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14. ABSTRACT
The Institute for Technology Development (ITD) has developed an airborne hyperspectral sensor system that collects electromagnetic reflectance data of the terrain. The system consists of sensors for three different sections of the electromagnetic spectrum; the Ultra-Violet (UV), Visible/Near Infrared (VNIR) and Short Wave Infrared (SWIR). Based upon previous research showing the value of measuring the long wavelengths of the electro-magnetic spectrum when attempting to detect soil moisture, a study was conducted to further refine applications of hyperspectral data for estimating soil moisture. The Short Wave Infrared (SWIR) sensor was used to gather data over an area in which soil moisture probes were located. We evaluated in situ soil moisture values and compared them to transformation results in order to correlate the transformations with field collected values of soil moisture at specific sampling stations. An airborne hyperspectral instrument with a SWIR sensor was flown twice over the Little River Experimental Watershed in Georgia, 2005 and 2007, to relate remotely sensed soil moisture to in situ measurements of soil moisture. A highly significant (R2 value of above 0.7 for both sampling dates) correlation to a soil moisture probe at 5 cm was computed. Models for the 20 cm and 30 cm depths were not able to estimate soil moisture to the same degree.

15. SUBJECT TERMS
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Abstract: Landscape assessment of soil moisture is critical to understanding the hydrological cycle at the regional scale and in broad-scale studies of biophysical processes affected by global climate changes in temperature and precipitation. Traditional efforts to measure soil moisture have been principally restricted to *in situ* measurements, so remote sensing techniques are often employed. Hyperspectral sensors with finer spatial resolution and narrow band widths may offer an alternative to traditional multispectral analysis of soil moisture, particularly in landscapes with high spatial heterogeneity. This preliminary research evaluates the ability of remotely sensed hyperspectral data to quantify soil moisture for the Little River Experimental Watershed (LREW), Georgia. An airborne hyperspectral instrument with a short-wavelength infrared (SWIR) sensor was flown in 2005 and 2007 and the results were correlated to *in situ* soil moisture values. A significant statistical correlation (R^2 value above 0.7 for both sampling dates) for the hyperspectral instrument data and the soil moisture probe data at 5.08 cm (2 inches) was determined. While models for the 20.32 cm (8 inches) and 30.48 cm (12 inches) depths were tested, they were not able to estimate soil moisture to the same degree.

INTRODUCTION

Soil moisture is a critical process in the water cycle and its assessment is of paramount importance in forecasting changes in the water balance of a region (Salvucci et al., 2002). In agricultural production, the spatial variability of soil moisture can be responsible for low or spatially variable crop yields, as soil moisture is required to make nutrients soluble for plant absorption.

Soil moisture fluctuates both spatially and temporally due to factors such as soil type, soil horizon, and other site-specific geologic and climatic conditions. Traditional efforts to measure soil moisture have been principally restricted to *in situ* measurements

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(Engman, 1999) and predominately reliant on direct field instrumentation and point data (Steele-Dunne et al., 2010), which can be costly when used to obtain spatially distributed data over a large region or landscape (Jensen and Hodgson, 2004). As an alternative to ground point data, remote sensing data are seen as a promising approach to evaluate soil moisture characteristics in different landscapes and sampling areas by providing in a regional description of the water redistribution at different temporal and spatial resolutions (McCabe and Wood, 2006).

The advantage of remote digital imaging is that relatively frequent measurements can be made. By subtracting spatially referenced data, time-displacement associations (i.e., time series) can be produced. Beginning in the 1920s, aerial photographs were used to delineate and map boundaries of different soil series by identifying dissimilarities in photographs (Helms et al., 2002). By focusing primarily on using vegetation as a proxy for soil water holding capacity, mapped soils, derived from those image demarcations, can aid managers and farmers in identifying homogenous zones within agricultural fields for guiding nutrient application rates using variable rate technology (VRT) (Baumgardner et al., 1985; Walthall et al., 2001; Gish et al., 2002; Daughtry et al., 2002).

More recently, soil scientists have used multispectral images for mapping land cover attributes and related moisture conditions. The wetness in the top few centimeters of soil can be measured remotely using multispectral remote sensing or certain radar bands (Njoku and Entekhabi, 1996). Transformations of the spectral reflectance in remotely sensed images can provide useful information on soil water content and, if augmented with existing soil and other geospatial information, can provide spatially representative estimates of soil moisture. Most studies using remotely sensed data to look for relationships with soil properties have focused on the 0.3 to 2.8 micrometer region of the electromagnetic spectrum (Bushnell, 1932; Barnes et al., 2003).

Despite numerous studies, a universal spectral range and sampling scheme has yet to be determined for best detecting soil moisture. Visible near-infrared (VNIR) (0.4–1.4 μm), near-infrared (NIR) (0.75–1.4 μm), short-wavelength infrared (SWIR) (1.4–3.0 μm), thermal infrared (3.5–20 μm), and microwave (0.3–300 cm) have each shown some promise. In general, the literature suggests that the longer the wavelength the better the potential ability to predict soil moisture. NIR appears to be a suitable option for bare-soil fields after a rainfall (Milfred and Kiefer, 1976) if the particle size and soil type are the same as the calibration set (Slaughter et al., 2001). NIR, when used in conjunction with visible bands, holds promise to categorize soil samples by moisture content, especially when soil variability is low (Mouazen et al., 2006). As a better alternative, SWIR has been shown to be more effective than VNIR at monitoring soil moisture changes (important to predicting soil moisture), as long as the soil moisture values remain at less than or equal to 50% of volumetric water content (Lobell and Asner, 2002), especially the creation of Gaussian models for soils from the Mediterranean region (Whiting et al., 2004). Measurements from the thermal infrared portion of the electromagnetic spectrum have also been conducted. Thermal infrared emissivity increases as soil moisture content decreases at low water content levels (Mira et al., 2010) and thermal infrared images with high spatial resolution can be used to map soil moisture at a fine scale (Katra et al., 2006).

