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Fusion of remotely sensed data from airborne and ground-based sensors to enhance detection of cotton plants

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ABSTRACT

The study investigated the use of aerial multispectral imagery and ground-based hyperspectral data for the discrimination of different crop types and timely detection of cotton plants over large areas. Airborne multispectral imagery and ground-based spectral reflectance data were acquired at the same time over three large agricultural fields in Burleson Co., Texas during the 2010 growing season. The discrimination accuracy of aerial- and ground-based data was examined individually; then a multi-sensor data fusion technique was applied on both datasets in order to improve the accuracy of discrimination. The individual classification accuracy of data taken with the aerial- and ground-based sensors were 90% and 93.3%, respectively. In comparison, the accuracy of discriminating crop types with fused data was 100% in the calibration and only 3.33% misclassification in the cross-validation. These results suggest that data fusion techniques could greatly enhance our ability to detect cotton from other plants.

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1. Introduction

During the past decade, hyperspectral and multispectral sensors have shown considerable promise as tools for efficiently monitoring plants in localized areas of fields. Spectral reflectance properties based on the absorption of light at specific wavelengths are associated with specific plant characteristics. For healthy crops, spectral reflectance in the visible wavelengths (400–700 nm) is low because of the high absorption of light energy by chlorophyll. In contrast, reflectance in the near infrared (NIR) wavelengths (700–1300 nm) is high because of the multiple scattering of light by different leaf tissues (Taiz and Zeiger, 2006). Reflectance in the green region is also higher than that in the blue and red regions of the spectrum. Stress or damage to crops can cause a decrease in chlorophyll content and change internal leaf structure (Curran, 1989). As a result, the reflectance in the visible region will decrease. Several studies have used hyperspectral measurements in support of crop management, such as crop type identification, plant nutrition deficiency assessment, crop stress or damage, yield estimation and growth status evaluation (Thenkabail, 2002; Zhao et al., 2005a,b; Plant et al., 2000; Muhammed, 2005; and Koger et al., 2003). Thenkabail et al. (2000) used narrow-band spectral data between 350 and 1050 nm to determine appropriate bands for characterizing biophysical variables of various crops, including corn, soybean and cotton. Gray et al. (2009) analyzed hyperspectral reflectance data with a variety of methods for differentiating soybean, soil, and six weed species commonly found in Mississippi agricultural fields.

Remote sensors have been fitted for different platforms, including ground-based, airborne, and spaceborne platforms, for various applications. In particular, airborne remote sensing technologies have made tremendous improvements recently and are now being used in precision agricultural applications (Lan et al., 2007a,b; Huang et al., 2008; Huang et al., 2010; Lan et al., 2009). Airborne multispectral techniques are much less expensive and less data-intensive than hyperspectral imaging systems and can rapidly provide continuous remotely-sensed data over a large field or region. Yang et al. (2006) examined airborne color-infrared digital imagery for assessing the effectiveness of different herbicide treatments for cotton regrowth control. Goel et al. (2003) used airborne hyperspectral data to estimate crop biophysical parameters within corn plots which were treated with different rate combinations of herbicide and nitrogen fertilizer. The incorporation of spectral reflectance data from additional wavelength regions resulted in a better regression model. As a result, more than 90% of the variation could be explained for many crop biophysical variables. Although hyperspectral imagery can provide hundreds of wavebands, it is expensive and requires significant efforts to properly process an

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image. Consequently, the use of hyperspectral imagery as a management-decision aide may not be a viable tool for all farmers. Furthermore, both satellite and aerial imagery can be compromised by cloud cover. In contrast, ground-based hand-held remote sensing instruments are not strongly influenced by environmental conditions but measurements are labor-intensive and time-consuming.

Considering the advantages of both airborne multispectral imagery and ground-based remote sensing data, multi-sensor data fusion techniques have recently been developed to combine data from multiple sensors or sources. This technique is used to provide inference that may not be possible or may not be good from a single sensor or source (Hall and Llinas, 1997; Hall and McMullen, 2004). However, few studies have incorporated multi-sensor data fusion for assessment of crop conditions. Bravo et al. (2004) combined hyperspectral reflectance data between 450 nm and 900 nm and fluorescence imaging to detect and recognize foliar disease in wheat. Kaleita (2003) developed a methodology for mapping surface soil moisture content across an agricultural field from optical remote sensing data and limited ground sampling data. The objectives of this work were to discriminate crop types using ground-based hyperspectral data, airborne multispectral imagery, and fused data from the ground-based and airborne spectral measurements.

