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Written for presentation at the
2003 ASAE Annual International Meeting
Sponsored by ASAE
Riviera Hotel and Convention Center
Las Vegas, Nevada, USA
27-30 July 2003

Abstract. A methodology for mapping surface soil moisture content across an agricultural field from optical remote sensing and ground sampling 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. After determining appropriate wavelengths for soil moisture estimation from spectral reflectance, a cokriging scheme was used to generate soil moisture maps. Results indicate that combining reflectance and ground measurements can yield more detailed maps of soil moisture than ground measurement alone.

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

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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 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. Remote sensing has the potential to provide measurements with better spatial resolution than can be achieved practically with in situ measurement.

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 sensors 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 (Ben-Dor, 2002; Bach and Mauser, 1994).
Materials and Methods

Description of Study Areas

A university research farm field in Urbana, IL was used in this study. The Grein field is an 8.2-acre field with moderate topographic variation on the University of Illinois Agricultural Engineering research farm. During the 2002 growing season when this study was conducted, Grein was planted in corn, alternating planted strips with bare swaths used to relate moisture and soil surface reflectance over the course of the season.

Data Collected

Surface Soil Moisture

Two types of surface soil moisture measurements were made. The first was gravimetric sampling, and was used to establish the relationship between moisture and ground-based spectral reflectance for this field. At each location, two 1.5 inch diameter soil cores were taken from the first three inches of soil and placed in a labeled zip-seal plastic freezer bag. The samples were taken back to the laboratory, where they were removed from the bags and weighed. The samples were then baked at 100°C for 23 hours, removed from the oven and re-weighed. The difference between the two weights was the gravimetric moisture. The second type of soil moisture measurement, used in conjunction with aerial imagery as discussed later in this paper, was made with the TH₂O 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. 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.

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. In order to reduce noise and computational resources, the original 2047-band scans were smoothed using a k-smoothing algorithm with a five-band window, and then pared down by eliminating every other point.

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.

Aerial hyperspectral data

Several remotely sensed images of the Grein field during the 2002 season were also available. These images were acquired from the RDACS/H3 pushbroom sensor from NASA/ITD Spectral Visions (Mao, 2000). The spectral range of these images is from 472 to 826 nm, with 6 nm spectral resolution. The ground resolution is approximately 1 meter. Images were calibrated using placard reflectance data provided by Spectral Visions, and georeferenced prior to analysis through identification of known target locations on the ground.

Data Analysis and Results

**Correlation Analysis And Model Development**

In order to determine the relationship between each band individually and soil moisture, a correlation analysis was performed using the spectral and soil data collected on ten dates from June through September of 2003. Figure 1 shows the results of this analysis.

![Figure 1. Correlation between surface soil moisture and reflectance by wavelength.](image)

The strongest correlation is in the region from about 500 nm to 700 nm, with a maximum absolute correlation of 0.69. Further analysis of the data on a date-by-date basis reveals that with the exception of two July dates, the correlations are the greatest in magnitude roughly around 550 - 620 nm, which lies in the yellow-orange region of the visible spectrum. At low
saturation and/or illuminance, colors in this region appear various shades of brown. As a consequence, it is no great surprise that it is in this region of the optical spectrum that soil reflectance is the most influenced by moisture.

Muller and Décamps (2001) propose that an exponential model of the form

$$\rho_{s(\lambda)} = \rho_{so(\lambda)} \exp (a_{s(\lambda)} M)$$

could be used to quantify the relationship between surface soil moisture and reflectance, where $\rho_{s(\lambda)}$ is the reflectance of the wet soil $s$ in the spectral band $\lambda$, $a_{s(\lambda)}$ is a reflectance attenuation factor for the soil $s$ in the spectral band $\lambda$ due to the soil moisture $M$, and $\rho_{so(\lambda)}$ is the theoretical reflectance of the soil in the spectral band $\lambda$ with a soil water content at air dryness.

Muller and Décamps were comparing SPOT satellite reflectance to a very thin layer (several millimeters) at the soil surface. The data presented here is from several inches, rather than millimeters, of the soil surface. In order to explore the applicability of the exponential model to this sort of data, which ultimately is likely to be more useful, reflectance data was graphed against moisture data. For the Grein field, the 605 nm band was selected based upon the results of the correlation analysis. A plot of 605 nm reflectance versus measured soil moisture content is shown in figure 2.

![Figure 2](image-url)

Figure 2. 605 nm reflectance versus soil moisture content. Data from 7/19/02 is plotted in a different symbol.

Figure 2 illustrates that reflectance decreases with increasing soil moisture, as expected, but that the rate of decrease in reflectance becomes more moderate with increasing soil moisture. This is likely because at very high soil moisture contents, the soil is already quite dark, and further moisture added to the soil has less and less an effect on the reflectance. This implies that an exponential is suitable.
Also notable in figure 2 is that the Grein data exhibits a cloud of points that falls off to the side of the curve the rest of the data seems to be following. Further investigation reveals that most of it is from 7/19/02. These data are plotted in a different symbol in figure 2. There is no obvious explanation for the deviation of the 7/19/02 data from the pattern followed by most of the rest of the Grein data. Nonetheless, for the sake of establishing a plausible exponential model, the 7/19/02 data was removed from the Grein dataset.