Microwave bands also have the capacity to measure soil moisture (Moran et al., 1998; Barnes et al., 2003) over a selection of topographic and vegetation cover settings (Jackson et al., 1997). On relatively unvegetated soil it is possible to obtain reasonably accurate soil moisture estimates using active microwave X- (2.4–3.8 cm) and C-band (3.8–7.5 cm) radar imagery (Jensen et al., 2005). Because of the signal ability to penetrate the earth, microwave technology allows scientists to gather data on the properties of the zone from the soil surface to the groundwater table (Crow et al., 2005). Extending this technology to routine measurements from a satellite system would supply notable spatial and temporal characteristics to hydrologic measurements (Engman, 1999). Additional microwave remote sensing investigations specific to our study area are expanded upon in the next section of this paper.

As an alternative to broad-band multispectral remote sensing sensors, which collect spectral information across relatively wide ranges of the electromagnetic spectrum, hyperspectral sensors collect remote sensing data as images, with each image representing a different spectral band with higher spectral resolution than broad-band sensors. When stacked together, the two-dimensional spatial (image) data sets create hyperspectral data cubes, with two dimensions containing spatial information and the third dimension containing spectral information (Warren et al., 1997; Vogt et al., 2004).

The possibilities of using hyperspectral data to obtain soil water content are still uncertain, but appear promising. For example, Grandjean et al., (2010) identified airborne hyperspectral sensing as one of the anticipated geophysical sensor technologies that will aid the dilemma of performing soil data collections at the catchment scale. The use of airborne hyperspectral sensing will bridge a technological gap for the purpose of developing steadfast and cost-effective geophysical mapping solutions, especially for data collection in digital soil property mapping (soil texture, soil water content, soil hydraulic properties, bulk density, and soil organic matter). While airplane-mounted sensors have distinct advantages over satellite-based systems, the approach has yet to be thoroughly tested. The ability to have data with finer spatial resolution and more control over temporal resolution from aircraft mounted sensors is an advantage over satellite-based data. The larger ground area covered in less time is a benefit over *in situ* measurements.

OBJECTIVES

The purpose of this research was to test the statistical correlation between spectral bands of an airborne hyperspectral sensor and soil moisture ground readings at three different depths. The research explored whether the reflectance values available in hyperspectral remote sensing datasets can be used in the monitoring of soil water content. This study contributes to an ongoing effort to obtain spatially accurate soil moisture data using remote sensors that can be used in hydrological and climatic research on such issues as drought prevention/risk, analyzing ground-atmosphere feedback, and crop irrigation techniques among others.

STUDY AREA

The Southeast Watershed Research Laboratory (SEWRL) of the U.S. Department of Agriculture has 30 instrumented stations continuously collecting soil water content for the Little River Experimental Watershed (LREW), a small watershed in south

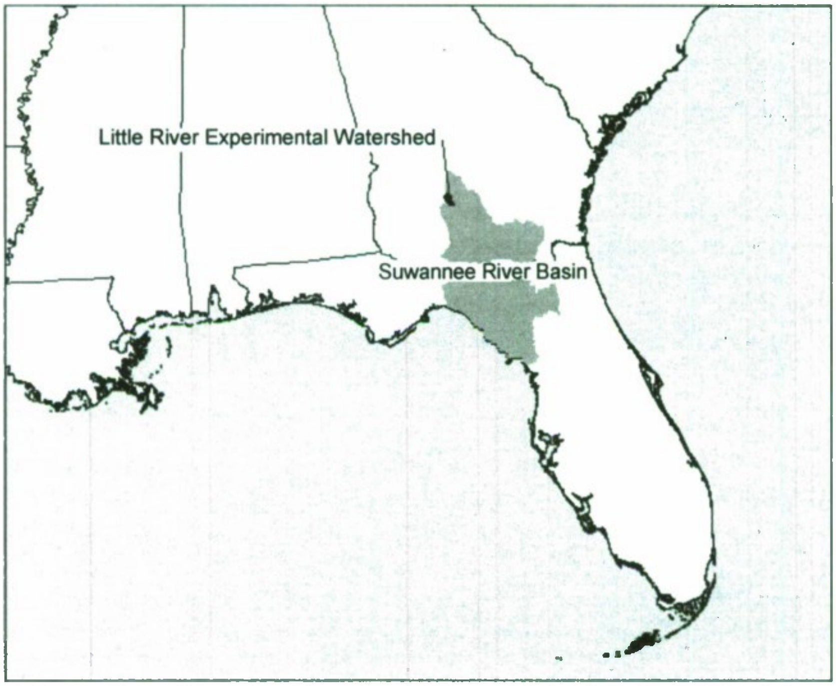

Fig. 1. Little River Experimental Watershed (LREW) and the Suwannee River Basin of southern Georgia and northern Florida.