2. Materials and methods

2.1. Study area

Ground-based remotely-sensed data were collected from agricultural fields in Burleson Co., TX on multiple dates throughout the 2010 growing season. Conventional planting and management practices for the fields were used. A total of ten sampling locations were randomly marked within each field with color flags. Airborne multispectral imagery of the study area was also acquired at the same time on two sampling dates (June 17 and August 11). However, images taken in June were compromised by cloud cover. Thus, only the imagery taken in August was used for data fusion analysis. The imagery covered three fields: cotton (30º34′2.52″N, 96º28′41.77″W); corn (30º33′34.27″N, 96°27′51.7″W); and soybean (30°33′7.53″N, 96°27′14.27″W).

2.2. Data collection

2.2.1. Airborne multispectral image

The airborne imaging system described in Yang (2010) was used to capture aerial images in this study. The system consists of four high-resolution charge-coupled device (CCD) digital cameras and a ruggedized PC equipped with a frame grabber and image acquisition software. The cameras are sensitive in the 400–1000 nm spectral range and provide 2048×2048 active pixels with 12-bit data depth. The four cameras are equipped with blue (430–470 nm), green (530–570 nm), red (630–670 nm), and near-infrared (810–850 nm) band pass interference filters, respectively.

The multispectral images were acquired under clear sky condition and during solar noon time on August 11, 2010 when crops were in their late reproductive stage of development. Each four-band image was georeferenced to the Universal Transverse Mercator (UTM), World Geodetic Survey (WGS 84), Zone 14, coordinate system based on ground control points around the field located with a GPS unit. The pixel size of all images was resampled to 1 m, and the total root mean square error (RMSE) was less than 1 m. All the data processing and analyses were performed in the Environment for Visualizing Images (ENVI) software package (Version 4.5, ITT Visual Information Solution, www.ittvis.com). Since the objective of this study was to evaluate the relationship between imagery data and ground-based reflectance data, the raw digital numbers of the image were converted into reflectance values. For radiometric calibration of the imagery, two 8 m $\times$ 8 m tarpaulins with different reflectance characteristics were placed near the fields during image acquisition. The actual reflectance values from the tarpaulins were measured using the ASD FieldSpec® Handheld spectroradiometer (VNIR; 325–1075 nm, 512-channel, and 1.6-nm sampling interval; Analytical Spectral Devices, Inc., Boulder, CO). The original multispectral images were converted to reflectance images based on the digital values of pixels of the tarpaulins and the reflectance data from the spectroradiometer.

2.2.2. Ground-based data collection

Canopy surface reflectance spectra were measured using the spectroradiometer. The instrument optimization and white reference measurements were performed prior to taking measurements (Castro-Esau et al., 2006). Reflectance was calculated as the ratio between the reflected radiation from the canopy and the incident energy on the white reference panel ($BaSO_4$). The spectroradiometer was adjusted to 10 scans per dark current and the integration time was set at 217 ms. The coordinates of sampling locations were recorded with an eXplorist XL® GPS unit (Magellan, Santa Clara, CA) and were used to match aerial and ground pixel data. The spectroradiometer was held approximately 0.3 m above and with a nadir-looking view of the plant canopies. Ten readings were taken and averaged to one value to represent the mean reflectance spectrum of the sampling area. The white reference was taken at the first and sixth locations or whenever the light condition changed. To determine whether the hyperspectral sensor performed better than the airborne multispectral sensor for crop variation detection, the reflectance data from the spectroradiometer was simulated to broadband data according to the bandwidth of the multispectral imaging sensor. The discrete 1.6-nm narrow-band reflectance data measured by the spectroradiometer were averaged into four broad spectral bands (430–470 nm, 530–570 nm, 630–670 nm, and 810–850 nm) of the airborne multispectral imaging sensor to obtain the simulated broad-band reflectance data at ground level. Due to noise in the 325–399 nm region, only the reflectance values between 400 nm and 1075 nm were used.

2.3. Data association

A shape file (vector data storage format) was created using the spatial coordinates of ten ground sampling locations within each field. The regions of interest were visually selected for cotton, corn, and soybean and the subset images of the regions of interest were exported into ArcGIS 9.3.1 (ESRI, Redlands, CA, USA). The ground sampling points were overlaid on the image. The values of the four spectral bands for the image pixels were geo-collocated with ground sampling points and were extracted for further analysis.

2.4. Data analysis

2.4.1. Principal component analysis

Principal component analysis (PCA) is a multivariate technique used as a tool for reducing high dimensional data (512-channel spectroradiometer data in this study). The information content contained in original variables is projected onto a smaller number of principal components (PCs) which are linear combinations of those variables. The process of PCA returns scores which are the estimated values for each principal component and PCA loadings. The PCA score plot can present the clustering of the data and the PCA loading plot can be used to investigate the contribution of each variable. PCA was performed using PRINCOMP procedure in SAS (SAS Institute, Cary, NC) to create a new principal component for each wavelength variable in the original data. Two principal components, PC1 and PC2, explain about 95% of the variance of the original variables and were used for classification.