The following exponential model was fit with $R^2 = 0.62$,

$$
\rho_{\text{s}(\lambda=605 \text{ nm})} = 0.303 \exp (-3.39 M)
$$

However, looking at the relationships between measured moisture and estimated moisture from inverting the above equation on an individual date basis indicates that there is a large degree of deviation. This is in part because on any given day, the range of moisture values present in the field is small when compared to the range for a series of days. As a result, the $R^2$ values are much lower for the individual days. This implies that accurate prediction of moisture directly from optical spectral measurements is less likely to be possible than general prediction of moisture regimes, such as "wet", "moderate", and "dry", for example.

**Data Fusion**

While the results of the correlation and model development analyses are not overwhelmingly indicative of a tight relationship between near-surface soil moisture and soil surface spectral reflectance, there remains a strong enough trend to suggest that supplementing sparse ground truth data with more dense reflectance data could lead to improved prediction of distributed soil moisture compared to ground truth data alone.

There are numerous ways to combine the ground truth and spectral reflectance data sets in a statistically meaningful way. Cokriging is one such approach. The major limitation of cokriging is that it requires a significant amount of data to establish semivariograms for both the primary data (in this case, the ground truth soil moisture) and the secondary data (in this case, spectral reflectance) and the cross-semivariograms between the two. Furthermore, there are restrictions placed on the properties of the variograms that are allowable for the cokriging scheme to function properly. However, the advantage of cokriging in the case of moisture and spectral data sets, is that it is possible to develop a moisture map from a very small number of ground sampling points, provided it is understood that the average estimation variance will be quite high compared to a map developed from a larger number of ground samples. This is not the case with other geostatistical approaches, such as kriging with a trend, which would require a larger number of ground samples in order to establish the trend. There is, then, an important distinction between the theoretical development of cokriging and the purpose for which it is being used here. The original intent of cokriging is to supplement sparse (and yet, not extremely limited) amounts of primary data with more exhaustive (and yet, not over-abundant) secondary data to generate as accurate a map as possible. The purpose of cokriging in this study is as a data fusion technique to combine extremely limited ground data with known geostatistical characteristics, with exhaustive related secondary data to generate a better estimate of the patterns of variation in the primary data.

For one date in the 2002 season at the Grein field, a bare-soil aerial image is available. This image, from 6/14/02, was taken at the same time that ground moisture measurements were being made with the Theta probe. Figure 3 is the 595 nm reflectance image. The flow path in the middle western portion of the field is clearly visible.
To reduce computational load because of the size of the image, only every 4th pixel in the easting and northing direction were maintained for analysis. Figure 4 shows the locations and 595 nm reflectance values of these pixels.

For surface moisture data, a total of 90 locations were sampled. These locations and moisture contents are shown in figure 5. An average soil moisture variogram computed through use of a fourth root transform from the individual sampling date variograms, as suggested by McBratney and Pringle (1999), was used to krig the 6/14/02 moisture data; the resulting estimated moisture field is shown in figure 6.
Figure 4. 595 nm reflectance values and selected pixel locations for the 6/14/02 image of the Grein field. The color scale represents reflectance values (%). Easting and Northing are given in UTM.

Figure 5. All moisture sampling locations and gravimetric moisture contents (%) for 6/14/02. Easting and Northing are given in UTM.
A variogram was also calculated for the 595 nm reflectance image. As is usually the case with remotely sensed data, the calculated semivariogram is quite regular, and was fitted with a 6.0E-5 nugget and a spherical model with a 1.4E-4 sill and 110 m range.

In order to compute the cross-semivariogram between the reflectance and moisture data, pixels from the original image that contained the ground sampling locations were identified. However, the resulting cross semivariogram between the spectral data and the moisture data was very irregular, making it difficult to model effectively. Yet specification of the cross-semivariogram is crucial for the cokriging technique. Therefore, in order to proceed with the cokriging, the semivariogram estimated for the spectral data alone was also used for the cross-semivariogram. This has the effect of modeling the moisture field directly as a function of the spectral field, but using the semivariogram for the moisture data preserves the general spatial variability properties of the surface soil moisture.

In order to test the cokriging scheme for a situation where minimal ground sampling is needed, the time series of moisture data were analyzed to determine if any locations had a stable moisture response relative to the field average. This analysis is outlined by Grayson and Western (1998). One site, located at (398399.5 E, 4434809 N), was at or very near the field average for every date sampled. Thus, this point was selected as the ground data for the cokriging scheme. The results of this cokriging are presented in figure 7. Comparing figures 6 and 7 reveals that there is a reasonable amount of correspondence between the two, but that the range of the cokriged field is much more limited than the true moisture data. Nonetheless, the cokriged field is a significant improvement over assuming the entire field is at the field average moisture content.
Conclusions

Spectral reflectance data was analyzed in conjunction with surface moisture data to determine the nature of the relationship between the two. In general, soil reflectance decreases with increasing moisture content. Furthermore, an exponential model, where the decrease in reflectance with increasing moisture content levels out at the high values of soil moisture, is appropriate for the soils analyzed in this study. For the field used in this study, the strongest relationship between reflectance and surface moisture was between 550 and 620 nm, which corresponds to the orange/brown region of the spectrum.

A combination of spectral data and limited surface soil moisture data was used to create soil moisture maps. Use of a cokriging technique allowed for more detailed maps of soil moisture than were possible from the limited data alone. For the extreme case of just one ground sample, it is still possible to generate a reasonable soil moisture map using remotely sensed data, particularly if the individual ground sample is representative of the mean of the field. This method shows potential for development as part of a data fusion technique to generate moisture maps from a minimum of samples.
References