Georgia (Bosch et al., 2007). The LREW is a sub-basin of the Suwannee River Basin of southern Georgia and northern Florida (Fig. 1). The study area has a mild climate with warm, humid summers and mild winters, and stream flow responses that are dominated by annual and seasonal precipitation trends (NOAA, 2002; Priest, 2004; Bosch, 2006b).

Prior studies conducted on sample plots in this area show high soil moisture variability between plots (Giraldo et al., 2008). However, within plots there is high homogeneity and temporal stability when using soil moisture readings. In addition, soil moisture measurements vary with different land use/land cover types (Giraldo et al., 2008, 2009).

PREVIOUS MICROWAVE INVESTIGATIONS CONCERNING SOIL MOISTURE IN THE LITTLE RIVER EXPERIMENTAL WATERSHED (LREW)

As previously stated, Jensen et al. (2005) and Crow et al. (2005) have shown that soil moisture estimates using microwave remote sensing techniques are possible, especially at the soil surface, but they can also be expanded to a few centimeters depth. Both active and passive sensors supply information on surface reflectivity that in turn is related to soil moisture through the Fresnel reflection equations (Ulaby et al., 1986; Jackson, 2003). Fresnel reflection equations allow microwave sensor measurements to be equated to soil moisture, based on relationships between reflected and transmitted electromagnetic waves.

Data were collected on the LREW using the National Oceanic and Atmospheric Administration (NOAA) Polarimetric Scanning Radiometer (PSR/CX) sensor during Soil Moisture Experiment 2003 SMEX03 (Jackson et al., 2005; Bosch et al., 2006a). The experiment was conducted over the LREW, Georgia, and sites in Oklahoma and Alabama. SMEX03 was the second in a chain of field campaigns conducted to validate brightness temperature data and soil moisture retrieval algorithms for the Advanced Microwave Scanning Radiometer for the Earth Observing System (AMSR-E) on the Aqua satellite. AMSR-E is a passive microwave radiometer sensing microwave radiation on 12 channels at six frequencies ranging from 6.9 to 89 GHz (0.3 to 4.3 cm). During SMEX03, researchers collected aircraft data with the PSR/CX sensor (X-Band, 2.5–3.7 cm wavelength with approximately 3 km spatial resolution), satellite AMSR-E X-Band (0.3–4.3 cm) data (40–75 km spatial resolution), and *in situ* measured soil moisture at 19 long-term sites and 49 supplemental sites (Jackson et al., 2005; Bosch et al., 2006a).

Jackson et al. (2005) found that both the PSR/CX and AMSR-E X-band channels were well calibrated and that X-band comparisons of the PSR/CX high-resolution data with the low-resolution data from AMSR-E indicated a linear scaling for the range of conditions studied in SMEX03. This work was followed by another analysis of AMSR-E in the LREW, where LREW and three other soil moisture networks were used (Jackson et al., 2010). They compared National Aeronautics and Space Administration (NASA) and Japan Aerospace Exploration Agency (JAXA) soil moisture products to the network observations, along with two alternative soil moisture products developed using the single-channel algorithm (SCA) and the land parameter retrieval model (LPRM). They found that the statistical results indicated that each algorithm performed differently at each site. Furthermore, the JAXA algorithm performed better than the NASA algorithm under light-vegetation conditions, whereas the NASA algorithm was more reliable for moderate vegetation. The SCA had the lowest overall root mean square error with a small bias, while the LPRM had a very large overestimation bias and retrieval errors.

Sahoo et al. (2008) estimated the soil moisture from AMSR-E using the 10.7 GHz (2.8 cm) frequency channel and compared it to the Land Surface Microwave Emission Model (LSMEM). In turn, they compared the two methods to *in situ* measured soil moisture datasets over the LREW and found that the LSMEM method performed better than the current operational AMSR-E retrieval algorithm.

DATA

A network of soil water measurement monitors has been established in the Suwannee River Basin to complement SEWRL's 30-year record of climatic, hydrologic, and water quality research (Fig. 2). Data are recorded from SEWRL's soil moisture sensors every half hour at three different depths: 5.08 cm (2 inches), 20.32 cm (8 inches), and 30.48 cm (12 inches) below the surface. These data are packaged into files and processed for each site (Bosch et al., 2007). Recorded information includes date and time of reading, soil temperature, soil water content, soil salinity, and precipitation data. A subset of these soil-moisture network stations was used for this study, and the

