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Fusion of remotely sensed data from airborne and ground-based sensors for cotton regrowth study

Huihui Zhang

Department of Biological and Agricultural Engineering, Texas A&M University

Yubin Lan

USDA ARS College Station, TX yubin.lan@ars.usda.gov.

Charles Suh, John Westbrook, W. Clint Hoffmann

USDA ARS, College Station, TX

Chenghai Yang

USDA-ARS, Weslaco, TX

Ronald Lacey

Department of Biological and Agricultural Engineering, Texas A&M University

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Abstract. *Timely detection and remediation of volunteer cotton plants in both cultivated and non-cultivated habitats is critical for completing boll weevil eradication in Central and South Texas. The study investigated the use of aerial imagery and ground-based remotely sensed 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 were 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%. These results suggest data fusion techniques could greatly enhance our ability to detect volunteer cotton plants occurring in cultivated and non-cultivated habitats.*

Keywords. Airborne multispectral imagery, remote sensing, data fusion

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(2950 Niles Road, St. Joseph, MI 49085-9659 USA).

Introduction

Remote sensing technologies have been widely used for modern agricultural management. Various types of data have been provided for detecting crop conditions or soil properties by optical sensors or instruments from ground-based, airborne and spaceborne platforms. Despite the availabilities of these sensors, few studies have examined multisensor fusion techniques for their data. Multisensor data fusion techniques combine data from multiple sensors or sources to perform interference that may not be possible or may not be good from a single sensor or source itself (Hall and Llinas, 1997; Hall and McMullen, 2004). In this study, the potential of multisensor fusion of ground-based and airborne imagery data was investigated for discriminating crop types. The method may be extended to other types of data.

Even when cotton plants (*Gossypium hirsutum* L.) stalks are destroyed after harvest, regrowth from stalks or growth of volunteer plants from unharvested seed can occur under favorable environmental conditions. Such plants allow boll weevils (*Anthonomus grandis* Boheman), to reproduce or acquire the necessary resources to overwinter. Given the limited resources and funds, there is an urgent need to develop or identify technologies that can be used to efficiently detect regrowth and volunteer plants in both cultivated and uncultivated habitats. One potential method may involve remote sensing with multispectral and hyperspectral sensors.

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 a specific wavelength 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., 2005 a and 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.

Nowadays, airborne remote sensing technologies have made tremendous improvements over the years and are now being used in precision agricultural applications (Lan et al., 2007a and b; Huang et al., 2008; Huang et al., 2009; Lan et al., 2009a). Multispectral cameras typically capture imagery that can be related to relative radiance in the visible and NIR regions. Multispectral data comprise a set of optimally chosen spectral wavebands that are not contiguous. Airborne multispectral techniques are much less expensive and less data-intensive than hyerspectral imaging systems and can rapidly provide continuously 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 combinations of weed control and N rates. 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 acquires significant efforts to properly process an image. Consequently, the use of hyperspectral imagery as management- decision aide may not be a viable tool for all farmers. Furthermore, both satellite and aerial imagery can be compromised by cloud cover.

Although optical sensors and instruments fitted for different platforms have been demonstrated as promising tools for crop spectral reflectance measurements, only a few studies incorporated multisensor 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 agriculture field from optical remote sensing data and limited ground sampling data. Further efforts are needed to apply multisensor fusion techniques to fuse data from different sensors and improve the performance of sensing systems.

Airborne multispectral imaging system can rapidly provide spectral information over a large field at a low spectral resolution. Ground-based hand-held remote sensing instruments are not strongly influenced by environmental conditions but are labor- and time- consuming. Considering the advantages of both airborne multispectral imagery and ground-based remote sensing data, the objectives of this work were to: investigate spectral reflectance characteristic of regrowth or volunteer cotton compared to other crops; examine the variability of spectral reflectance within each field; and distinguish different crop types using ground-based hyperspectral data, airborne multispectral imagery, and the fused data from the ground-based and airborne spectral measurements.

