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Remote Sensing Of Site-Specific Soil Characteristics for Precision Farming

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Remote Sensing Of Site-Specific Soil Characteristics for Precision Farming

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Abstract. *A methodology for assessing distributed surface soil moisture content from optical remote sensing is developed. This study uses both ground-based and remotely sensed spectral measurements of soil reflectance in visible and near-infrared wavelengths and concurrent measurements of volumetric soil moisture within the top 6 cm to establish a relationship between spectral response and moisture. Various approaches, including principal component analyses and regression techniques are investigated to determine the potential for quantifying soil moisture from the spectral reflection data. Preliminary investigations have yielded R^2 values as high as 0.62 when comparing predictions to actual moisture values. Investigation of predicting soil organic matter content from the same data is also performed.*

Keywords. Soil moisture, Remote sensing, Spectrophotometry, Precision Agriculture

Introduction

Soil moisture is commonly defined as the amount of water in the top several meters of soil that interacts with the atmosphere through evapotranspiration and precipitation and is available for use by vegetation. In agriculture, knowledge of root zone soil moisture can aid in irrigation management and crop yield estimation. In hydrologic studies, knowledge of near-surface soil moisture is important for predicting runoff and erosion processes, which in turn dictate contaminant movement.

There has also been some research to explain and quantify the importance of soil moisture as it pertains to crop yield. A study by Power et al. (1961) found that 53% of the variation in wheat yield was explained by variability in soil moisture at the time of sowing. Stewart et al. (2002) found that soil variables associated with water retention and soil moisture availability were highly correlated with wheat yield. Moore and Tyndale-Biscoe (1999) used a wheat crop growth model to determine that for most fertilizer rates, between 38% and 90% of the variability in yield was removed by eliminating the variation in soil moisture holding capacity. They suggest that spatially variable treatments to adjust the soil's hydrologic properties, for example, selective application of deep tillage treatment, should be investigated. Machado et al. (2000) investigated several influences on the variability in corn crop yields over a three-year period and found that moisture, among other factors, played a significant role.

Traditionally, soil moisture is measured by *in situ* techniques such as gravimetric measurement of soil samples, or measurements from an imbedded sensor. These measurements, however, are essentially point measurements and in general do not adequately account for the spatial variability present in soil moisture. Furthermore, these measurements can be quite expensive and tedious to make, especially at a sufficiently fine sampling interval, which requires large numbers of measurements. Measurement of other soil characteristics, such as soil organic matter content, has the same complications. Remote sensing has the potential to provide measurements with better spatial resolution than can be achieved practically with *in situ* measurement.

Microwave data is currently thought of as the best imagery from which to determine soil moisture characteristics, due to a number of complicating factors that have hindered the use of optical wavelengths for soil moisture assessment. However, hyperspectral imagery is becoming increasingly feasible to work with, with the advent of high speed and high memory computer technologies, and may provide much more information that can be used in soil studies than multispectral or single band sensors.

In the microwave regions of the electromagnetic spectrum, the principal target parameter affecting the measured microwave emissivity is volumetric moisture. Thus there is a strong soil moisture signal in microwave images. Furthermore, microwave radiation has the advantage of being able to penetrate into soil to a wavelength-dependent depth, and is, in some wavelengths, able to penetrate through vegetation cover. These are significant advantages of microwave remote sensing and are why there has been a vast body of research into determination of soil moisture from microwave sensors (Jackson and Schmugge, 1995 and Jackson et al., 1999). However, the resolution that is practically achievable from microwave sensors is not as fine as that with comparable optical sensors, because in general footprint size increases as wavelength increases. Even ground-based microwave sensors mounted on a boom or truck have spatial resolutions on the order of several meters. Also, in longer microwave wavelengths, there is significant potential for radio frequency interference. Furthermore, due to the limited applications of microwave imagery for agricultural studies and the currently relatively high cost of acquiring microwave data, microwave sensors are not as practical from an economic standpoint as sensors in optical wavelengths for these types of applications.

