



American Society of  
Agricultural and Biological Engineers

*An ASABE Meeting Presentation*

*Paper Number: 061173*

## **Fusion of Remotely Sensed Imagery and Minimal Ground Sampling for Soil Moisture Mapping**

**Amy Kaleita, Assistant Professor**

Agricultural and Biosystems Engineering, Iowa State University, Ames IA.

**Written for presentation at the  
2006 ASABE Annual International Meeting  
Sponsored by ASABE  
Oregon Convention Center  
Portland, Oregon  
9 - 12 July 2006**

**Abstract.** *A methodology for mapping surface soil moisture content across an agricultural field from optical remote sensing and limited ground sampling is developed. This study uses remotely sensed spectral measurements of soil reflectance in a single visible wavelength and historical measurements of volumetric soil moisture within the top 6 cm, in conjunction with a single ground measurement. Results indicate that combining reflectance and ground measurements can yield more detailed maps of soil moisture than ground measurement alone.*

**Keywords.** Geostatistics, Theta probe, data fusion.

---

The authors are solely responsible for the content of this technical presentation. The technical presentation does not necessarily reflect the official position of the American Society of Agricultural and Biological Engineers (ASABE), and its printing and distribution does not constitute an endorsement of views which may be expressed. Technical presentations are not subject to the formal peer review process by ASABE editorial committees; therefore, they are not to be presented as refereed publications. Citation of this work should state that it is from an ASABE meeting paper. EXAMPLE: Author's Last Name, Initials. 2006. Title of Presentation. ASABE Paper No. 06xxxx. St. Joseph, Mich.: ASABE. For information about securing permission to reprint or reproduce a technical presentation, please contact ASABE at [rutter@asabe.org](mailto:rutter@asabe.org) or 269-429-0300 (2950 Niles Road, St. Joseph, MI 49085-9659 USA).

---

## 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.

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. The most economical remotely sensed data for agricultural purposes is that in the visible and near infrared regions of the electromagnetic spectrum. Previous studies have explored the use of this type of data in estimating soil moisture content. 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. Muller and Décamps (2001) used simulated SPOT reflectance data derived from an aerial platform to model soil moisture over French agricultural fields under bare-soil conditions. Kaleita et al. (2005) determined that a linear relationship could be used to explain the variation in surface reflectance in the visible region by soil moisture content, but the maximum  $R^2$  for soil moisture models across the given study field was only 0.6. Thus, it is worth investigating the potential to combine remotely sensed data with other available data, in order to improve the resulting soil moisture map.

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.

Wilson et al. (2005) present a method based on multiple linear regression for generating a spatial map of soil moisture based upon a combination of different data influential data, such as terrain attributes.

$$\theta_{it} = \bar{\theta}_t + \sum_j \sigma_{\bar{\theta}_t} \cdot p_{\bar{\theta}_t T_j} \cdot \frac{(T_{ji} - \bar{T}_j)}{\sigma_{T_j}} + \varepsilon_i \quad (1)$$

where  $\theta_{it}$  is the volumetric moisture content at location  $i$  and time  $t$ ,  $\bar{\theta}_t$  is the areal mean soil moisture at time  $t$ ,  $p_{\bar{\theta}_t T_j}$  is the standardized partial regression coefficient of  $\theta$  on  $T_j$  at  $\bar{\theta}_t$ ,  $\sigma_{\bar{\theta}_t}$  is the areal standard deviation of soil moisture at  $\bar{\theta}_t$ ,  $T_{ji}$  is the spatial attribute  $j$  at location  $i$ , and  $\bar{T}_j$ ,  $\sigma_{T_j}$  is the areal standard deviation of the spatial attribute  $j$ , and  $\varepsilon_i$  is an error term.

One problem with this approach is that in order to establish the partial regression coefficients, one must have data of soil moisture and all attributes collocated in both time and space. This approach also assumes that all data sources are equally reliable.

The purpose of this study is to investigate a simpler variant of the MLR-based approach in order to use remotely sensed data in combination with an understanding of average soil moisture patterns within a given field.