Materials and Methods

Study Area

Ground remotely-sensed data were collected from about twenty agricultural fields in Burleson Co., TX on multiple dates throughout the 2010 growing season. A total of ten sampling locations were randomly marked within each field with color flags. Fields were observed for volunteer cotton plants. If any volunteer cotton plant was located, spectral measurement would also be taken from the volunteer cotton plant. 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 (30°34'2.52"N, 96°28'41.77"W); corn (30°33'34.27"N, 96°27'51.7"W); and soybean (30°33'7.53"N, 96°27'14.27"W).

Data Collection

<u>Airborne Multispectral Image</u>

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 to 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 x 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 FieldSpec spectroradiometer. 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.

Ground-based Data Collection

Canopy surface reflectance spectra were measured using with an ASD FieldSpec® Handheld spectroradiometer (VNIR; 325-1075 nm, 512-channel, and 1.6 nm sampling interval; Analytical Spectral Devices, Inc., Boulder, CO). 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 at the same height and with a nadir-looking view at the top of 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 had better performance than 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 the airborne multispectral imaging sensor's four broad spectral bands (430 to 470 nm, 530 to 570 nm, 630 to 670 nm, and 810 to 850 nm) to obtain the simulated broad band reflectance data at ground level. Due to noise in the 325 to 399 nm region, only the reflectance values between 400 nm to 1075 nm were used.

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 four bands values of the image pixels which were geo-collocated with ground sampling points were extracted for further analysis.

Data Analysis

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 proc PRINCOMP 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 were used for classification.

Data Fusion

Discriminant analyses were applied on several datasets: 1) derived reflectance values from four bands 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 datasets 1 and Fieldspec reflectance data at 1.6 nm bandwidth.

The DISCRIM procedure in SAS was applied on 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.

Results and Discussion

Reflectance Spectra

Not all the ground measurement results were reported in this manuscript. Only reflectance spectra of a volunteer cotton plant located in a soybean field and reflectance spectra of the three fields surveyed by airborne imagery.

Volunteer Cotton in Soybean Field

A volunteer cotton plant (grown from unharvested seed) was found in a soybean field. A total of five reflectance readings were taken from the volunteer cotton plant and the soybean

plant beside it. After visually inspecting the volunteer cotton plant, both plants were found about to be the same height, and the color of the cotton plant was much darker than the soybean plant. The mean reflectance spectra of these two plants are given in Figure 1. Compared to the reflectance spectra of the soybean plant, the volunteer cotton plant had a slightly higher reflectance in the visible region, but less reflectance in the NIR region.

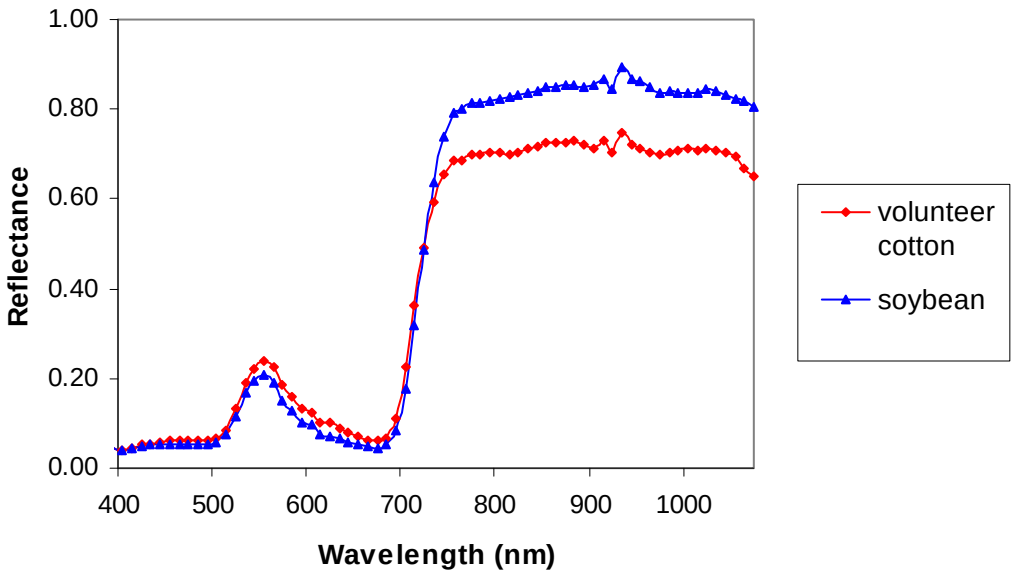

Figure 1. Reflectance spectra of volunteer cotton plant in soybean field taken by Fieldspec spectroradiometer.