There have been efforts to use optical wavelengths in estimation of soil moisture from multispectral remote sensing data. Moran et al. (1994) and Gillies et al. (1997) explain a method for determining crop water deficit (which translates to soil moisture) using remotely sensed vegetation indices and surface temperatures. The “triangle method", as some have called it, is based on the previously defined notion of Crop Water Stress Index (CWSI), which has been in use since the late 1970's for a number of agricultural water-related purposes (Moran et al., 1994). The theoretical basis for the approach is rooted in evapotranspiration equations for several extreme conditions: full-cover, well-watered vegetation; full-cover vegetation with no available water; saturated bare soil; and dry bare soil. There is also research to suggest that hyperspectral senors are better suited to determination of soil moisture from optical wavelengths. It is commonly observed that a soil is usually darker when wet than when dry. This darkening is presumably based on two processes: 1) the internal reflection of incoming radiation in the soil water surrounding the soil particles, and 2) the absorption of radiation by water in the soil. Bach and Mauser (1994) explain these processes and note that “the spectral resolution of multispectral sensors . . . is not sufficient to determine soil water content from spectral reflectance. Instead, hyperspectral data . . . is needed to allow the identification of specific water absorption features." In the spectral region 500 to 800 nm, darkening of the soil is due only to internal reflection. In longer wavelengths, minor water absorption bands at 960 and 1100 nm and major absorption bands at 1450, 1950, and 2700 nm mean that water absorption is the primary contributor to wet soil darkening at wavelengths over about 800 nm.

Materials and Methods

Description of Study Areas

A university research farm field in Urbana, IL was used in this study. CW-1 is a 4.8-acre soybean field with little topographic variation on the University of Illinois Agricultural Engineering research farm. During the 2001 growing season when this study was conducted, CW-1 was primarily used for a weed mapping study, and as a consequence, only the western portion was planted with soybeans. The eastern portion was not planted; rather, weeds were allowed to grow for a majority of the season.

Data Collected

Surface Soil Moisture

The soil moisture sensor used in the ground truth data collection is the TH_2O Theta Probe by Dynamax Inc. (Houston, TX; www.dynamax.com). This is a dielectric sensor that sends a microwave signal and analyzes the reflected signal to measure dielectric constant of the soil. The Theta Probe output is a voltage reading, which is then converted to volumetric water content based upon calibration coefficients obtained by comparing Theta Probe readings to gravimetric sampling. The manufacturer states that with this calibration, the accuracy of the volumetric water content measurements is within ±2%. The volume of soil contributing to this measurement for the Theta Probe is roughly a cylinder 60 mm wide and 60 mm long. The exact dimensions of this region of influence are difficult to determine precisely because they are a function of soil density and soil water content. This probe works well for wide variety of soils and water contents (4% - 60%). In this study, the probe was inserted directly into the soil surface, resulting in soil moisture readings for roughly the top 2.5 inches of soil.

Moisture data collection with the theta probe was fairly straightforward. The probe was connected to a datalogger that was launched from a laptop computer prior to data collection. In general, the acquisition rate was set at 1 reading per second. At this rate, the logger could record for four hours, which was sufficient, since data collection was generally limited to a two to three hour window. At each sampling location, the probe was inserted into the soil surface. In some cases when there were significant clods, it was necessary to clear a small area by brushing the clods aside so as to insert the probe into a continuous soil surface. The probe was left in the soil for 5 to 6 seconds at the least to ensure an equilibrated reading. In general, the probe response was immediate so there was little need for extended response time. For each sampling point, several probe insertions were done. At CW-1, four readings in a box formation were done, with a distance of roughly twelve inches on each side. Unless there was a complicating factor, such as herbicide spraying being done in a portion of the field during the data collection time window, 64 locations evenly distributed throughout the field were sampled in this way.