## **Methods**

### ***Study Area***

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. Both the surface soil moisture data and imagery were collected on 6/14/2002.

### ***Surface Soil Moisture Data***

Soil moisture measurements were made with the ML2x Theta Probe by Dynamax Inc. (Houston, TX). 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 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. A total of 86 sampled locations were used in this analysis.

### ***Aerial Hyperspectral Imagery***

An early-season aerial image of the Grein field during the 2002 season were also available. This image was 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. Figure 1 shows the 595 nm reflectance image. 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.

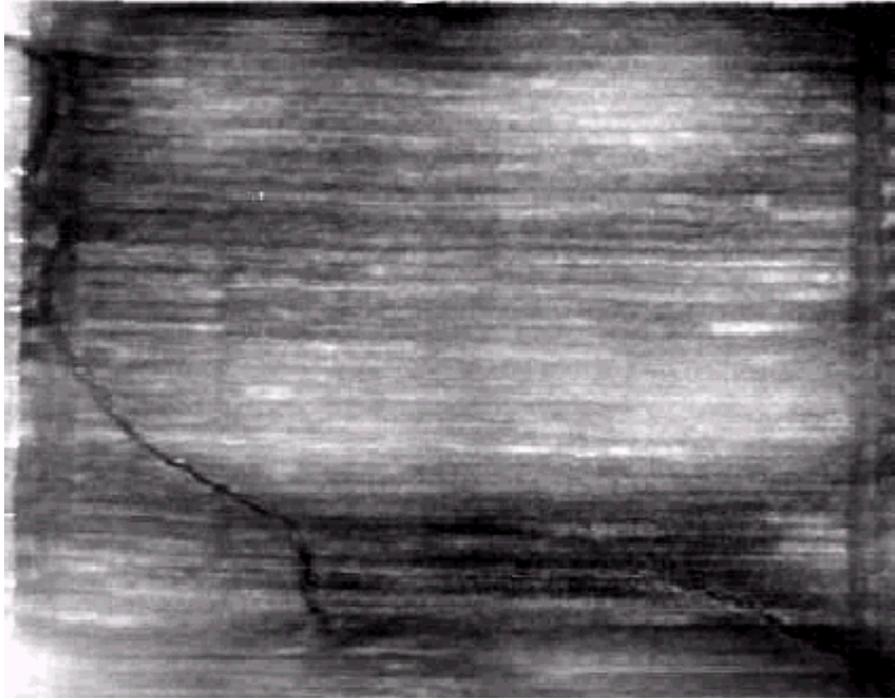


Figure 1. Aerial image for 6/14/02, 595 nm wavelength over the Grein field.

### **Previous research**

Kaleita, et al. (2005) presented the relationship between surface soil moisture and ground-based reflectance data for this field, showing an inverse relationship between the two, particularly in the 500 – 600 nm region of the spectrum. A subset of this data, excluding one anomalous data set, is shown in figure 2.

A second study presented an analysis of ten days of moisture data collected at this field (Kaleita et al. 2004). This study found that a single base pattern of soil moisture accounted for approximately half of the variability in any given day's soil moisture pattern for this field. This temporally stable pattern represents the average fractional deviation from the field mean moisture, and is calculated from a series of observations from across the area in question as

$$\delta_{it} = \frac{\theta_i - \bar{\theta}_t}{\bar{\theta}_t} \quad (2a)$$

$$\bar{\delta}_i = \frac{1}{m} \sum_{t=1}^m \delta_{it} \quad (2b)$$

where  $\theta_i$  is the moisture at the  $i^{\text{th}}$  location, and  $\bar{\theta}_t$  is the field average of all  $\theta_i$  on the  $t^{\text{th}}$  sampling occasion,  $m$  is the total number of sampling occasions, and  $\delta_{it}$  represents the deviation in soil moisture of the  $i^{\text{th}}$  location from the field average on the  $t^{\text{th}}$  sampling occasion.

This pattern for the Grein field is shown in figure 3 along with elevation data.