Comparison of Cotton, Corn and Soybean Spectra

The ten reflectance spectra of cotton, corn and soybean plants were plotted in Figure 2. The spectrum 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, even from one crop type within a field, the reflectance spectra would be different.

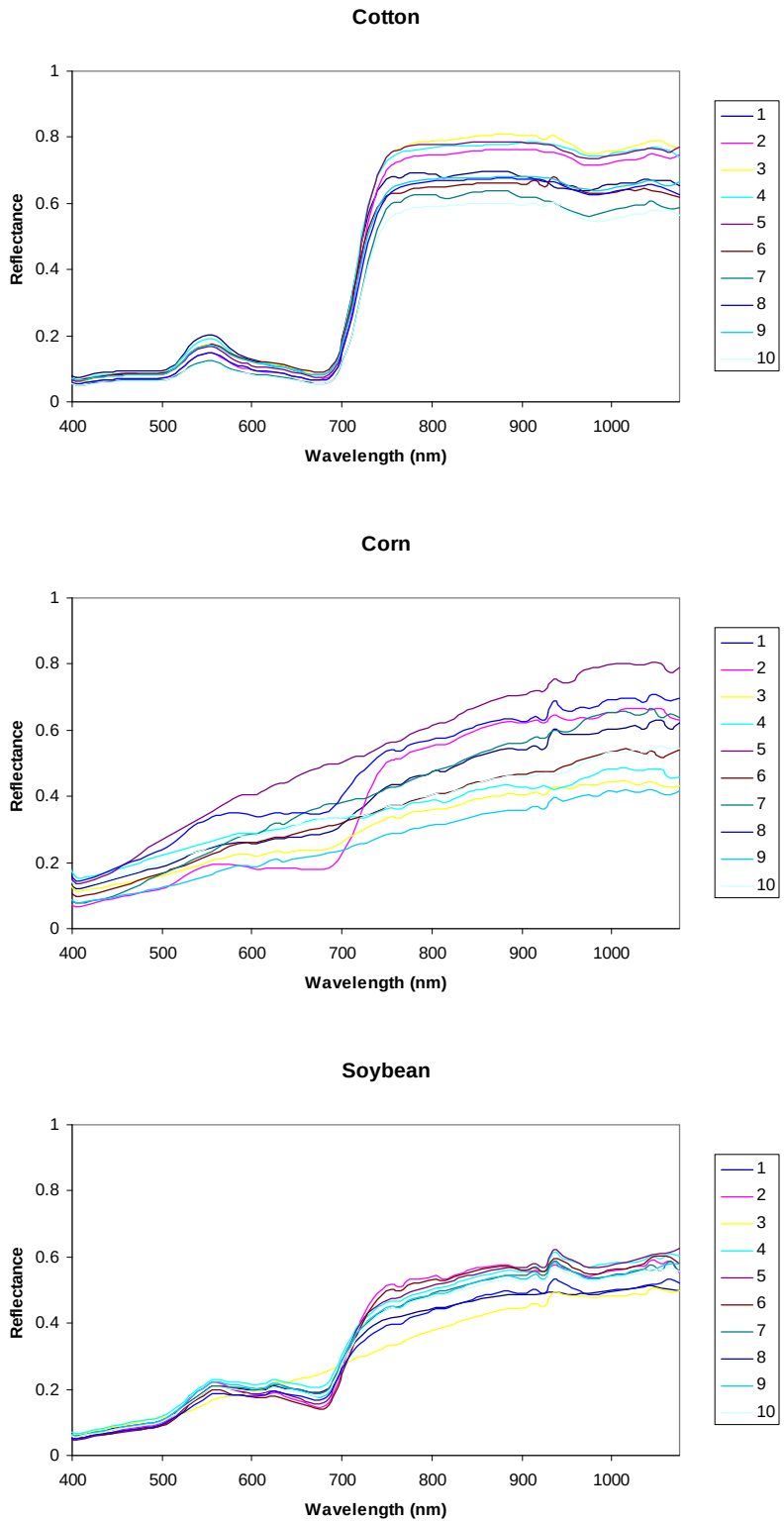

Figure 2. Reflectance spectra of cotton, corn and soybean plants were measured with a Fieldspec spectroradiometer at the ten sampling locations.