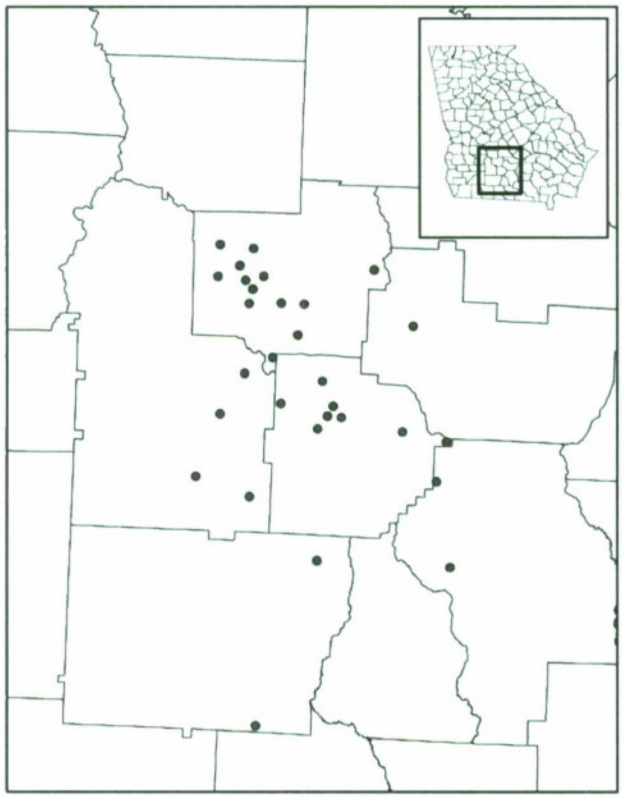

Fig. 2. Locations of soil moisture sensors in the LREW.

number of stations used was chosen to optimize hyperspectral data collection. Flights across the LREW were conducted on November 30, 2005 and March 6, 2007. For the November 30, 2005 flight, 18 soil moisture probes were chosen, and for the March 6, 2007 flight, 29 soil moisture probes were chosen.[8] Flight lines were drawn over the selected soil moisture meters for each flight using United States Geological Survey (USGS) Digital Ortho Quads (DOQ).

The aircraft-mounted SWIR HyperSpectral Imaging (HSI) sensor, developed by the Institute for Technology Development (ITD) of the Stennis Space Center, was used to collect electromagnetic reflectance data over the soil moisture probe stations. The system consists of sensors for three different sections of the electromagnetic spectrum: ultraviolet (UV), VNIR, and SWIR. The sensor was mounted aboard a Cessna, which flew at a nominal 6,000 feet above the ground, resulting in a ground spatial resolution of the image data at just over 6 meters. The extent of the image in the along-track direction was dictated by the distance the aircraft flew while the sensor was recording data. Flight lines were typically established by drawing multiple lines over a digital

[8]The first flight in 2005 was used to preliminarily test the feasibility of the project. Based on the results from the first flight, a more vigorous statistical design and analysis were conducted for the second flight in 2007.

map of the target area. The lines were oriented so that all the targets could be covered within the sensor's field of view using the minimum number of flight lines. The latitude/ longitude of the start and stop points for each line were recorded. The start/stop and latitude/ longitude pairings were then uploaded into the GPS in the aircraft.

The ITD SWIR HSI sensor allows light to pass through a lens and enter into a spectrograph through a slit. The spectrograph in the sensor breaks light passing through the slit into wavelengths that are in the SWIR range. The resulting light illuminates a charge-coupled device (CCD) array and is dispersed with the shorter wavelengths illuminating the top of the CCD array, and then gradually moving through the spectrum with the longer wavelengths illuminating the bottom of the CCD array.

The CCD array has 240 lines and 320 columns. The number of lines determines the maximum number of spectral bands that can be collected and the number of columns dictates the maximum number of cells of spatial information per line. With this SWIR CCD array, 240 lines of spectral band information could be obtained; however, for this research project, the number of photons that are collected in one 1×1 cell of the CCD array may not result in enough energy to excite the sensing element. To accommodate for this possibility, the sensor has the capability to aggregate several cells together. By increasing the number of cells that are aggregated together during data collection, a larger area can be created so that the accumulation of photons received by the combination of cells can increase the sensitivity for each recording element, thus improving the quality of the data.

Binning was used to aggregate cells to create a larger sensing element that records the number of detected photons for measurement. The two advantages to binning are: (1) it increases the signal to noise ratio for the data; and (2) binning the spatial dimension increases the spatial resolution. Increasing the binning in the spectral dimension decreases the number of bands that is collected. For a sensor that collects a maximum of 240 spectral bands, a binning of the data by two causes the number of bands that is collected to be decreased by a factor of two, leaving 120 bands of data. Likewise, binning the data by four causes the data to be decreased by a factor of four, leaving 60 bands of data.

For the first flight on November 30, 2005, each of the 240 spectral sensing lines (elements) was binned with their neighbors to enhance the signal measurement. This resulted in every pair of the spectral sensing elements being binned together for data measurement and subsequently 120 bands of SWIR data were collected for each flight line in the image data. By binning spectrally instead of spatially, measurements of the spectral absorption troughs and reflection peaks were made while maintaining visual identification of the targets on the ground. High and low bands outside the spectral response of the spectrograph were omitted from the analysis. The resulting data set contained 85 bands of information with spectral response in the range of 937 to 1700 nanometers in wavelength.

For the second flight on March 6, 2007, four adjacent spectral sensing elements were binned together to further increase the signal measurement. This resulted in recording 60, or half, of the first flight's number of spectral bands. All 60 bands of SWIR data were collected for each flight line in the image data. Again, the high and low bands outside the spectral response of the spectrograph were omitted from the analysis. Therefore, the data set that was used for analysis contained 43 bands of reflectance data with a wavelength range of 910 to 1686 nanometers.