Numerous researchers have observed that there are locations within a given area that have consistent behavior relative to the areal average moisture content (Vachaud et al. 1985,

Grayson and Western, 1998). Measurement at one of these “average soil moisture monitoring sites” can provide consistent estimates of  $\bar{\theta}_t$  from just one location. Kaleita et al. (2004) found that a particular location in the northeast section of the Grein field consistently had a moisture content within 0.01 of the field average.

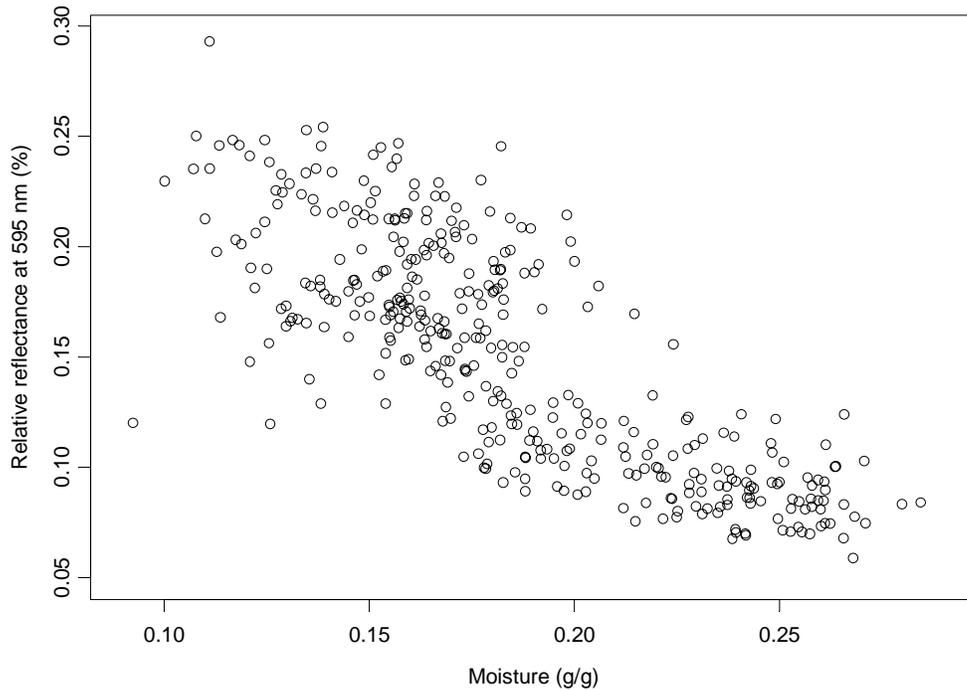


Figure 2. Relationship between surface reflectance at 595 nm and near-surface gravimetric soil moisture content, based on Kaleita et al. (2005).