After sampling was completed, the data was off-loaded onto a pc, and using a spreadsheet, the voltages were converted to moisture readings. The 1-second data was then manually distilled to the location-average moisture data. This was a fairly straightforward procedure since the moisture readings were nearly instantaneous, and the soil readings are dramatically different from the readings taken while the probe was not inserted into the ground. The data were also time-stamped, which eases relation of the moisture data to the spectrometer and GPS data, which were also time-stamped.

Soil Organic Matter Content

Soil samples were collected at 32 locations within the field. Each of these points coincided one of the aforementioned locations. Samples were analyzed for organic matter content and various nutrients. Values of organic matter ranged from 2.4 to 3.7 and were spatially organized into two main groups, one with lower organic matter than the other. Spatially, the distribution was similar to the delineation of two soil types in the field. The organic matter data was kriged to create a map of organic matter for the entire field.

Ground-based hyperspectral data

Ground-based spectral reflectance data was collected using an HR2000 High-resolution Miniature Fiber Optic Spectrometer (Ocean Optics Inc., Dunedin, FL; www.oceanoptics.com). The HR2000 is a small-footprint, modular spectrometer with a spectral resolution of 0.065 nm, measuring in wavelengths from 331.54 nm to 1068.97 nm. The view angle is approximately 25 degrees. Upwelling radiation is measured in digital counts, thus in order to convert this to reflectance data it is necessary to take measurements of a reflectance standard to which to compare the soil scans.

Spectral reflectance data from the HR2000 spectrometer was collected over the locations where the ground was sampled for surface moisture. In order to normalize the digital count data recorded from the spectrometer it was necessary to take a reference scan immediately prior to every soil surface scan. The reference scan was taken from a piece of standard white office paper positioned about 16 inches underneath the sensor. The soil surface scan was then taken by holding the spectrometer five feet above the soil surface, being sure to avoid shadows from the operator or equipment. From this height, the spectrometer measures a circular area on the ground with a diameter of about 2.2 feet.

Furthermore, because the reflectance signal changes with changing solar angle, in order to reduce the effect of this on the set of ground truth data, the data was collected in a consistent time frame, and at such a time as the difference in solar angle from the beginning of the data collection to the end of the data collection would be minimal. Generally data collection began between 10:00 and 10:30 AM and was finished by 1:00 or 1:30 PM.

The data files for each scan were saved with a time-stamp in the file header so that for each location the corresponding spectral data could be matched with the moisture data. In order to determine relative reflectance, the soil scan was normalized by the white paper reference scan for each location. Due to the low signal strength in the wings of the raw spectrum, the normalized reflectance data in the wings are likely more unreliable than data closer to the interior of the spectrum.

Data Analysis and Preliminary Results

After examining the entire set of CW-1 spectral data, it was determined that some of the spectra were too influenced by the presence of vegetation. Specifically, the points in the soybean-planted section of the field for the 7/26 data showed significant influence from the vegetation signal in the wavelengths between about 650 and 900 nm. Because of this signal, these 36 data points were removed from the subsequent analysis to determine the relationship between the spectra and soil moisture. For the purpose of the statistical analysis, all of the CW-1 spectral and moisture data were combined into one data set, which, after the removal of the aforementioned points, consisted of 186 samples.

Correlation Analysis

In order to determine the relationship between each band individually and soil moisture, a correlation analysis was performed. In addition to performing this analysis on the 1023-band HR200 spectral data with the soil moisture, the data was also aggregated to resolutions of other sensors. One was 60-band aerial hyperspectral data used in the Illinois Laboratory for Remote Sensing, others were the Landsat Thematic Mapper (TM), the Landsat Multispectral Scanner (MSS) and the Advanced Very High Resolution Radiometer (AVHRR). Only bands from Landsat TM and MSS and AVHRR that were within the spectrometer range were included. Figure 1 shows the results of this analysis.