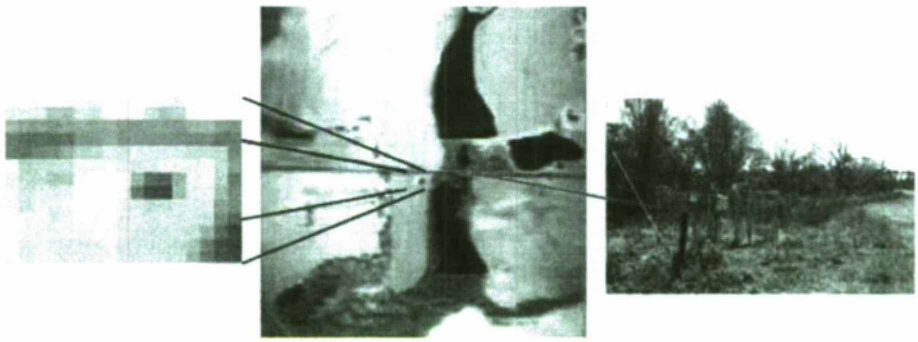

Fig. 3. Calibration tarps and soil moisture meter 66 in the HSI image.

The data for the second flight were corrected for atmospheric effects and system noise. Atmospheric correction is used to adjust for the absorption characteristics of the atmosphere and to convert the data to percent reflectance (Price, 1987; Chavez and Mackinnon, 1994). It uses a regression line with one graph point representing the raw digital number for the dark point on the x-axis and the corresponding percent reflectance of the radiometer data on the y-axis, while the other graph point represents the raw digital number for a bright point on the x-axis and the corresponding percent reflectance of the radiometer data on the y-axis. These regression equations were used to transform all the raw image data to percent reflectance. An Analytical Spectral Devices (ASD) SWIR radiometer was used to capture radiometric data for comparison with the hyperspectral data.

SWIR spectra were extracted from the radiometer data in percent reflectance units of measure and paired with SWIR spectra extracted from the noise-reduced image data to generate a regression equation for calibration. The linear regression equation from these pairings was used to transform all the image frames to percent reflectance. The resulting data sets contained bands with a spectral response between 910 to 1700 nanometers in wavelength.

The Saviszky Golay noise removal method (Press et al., 1997, p. 994) was performed to extract noise that is inherent in the system. This method uses moments of the data values across the spectra to maintain the signal while minimizing fluctuations caused by noise in the data, transforming the raw data to a new data set where the noise is minimized. Calibration tarps were placed on the ground along the flight line (Fig. 3). The total size of the joined sections of tarp was 36.58 m (120 feet) across track by 9.14 m (30 feet) along track. Each section covered a 4.57 m (15 feet) × 4.57 m (15 feet) area (thus, a total of 16 sections). The tarps have eight reflectance sections and are manufactured to have gradually greater reflectivity from one section to the next (across track). They were factory measured to have 2%, 4%, 8%, 16%, 32%, 48%, 64%, and 88% reflectance. However, in practice the tarp reflectances deviate slightly from these manufactured settings. In order to ensure a true measurement of reflectance across each of the tarp sections, radiometer readings were taken on the ground during the time of airborne data acquisition (Lewis and Finn, 2007).

For both flights, regions of interest (ROI) corresponding with the location of the soil moisture probes were used to extract the spectral information from the SWIR data

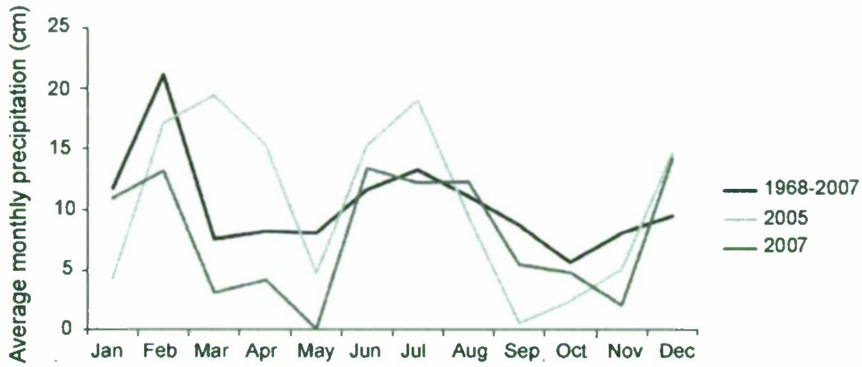

Fig. 4. Average monthly precipitation for LREW from 1968 to 2007, with 2005 and 2007 highlighted (data from LREW database).

set for each of the soil moisture probe locations. Each ROI covers a 3 ×3 pixel mask around the soil moisture probe and the ground spatial resolution of the image data is just over 6 meters. Thus the ROI for each soil moisture probe is approximately 18 by 18 m. The 3 × 3 window of pixels within each ROI were then averaged to create one spectral value for each of the soil moisture probes. For the soil moisture probe data, the corresponding time of the HSI sensor data collection flight was used to obtain soil moisture values for the correlative soil moisture probes used. These sensor data for the 5.08 cm (2 inches), 20.32 cm (8 inches), and 30.48 cm (12 inches) probes were used for correlation to the SWIR spectral information.