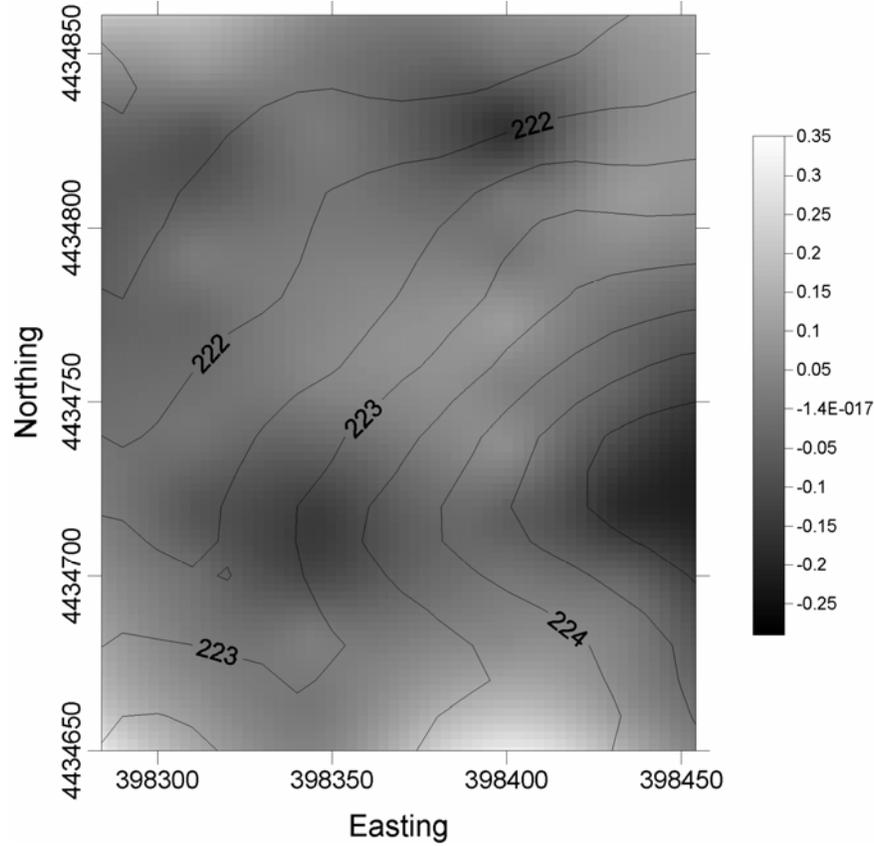


Figure 3. Temporally stable base pattern of near-surface soil moisture for the Grein field, built from 10 observations of distributed gravimetric soil moisture. Values represent fractional deviation from the field average moisture content. Elevation values in meters are also given. (Kaleita et al. 2004).

### Data Analysis

Equation (1) was reformulated as

$$\theta_{i,t} = \bar{\theta}_t + W_\delta b_\delta (\bar{\theta}_t \times \bar{\delta}_i) + W_R b_R (R_{it} - \bar{R}_t) \quad (3)$$

where  $W_\delta$  and  $W_R$  are the weightings for the temporally stable base pattern  $\bar{\delta}_i$  and the reflectance image data  $R_{it}$  respectively, and  $b_\delta$  and  $b_R$  are the individual single linear regression coefficients of  $\bar{\delta}_i$  and the reflectance image data  $R_{it}$  on  $\theta$ . Using the single linear regression coefficients rather than the multiple linear regression coefficients means that the model can be built using data from different points in space and time. In this case, the relationship between  $R_{it}$  and  $\theta$  is taken from the data presented in Kaleita et al. (2005). Also,  $b_\delta$  is assumed to be 1, because for every incremental change in  $(\bar{\theta}_t \times \bar{\delta}_i)$  there is theoretically an equal incremental change in  $\theta_{i,t}$ .

For this study, we give equal weighting to both the remotely sensed image and to the temporally stable base pattern. The temporally stable pattern explained 52% of the variance in the ten-day

moisture data set, while the reflectance data in the 595 nm waveband explained 47% of the variance in the soil moisture data collected from this field. While these explained variances are not relative to one another, we elected to use them as a basis for setting  $W_{\delta} = W_R = 0.5$ . This arbitrary choice potentially allows for data from different sources and at different resolutions to be used in combination with each other.

## Results

Figure 4 shows the results of applying equation (3). Also shown are the observed volumetric moisture content data from that day.