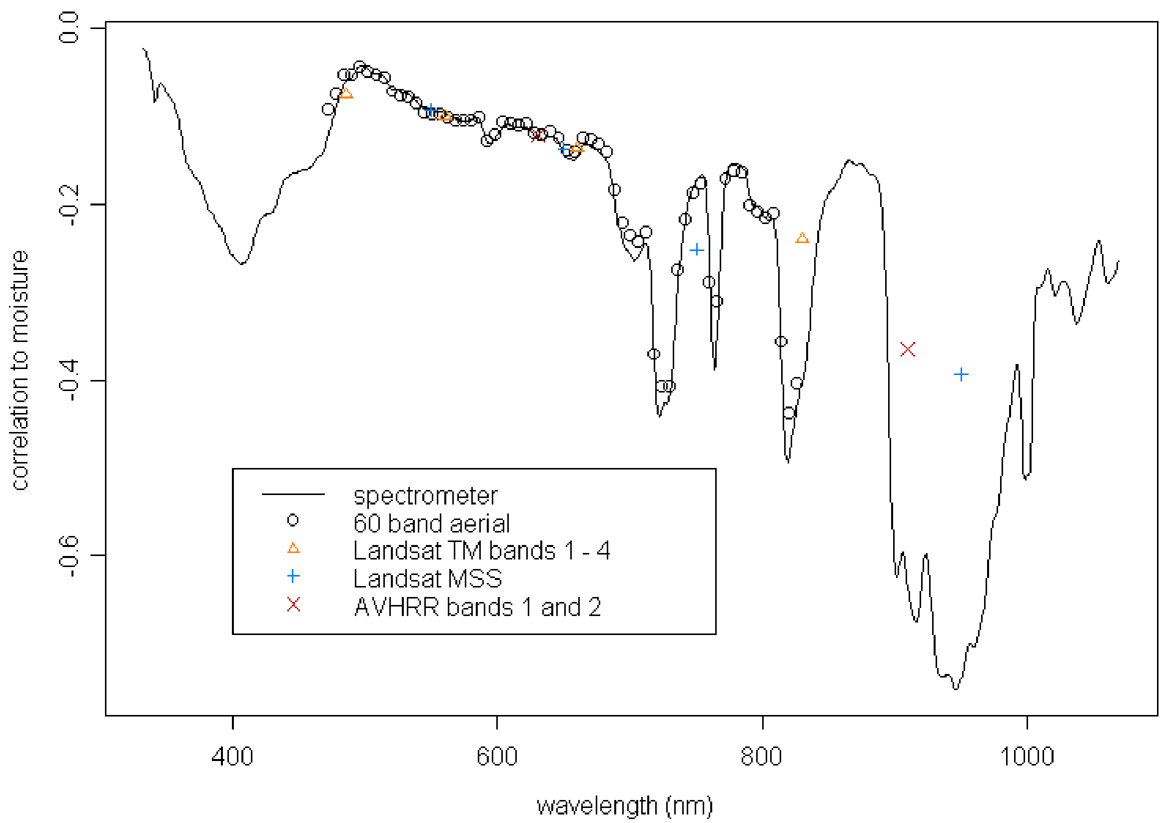

Figure 1. Correlation analysis for various spectral resolutions.

The maximum correlation for the 1023-band data is -0.75, and occurs at a wavelength of 945.64 nm. Several other bands show some correlation with moisture, specifically 818.9 nm and 722.13 nm, with correlations of -0.49 and -0.44 respectively.

The synthetic 60-band data, which does not have as large a range as the 1023-band data and thus does not include the 945.64 nm wavelength, shows roughly the same correlations as the 1023 band data for the range that it does have. However, the magnitudes of the correlations are slightly decreased for the 60-band case, where the spectral resolution is far coarser.

For the case of the synthetic satellite data, the strength of the correlations is significantly degraded. This is illustrative of the fact that hyperspectral data is better suited to moisture studies than multispectral data, since the bandwidths in the latter case are likely too wide to capture the signals easily seen in more finely spectrally resolved data.