2.4.2. Data fusion

Discriminant analyses were applied on several datasets: (1) derived reflectance values from four bands of multispectral imagery; (2) simulated broad-band reflectance values from the Fieldspec spectroradiometer; (3) principal components derived from reflectance values taken with Fieldspec spectroradiometer at 1.6-nm sampling interval; (4) combined dataset 1 and 2; (5) principal components derived from dataset 4; and (6) principal components derived from the combination of dataset 1 and Fieldspec reflectance data at 1.6-nm bandwidth.

The DISCRIM procedure in SAS was applied on the aforementioned datasets for classification. The parameters being used to develop discriminant function were pooled covariance matrix and prior probability of the groups. The DISCRIM procedure divided the data into two subsets. One subset was used to develop a calibration model and the other to validate the model. "One data out" method was used for cross-validation in this procedure. The output matrix provided the misclassification rate of calibration and cross-validation.

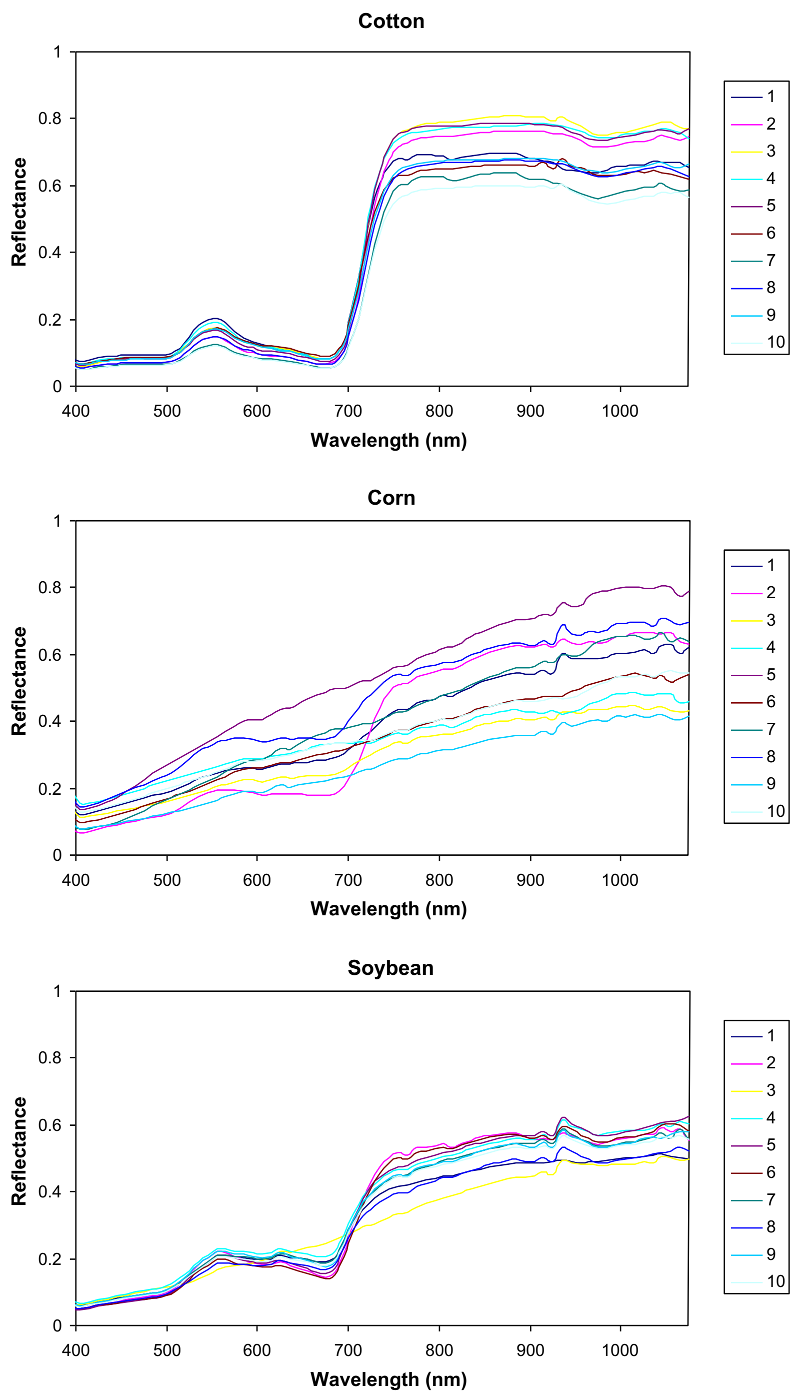

Fig. 1. Reflectance spectra of cotton, corn and soybean plants were measured with a Fieldspec spectroradiometer at 10 sampling locations.

