. When assumptions about spatial autocorrelation were relaxed (RF2) and only within map unit spatial autocorrelation was taken into account, the F-values were most similar to the F-values for the RF1 approach, although not identical. The less computationally demanding RF2 approach may be the most realistic approach for taking into account spatial autocorrelation. The RF2 approach indicated that there were two major peaks at 537 to 573 and 816 to 822 nm; however, maps at these wavelengths did not necessarily provide more information about soil properties than the maps of the bands indicated by the approach that did not take into account spatial autocorrelation (AOV).

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