Principal Component Analysis

In order to further investigate the relationships between the spectral data and the moisture data, a principal component analysis (PCA) was performed on the 1023-band data set. This analysis identifies the signals that explain the most of the variance in a given data set. These new signals, or components, are linear combinations of the original data. This analysis also results in components that are independent from one another. In this way, a many-band data set with a lot of redundant information can be reduced to a smaller number of statistically significant and independent bands.

The results of the principal component analysis on the 1023-band data set reveal that the first three principal components together account for 96% of the variance in the data set. The first one explains 77.6%, the second 14.6%, and the third 3.7%. When comparing these components to organic matter and surface soil moisture, there is a noticeable relationship between the first component and organic matter. Similarly, there appears to be a relationship between the third component and soil moisture. Figures 2 and 3 shows these relationships. A simple linear regression on this data reveals that the first component and organic matter are linearly related with an R^2 value of 0.73, whereas the third component and soil moisture are linearly related with an R^2 value of 0.44.

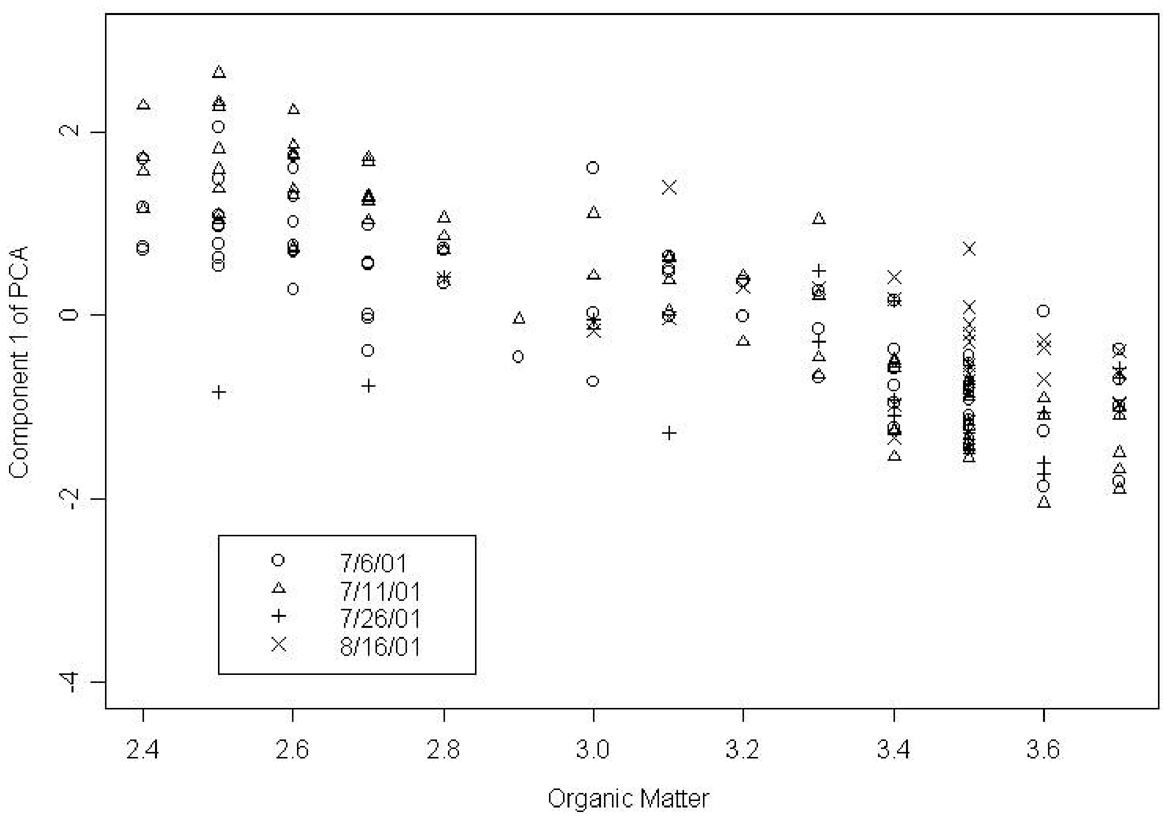

Figure 2. Principal component 1 compared to organic matter.