ANALYSIS AND RESULTS

Figure 4 compares the average monthly precipitation for this area with the monthly precipitation for the years of data acquisition, 2005 and 2007. During the months of data acquisition, soil moisture conditions were relatively dry for November 2005 and wet for March 2007 (Fig. 5). Figure 6 shows an example of the data set collected over the University of Georgia Tifton Campus in Tifton, Georgia.

In order to evaluate the utility of the SWIR as a viable tool for soil moisture data collection, the hyperspectral data sets for the two dates were used to establish a General Linear Model (GLM) for each of the three different probe types. In addition, an R^2 analysis was used to determine the strength of the linear relationship between the probe and SWIR spectral band data. Recall from the data section that for the 2005 flight each of the 240 spectral sensing lines were binned with their neighbors to enhance the signal measurement. For the 2007 flight four adjacent spectral sensing elements were binned together to further increase the signal measurement.

November 30, 2005

Data from 18 of the soil moisture probes were examined for the November 30, 2005 flight. Many of the soil moisture probes were located in generally bare or unobstructed soil, but some were nestled in significant ground cover, which made it difficult to draw ROIs with confidence. While none of the soil moisture probes may have

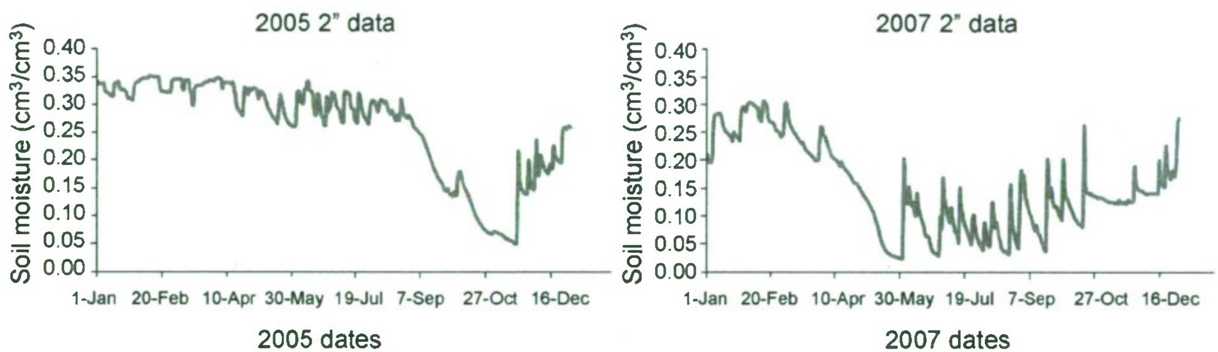

Fig. 5. Soil moisture conditions for the two years of data collection using data from rain gauge 08 (data from LREW database).

Fig. 6. SWIR data over the University of Georgia's Tifton Campus (31°28′37″ N, 83°31′54″ W) located within the watershed, and which served as one of the data collection areas (red, green, and blue components are the 1222, 1106, and 1563 nanometer wavelengths, respectively).

been in 100% bare soil and completely unobstructed from other ground artifacts, six soil moisture probes seemed to reside in significant ground cover or were close to other artifacts such as roadways or hay bales within 20 meters of a soil moisture station. Ultimately, these six entries of the soil moisture probe/spectral data pairings were removed from the analysis and the remaining 12 pairings of data used for the 2005 analysis.

Correlations determined for the 12 pairings of spectra per band and the 2-inch soil moisture data are shown in Figure 7. Both absolute maxima and minima, and local maxima and minima, can provide influencing locations across the spectra for classification algorithms. The locations where the absolute and/or local maxima and minima of the correlations provided points for classification algorithms were at bands 15, 55, and 81, which correspond with wavelengths of 1062, 1422 and 1664 nanometers (Table 1).

A new GLM was generated to model the 5.08 cm (2 inches), 20.32 cm (8 inches), and 30.48 cm (12 inches) soil moisture data with bands 15 (1062 nm), 55 (1422 nm), and 81 (1664 nm). On the 2-inch model, band 15 did not exhibit a significance value below 0.05. Thus, the model was executed again using only bands 55 and 81. The results, shown in Table 2, show the 2-inch and 12-inch models to be significant at the $\alpha = 0.05$ level. Although close, the-8 inch model is not significant at the 0.05 level. The 2-inch model explained 79% of the variance in surface soil water content, whereas the 8-inch and 12-inch models were less significant.

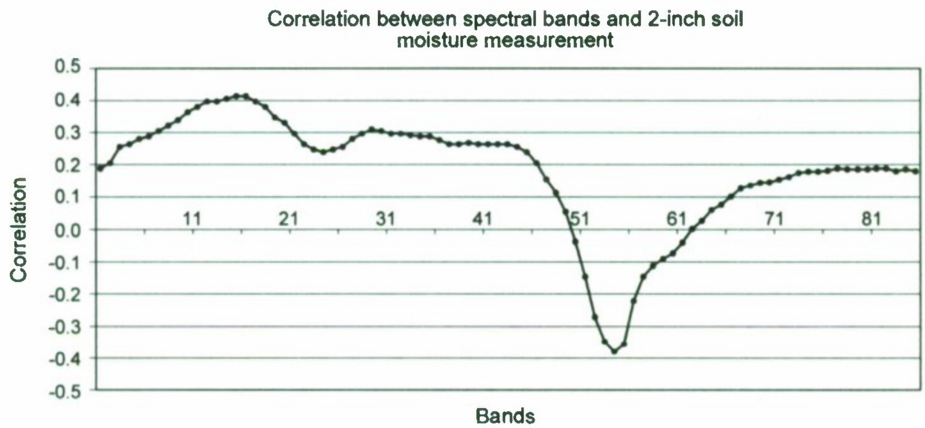

Fig. 7. Correlations between spectrum and 2-inch soil moisture from November 30, 2005 flight.