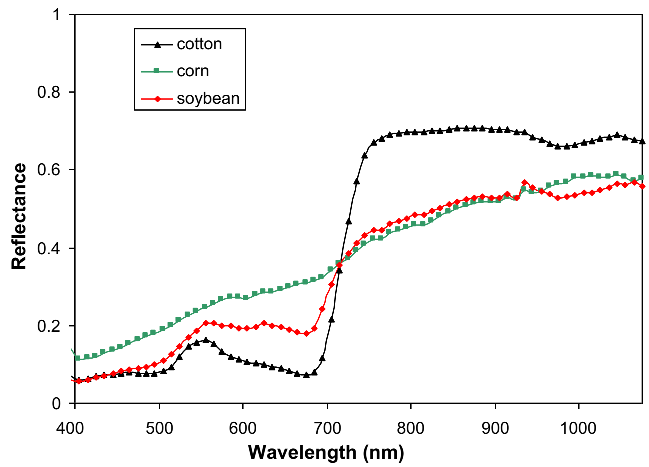

Fig. 2. The mean reflectance spectra of three crop types taken with a fieldspec spectroradiometer.

3. Results and discussion

3.1. Comparison of cotton, corn and soybean spectra

The ten reflectance spectra of cotton, corn and soybean plants are plotted in Fig. 1. The spectra for cotton plants had the shape of a typical spectral curve for healthy plants, which means that canopies absorbed most blue and red light, reflected some green light (10–20%) and most near infrared light (60–80%). The reflectance spectra showed differences, especially in the NIR region, among ten sampling locations within each field. Therefore, the reflectance spectra of individual plants even varied within a field.

Fig. 2 gives the average reflectance spectra of cotton, corn, and soybean plants from three fields. It is obvious that these spectra differed in both the visible and NIR regions. In the late growth stage, the senescent corn and soybean plants reflected more visible light but less NIR light.

Table 1
Summary of principal component analysis.

Data source	No. of PCs	Explained variation (%)
Fieldspec (1.6 nm)	PC1	70.8
	PC1, PC2	95.1
1.6 nm Fieldspec + image	PC1	70.8
	PC1, PC2	95.1
Simulated Fieldspec + image	PC1	77.4
	PC1, PC2	94.2

3.2. Data fusion

Principal component analysis was performed on three datasets to reduce the dimensionality of the datasets. Table 1 shows that the first PCs explained about 95% of the variation for the datasets. Only the first two PCs, PC1 and PC2, were used for discrimination analysis.

The classification results are reported in Table 2. The classification performance was evaluated by the misclassification rate in both the calibration and cross-validation steps in the DISCRIM procedure. Using the reflectance values derived from imagery alone, the classification accuracy was 90% in both the calibration and cross-validation steps. With simulated Fieldspec broad-band reflectance values, the classification accuracy increased in the calibration (93.3%) but decreased in the cross-validation step (86.7%). When using a combination of these two datasets, there was only a 3.3% misclassification rate in the cross-validation step and different crop types were distinguished from each other with 100% accuracy. When using the principal components from the original datasets, the classification accuracy with fused data was higher than for the reflectance values derived from the imagery and the reflectance values taken by Fieldspec alone.

4. Conclusions

In this study, both ground-based handheld spectroradiometer data and airborne imagery were used to discriminate cotton from other crops. Discriminant analyses were performed on six datasets which were based on airborne multispectral imagery, ground-based spectroradiometer data, and fused data from the airborne and ground-based spectral measurements. The fused dataset performed better in discriminating crop types than did the datasets using a single sensor alone. The overall results indicate the potential of fusion of remotely-sensed data from multiple sensors as an effective tool for detecting cotton from other crops. The method may be extended to the fusion of other types of data, such as imagery data, ultrasonic crop height sensor data, and soil moisture sensor data.

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Table 2
Summary of misclassification matrices obtained from the DISCRIM procedure.

Data source	Dataset	Calibration (%)	Cross-Validation (%)
Image	Four bands	10.0	10.0
Fieldspec (simulated broad band)	Four bands	6.7	13.3
Fieldspec (simulated broad band) + image		0.0	3.3
PCA (Fieldspec)	PC1	30.0	30.0
	PC1, PC2	3.3	6.7
PCA (1.6 nm Fieldspec + image)	PC1	30.0	30.0
	PC1, PC2	3.3	6.7
PCA (simulated Fieldspec + image)	PC1	6.7	10.0
	PC1, PC2	3.3	3.3

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