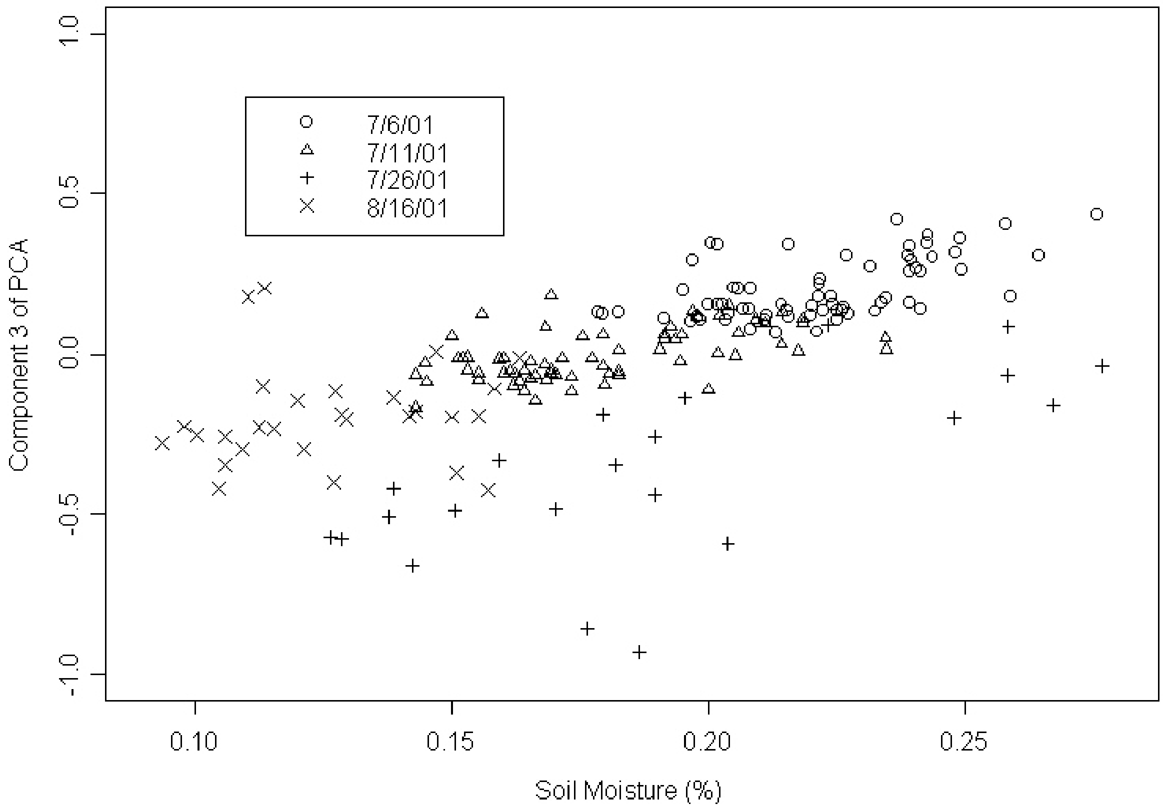

Figure 3. Principal component 3 compared to soil moisture.

In order to further understand these components, we can examine the weighting of each band in each of the components to determine which wavelengths contribute to each component. Figure 4 shows the band weightings for components 1 and 3.