Table 1. Wavelength for Significant Spectral Bands for Soil Moisture for November 30, 2005 Flight

Spectral band	Wavelength, nm
15	1062
55	1422
81	1664

Table 2. Model Coefficients and Statistical Significance for Raw Data for November 30, 2005 Flight

Model	R^2	$Pr > F$
inch-2 = .7728 + (–.0399 * b55) + (.0107 * b81)	0.786	0.001
inch-8 = .3895 + (.0193 * b55) + (.0055 * b81)	0.485	0.050
inch-12 = .7549 + (–.0468 * b55) + (.0148 * b81)	0.560	0.026

March 6, 2007

Data from 29 soil moisture sites and spectra pairings from the non-atmospherically corrected data set were used in the GLM analysis for the 2007 data. The 2-inch soil moisture data were correlated with the spectra pairings (Fig. 8).

Nine bands (Bands 29, 30, 32, 33, 34, 36, 38, 39, and 43 [Table 3]) were then used to generate a GLM to model for the 5.08 cm (2 inches), 20.32 cm (8 inches), and 30.48 cm (12 inches) soil moisture data. The 2-inch and 8-inch models are significant at the $\alpha = 0.01$ level with R^2 values above 0.70 (Table 4). The 12-inch model is significant at the 0.05 level with an R^2 of 0.62.

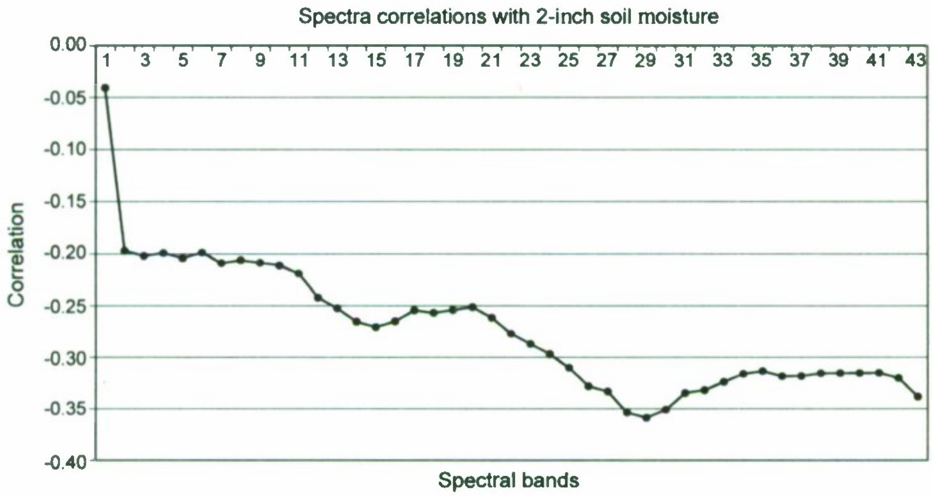

Fig. 8. Correlations between spectrum and 2-inch soil moisture from March 6, 2007 flight.

Table 3. Wavelength for Significant Spectral Bands for Soil Moisture for March 6, 2007 Flight

Spectral band	Wavelength, nm
29	1299
30	1317
32	1354
33	1372
34	1391
36	1428
38	1465
39	1483
43	1557

A GLM was also generated for the raw data/atmospheric calibrated data set. The significance and R^2 are the same (as in Table 4), with the model coefficients being different. These results are shown in Table 5.

CONCLUSIONS

The results of this research show the relationship between SWIR data and soil moisture and identify possible wavelengths for determining soil moisture for a given soil type and vegetation distribution. The results for the 2-inch model from both flights, shown in Tables 2 and 4, were significant and have a coefficient of determination (R^2) value above 0.70. The wavelengths that best model the soil moisture at the 2-inch

Table 4. Model Coefficients and Statistical Significance for Raw Data of the March 6, 2007 Flight

Model	R^2	$Pr > F$
inch-2 = 0.1919 + (0.007 * *b*29) + (–0.0084 * *b*30) + (0.0015 * *b*32) + (0.0024 * *b*33) + (–0.0023 * *b*34) + (0.0008 * *b*36) + (–0.0007 * *b*38) + (0.0007 * *b*39) + (–0.0008 * *b*43)	0.707	0.0022
inch-8 = 0.3102 + (0.0063 * *b*29) + (–0.0097 * *b*30) + (0.004 * *b*32) + (0.0027 * *b*33) + (–0.0034 * *b*34) + (0.0008 * *b*36) + (–0.0006 * *b*38) + (0.0011 * *b*39) + (–0.0018 * *b*43)	0.751	0.006
inch-12 = 0.324 + (0.0035 * *b*29) + (–0.004 * *b*30) + (–0.0011 * *b*32) + (0.0035 * *b*33) + (–0.0027 * *b*34) + (0.0013 * *b*36) + (–0.0008 * *b*38) + (–0.0007 * *b*39) + (–0.0015 * *b*43)	0.623	0.015