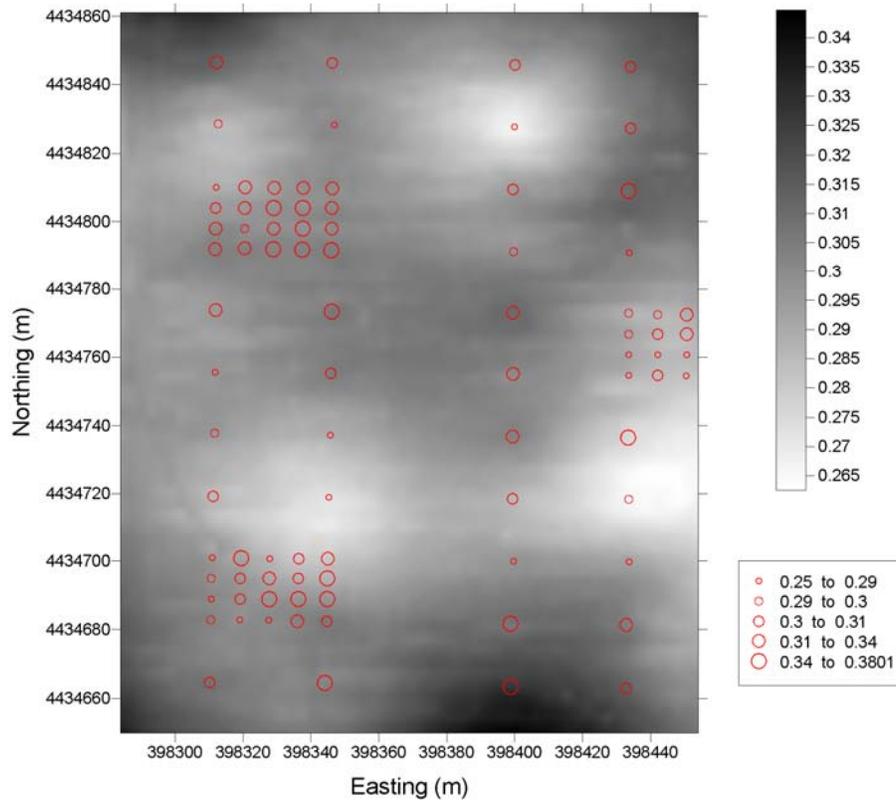


Figure 4. Results of the data fusion scheme overlain with ground truth data. The shading scale and legend represent volumetric surface soil moisture. Easting and Northing are given in UTM.

This map captures some of the features of the observed data, such as the wet portion in the southeastern section of the field and the dry section in the northeastern section of the field. It also captures the wet ephemeral waterway in the southwestern section of the field, which some of the observed data correspond to also. The range of moisture values in the observed and estimated moisture contents are similar, as are the variances. The resulting map misses other features, such as the size of the wet region in the southeastern section of the field, and the level of wetness of the region around [398330, 4434800].

## Conclusions

A combination of spectral data and limited surface soil moisture data was used to create a soil moisture map using a linear regression-based technique. This technique exploits a knowledge of common patterns within a given area in combination with one ground sample and a remotely sensed image. This method shows potential for development as a data fusion technique to generate moisture maps from remote sensing and a minimum of samples.

## References

- Gillies, R. R., T. N. Carlson, J. Cui, W. P. Kustas, and K. S. Humes. 1997. A verification of the 'triangle method' for obtaining surface soil water content and energy fluxes from remote measurements of the Normalized Difference Vegetation Index (NDVI) and surface radiant temperature. *Int. J. Remote Sensing* 18(5): 3145-3166.
- Grayson, R. B., and A. W. Western. 1998. Towards areal estimation of soil water content from point measurements: time and space stability of mean response. *J. Hydrology* 207: 68-82.
- Kaleita, A. L., L. F. Tian, and M. C. Hirschi. 2004. Identification of optimal sampling locations and grid size for soil moisture mapping. *ASAE Paper No. 041146*. St. Joseph, MI.
- Kaleita, A. L., L. F. Tian and M. C. Hirschi. 2005. Relationship between soil moisture content and soil surface reflectance. *Transactions of the ASAE*. 48(5): 1979-1986.
- Mao, C. 2000. Hyperspectral focal plane scanning - an innovative approach to airborne and laboratory pushbroom hyperspectral imaging. In: 2nd International Conference on Geospatial Information in Agriculture and Forestry. Lake Buena Vista, Florida, USA. 1:424-428.
- Moran, M. S., T. R. Clarke, Y. Inoue, and A. Vidal. 1994. Estimating crop water deficit using the relation between surface-air temperature and spectral vegetation index. *Remote Sens. Environ.* 49(3): 246-263.
- Muller, E, and H. Décamps. 2001. Modeling soil moisture-reflectance. *Remote Sens. Environ.* 76(2): 173-180.
- Vachaud, G., A. De Silans Passerat, P. Balabanis, and M. Vauclin. 1985. Temporal stability of spatially measured soil water probability density function. *Soil Sci. Soc. Am. J.* 49: 822-827.
- Williams, D. J., A. W. Western, R. B. Grayson. 2005. A terrain and data-based method for generating the spatial distribution of soil moisture. *Adv. Wat. Resources.* 28: 43-54.