Figure 3 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 corn and soybean plants were senescent, and tended to reflect more visible light and less NIR light.

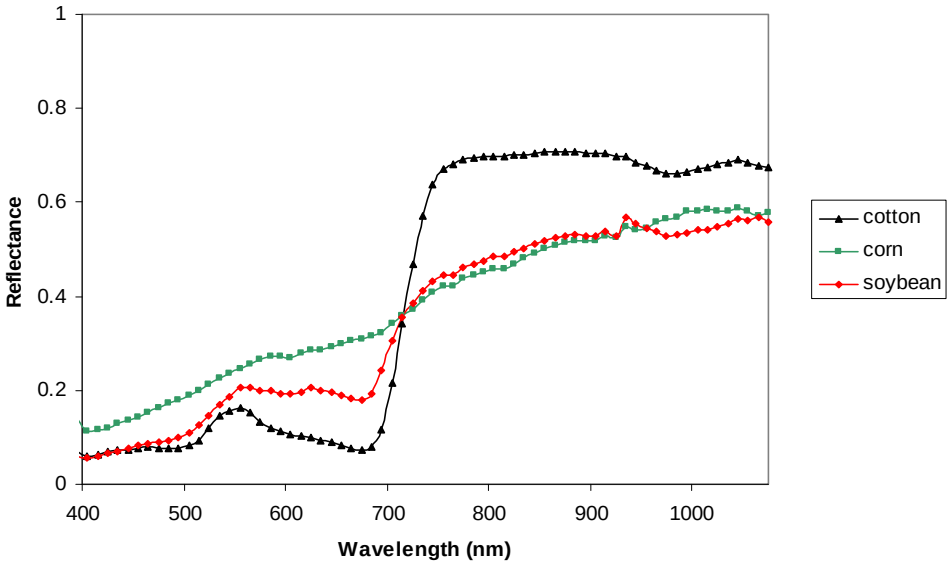

Figure 3. The mean reflectance spectra of three crop types taken with a FieldSpec spectroradiometer

Data Fusion

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

Table1. Summary of principal component analysis

Data Source	No. of PCs	Explained Variation (%)
Fieldspec (1.6nm)	PC1	70.76
	PC1, PC2	95.1
1.6nm Fieldspec + Image	PC1	70.75
	PC1, PC2	95.1
Simulated Fieldspec + Image	PC1	77.35
	PC1, PC2	94.2

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, different crop types were distinguished from each other with 100% accuracy and only 3.3% misclassification rate in the cross-validation step. When using the principal components from the original datasets by principal component analysis, the classification accuracy with fused data was higher than the reflectance values derived from the imagery and the reflectance values taken by Fieldspec alone.

Table2. Summary of misclassification matrices obtained from the DISCRIM procedure.

Data Source	Dataset	Calibration (%)	Cross-Validation (%)
Image	Four bands	10	10
FieldSpec (simulated broadband)	Four bands	6.7	13.33
FieldSpec (simulated broadband)+Image		0	3.33
PCA (Fieldspec)	PC1	30	30
	PC1, PC2	3.3	6.67
PCA (1.6nm Fieldspec + image)	PC1	30	30
	PC1, PC2	3.33	6.67
PCA (simulated Fieldspec + image)	PC1	6.67	10
	PC1, PC2	3.33	3.33

Summary and Conclusions

In this study, both ground-based handheld spectroradiometer data and airborne imagery were used for a volunteer cotton study. The reflectance spectrum of the volunteer cotton plants was found to differ from that spectrum of a normal soybean plant. The variability of the reflectance spectra of cotton, corn and soybean plants from ten sampling locations within each farm were examined using a handheld spectroradiometer. Even for the same crop type in the same field, the reflectance spectra differed, especially in the near infrared region of the spectrum. Discriminant analyses were performed on six datasets which were taken 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

indicated the potential of multisensor data fusion of remotely sensed data from different sensors as an effective tool for detecting cotton regrowth and volunteer plants. 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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