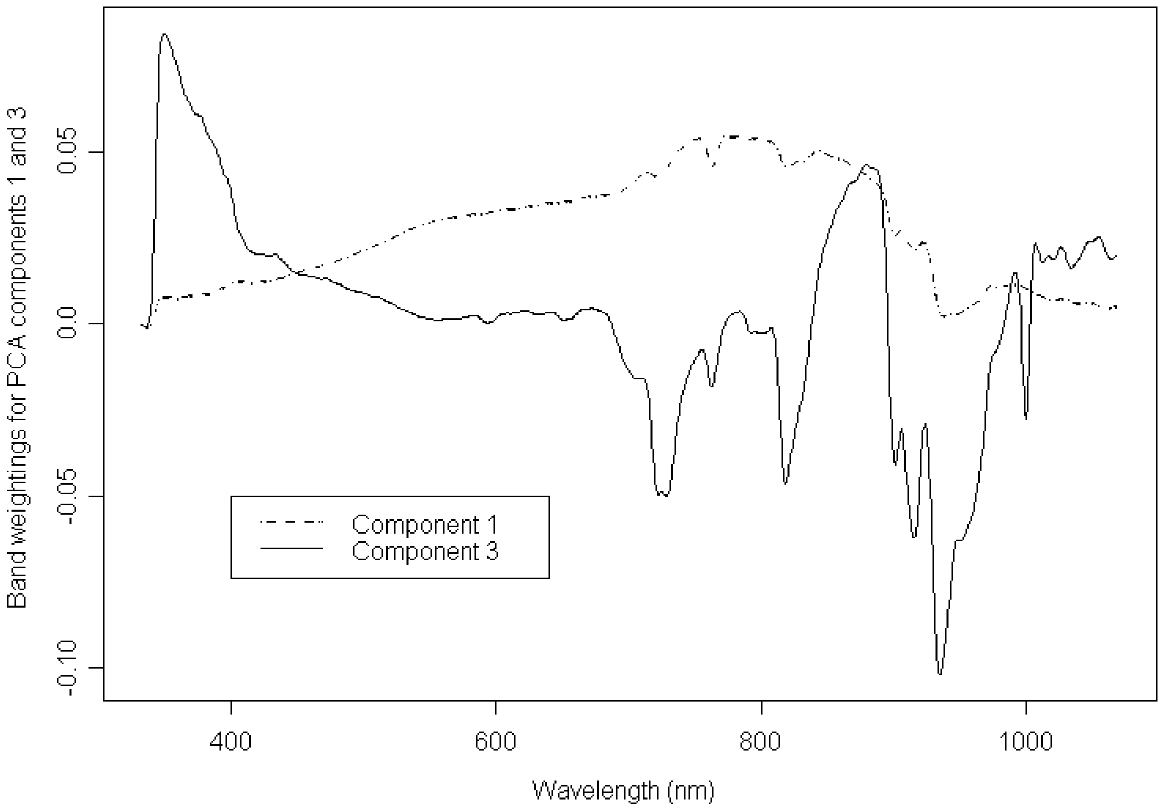

Figure 4. Band weightings for components 1 and 3 of PCA.

The band weightings for component 1 are fairly smoothly varying, generally increasing until the maximum and decreasing thereafter. The maximum contribution to component 1 occurs at the wavelength 783.14 nm. The band weightings for component 3 are quite different from those of component 1. Whereas the loadings for component 1 are fairly smooth, the loadings for component 3 are more variable, and have several maxima and minima. There is a noticeable peak at the low-wavelength edge of the spectral range, but the reliability of this data, as mentioned previously, is relatively low. Removing the initial peak in the third component's weightings by setting the weightings for wavelengths less than 555 nm to zero increases the R^2 value for the third component and soil moisture from 0.44 to 0.57. The next major contribution to the third component is a narrow minimum centered at the wavelength 934.63 nm. This is similar to the correlation minima at 945.64 nm. Other strong contributions to component 3 include the wavelengths 879.74 nm, 818.21 nm, and 727.95 nm. The latter two are also quite similar to wavelengths identified by the correlation analysis.

Soil Moisture Prediction

Using five bands identified by the correlation and principal component analyses, a simple linear regression on the 186 samples was performed. The bands from the 1023-band data were

945.64 nm, 934.63 nm, 879.74 nm, 818.21 nm, and 727.95 nm. The results of this regression, which had an R^2 of 0.62, are shown in figure 5.