Table 5. Model Coefficients and Statistical Significance for Raw Data/Atmospheric Calibrated Data Set

Model	R^2	$Pr > F$
inch-2 = 0.1867 + (2.5693 * *b*29) + (–4.2692 * *b*30) + (1.344 * *b*32) + (4.001 * *b*33) + (–4.6004 * *b*34) + (1.6065 * *b*36) + (–1.4813 * *b*38) + (1.2715 * *b*39) + (–0.7973 * *b*43)	0.707	0.0022
inch-8 = 0.3024 + (2.2851 * *b*29) + (–4.9023 * *b*30) + (3.6488 * *b*32) + (4.5346 * *b*33) + (–6.8813 * *b*34) + (1.6930 * *b*36) + (–1.1350 * *b*38) + (2.0093 * *b*39) + –1.7591 * *b*43)	0.751	0.006
inch-12 = 0.3193 + (1.2527 * *b*29) + (–2.0254 * *b*30) + (–0.9960 * *b*32) + (5.7496 * *b*33) + (–5.5158 * *b*34) + (2.8533 * *b*36) + (–1.6404 * *b*38) + (1.2887 * *b*39) + (–1.3868 * *b*43)	0.623	0.015

depth are in the 1300 to 1670 range (Tables 1 and 3). Of interest for future work is the ability of particular bands to continuously predict soil moisture over time and different areas, including the strength and direction of correlation.

The data analysis illustrates that the ability for remotely sensed SWIR data to estimate soil moisture deteriorates at the 8-inch and 12-inch depths. Although the 8-inch depth model had an R^2 value of 0.75 and the 12-inch depth model had a slightly lower R^2 value of 0.62 for the models created from the second flight, the first flight's models were not as strong (R^2 of 0.49 and 0.56, respectively). It is not precisely known if the difference in R^2 values between the two flights is due solely to differences in soil moisture. Although we suspect that is the primary cause, other environmental factors differed between the two flight dates, including atmospheric conditions and vegetation cover.

Ground cover can inhibit the ability for remotely sensed data to model soil moisture (e.g., Bosch et al., 2006a). Light or the electromagnetic wave needs to have an unobstructed interaction with the soil and then a clear path to the sensor for the SWIR sensor to provide relevant data for measuring soil moisture at the 2-inch depth. Logistical issues for future work would include reducing the spatial resolution of the spectral data to minimize interaction with artifacts such as roadways and buildings. In addition, researchers could look more closely at the relationship between reflectance and soil moisture where there is ground cover and ascertain the Normalized Difference Vegetation Index (NDVI) in those areas. This could establish a minimum NDVI for ground cover that would allow for estimation of soil moisture. Alternatively, they could establish the vegetative (spectral) response of the ground cover to use as a proxy for soil moisture.

The benefits of hyperspectral data are twofold. First, the spatial resolution (ca. 6 m for this study) is much finer than the datasets used in previous LREW studies by Jackson et al. (2005) and Bosch et al. (2006a) (ca. 3 km for the PSR/CX X-band and 40–75 km for the AMSR-E X-band). In addition, it is worthwhile to note that this higher spatial resolution (by an order of magnitude) is particularly important for investigations of watersheds, where accurate spatial representation can impact water resource decisions. Furthermore, although hyperspectral flights are weather dependent, as they are mounted on aircraft and not satellites, researchers have some control over the temporal resolution. Therefore, the inherent characteristics of the hyperspectral data directly relate to its strengths in determining soil moisture.

Even though the use of microwave sensors does warrant further research, the goal of this study was to investigate the potential utility of hyperspectral data with SWIR sensors to determine soil moisture. Our results indicate that, at least for a 2-inch depth, hyperspectral sensors can be used to identify soil moisture, most notably in the SWIR range. For situations where satellite-mounted microwave sensors are not an optimal choice, especially in regard to spatial or temporal constraints, aircraft-mounted hyperspectral sensors can be a valid and useful alternative. Although the sensor used in this study was limited to UV, VNIR, and SWIR, additional future studies using hyperspectral sensors with microwave and thermal capabilities are of interest, as this study has shown the potential of hyperspectral data for soil moisture evaluation.

Aside from the microwave data sources mentioned above (PSR/CX and AMSR-E), the Moderate Resolution Imaging Spectroradiometer (MODIS) can be used to derive the temperature/vegetation dryness index (TVDI), which can be used to make inferences about soil moisture. The spatial resolution of MODIS is finer than PSR/CX and AMSR-E (between 250 and 1000 m), but it is still coarser than the hyperspectral data used in this study. In addition, the temporal resolution differences (satellite versus aircraft) may also be a determining factor in sensor choice. Although an area of potential future research would be to evaluate the potential of MODIS to determine soil moisture in the LREW, it is beyond the scope of this study.

The research described herein provides evidence for the utility of developing SWIR remote sensing analysis to assess soil moisture, particularly for soil moisture measurements at the depth of two inches. The ability to use remote sensing techniques to obtain soil moisture information over a large area could decrease reliance on *in situ* point measurements, as well as quickly provide data to researchers and agriculturalists. Further studies to test the relationships established in this study and to test their applicability to other geographic areas could provide new insights in soil moisture research.

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