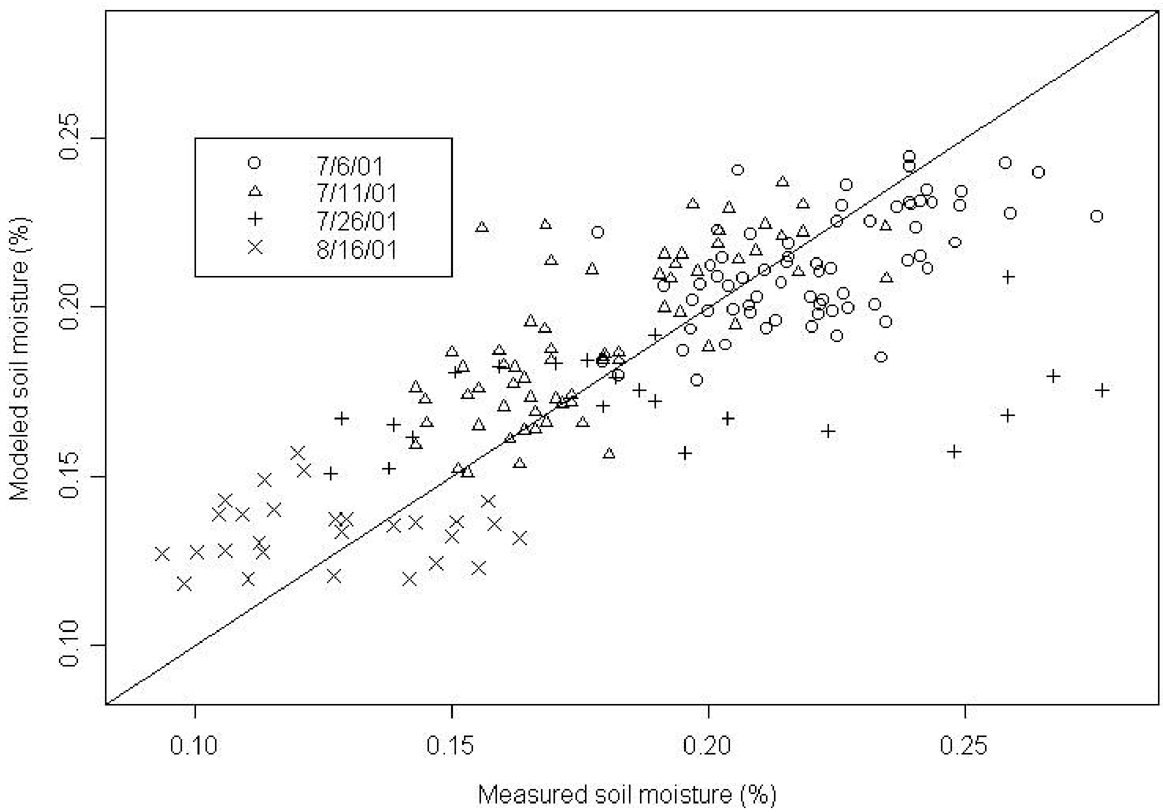

Figure 5. Linear regression model of soil moisture using five spectral bands.

Conclusion

The results of analyzing the spectral data in conjunction with surface soil moisture and organic matter data suggest that there is potential for hyperspectral data to be used to infer moisture status and organic matter content. A correlation analysis between surface soil moisture data and soil surface reflectance revealed correlations as high as 0.75. A regression analysis of several bands selected through the correlation analysis and a principal component analysis gave a relationship with an R^2 of 0.62. Furthermore, the results of the principal component analysis suggest a relationship between surface reflectance and soil organic matter content. However, more in-depth experimentation needs to be done to determine the extent to which this potential can be realized. Furthermore, the usefulness of this data in a precision farming environment must be investigated.

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