DIFFERENTIATION OF COTTON FROM OTHER CROPS AT DIFFERENT GROWTH STAGES USING SPECTRAL PROPERTIES AND DISCRIMINANT ANALYSIS

H. Zhang, Y. Lan, C. P. Suh, J. K. Westbrook, R. Lacey, W. C. Hoffmann

ABSTRACT. *The spectral reflectance properties of cotton (*Gossypium hirsutum *L.), corn (*Zea mays *L.), soybean [*Glycine max *(L.)], and sorghum [*Sorghum bicolor *(L.)] crops during their different growth stages were examined, and spectral data were used to distinguish cotton from other crops. Two field blocks with two different soil types, Belk clay (BaA) and Ships clay (ShA), were set up with cotton, corn, soybean, and sorghum in each block and grown using conventional production practices for the area. Spectral information was collected from all crops at different growth stages from May to July 2009. Reflectance spectra and the first derivative of the spectra were analyzed to characterize the spectral properties of crop types and compare the crops grown in different soil types. The red-edge points of cotton, soybean, and sorghum shifted with the growth stage. Principal component analyses were successful in reducing the dimensionality of the hyperspectral data and identifying significant features from the original data. Most significant wavelengths selected were in the 548-556 nm, 679-682 nm, 756-764 nm, and 928-940 nm regions of the spectrum. Discriminant analysis was able to differentiate cotton from other crop types at four critical growth stages with 100% accuracy of classification for all four observation dates.*

Keywords. *Corn, Cotton, Hyperspectral, Red edge, Reflectance, Sorghum, Soybean.*

The need to minimize populations of overwintering boll weevils (*Anthonomus grandis* Boheman) is widely recognized by eradication programs. One tactic to reduce overwintering survival of boll weevils is timely post-harvest stalk destruction. Even where cotton plants (*Gossypium hirsutum* L.) are destroyed after harvest, regrowth from stalks or growth of volunteer plants from unharvested seed can occur when environmental conditions permit. Occurrence of regrowth or volunteer cotton, particularly fruiting plants, is a major concern of the Texas Boll Weevil Eradication Foundation (TBWEF) because such plants extend the opportunity for weevils to reproduce and/or acquire the necessary fat reserves to overwinter.

Presently, regulations established by the Texas Department of Agriculture (TDA) permit the existence of regrowth or volunteer plants beyond the crop destruction deadline as long as the plants do not possess fruiting structures. TDA is solely responsible for monitoring fields and administering fees for non-compliance of maintaining hostable cotton plants past the stalk destruction deadline, but limited resources restrict the frequency and coverage of field inspections. Detecting volunteer cotton in other crops or uncultivated habitats is also problematic because these plants are usually hidden by the surrounding vegetation. Thus, there is a 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 detecting stressed 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, reflectance in the green and NIR regions will decrease. Reflectance at the boundary between the visible and NIR region of the spectrum is called the "red-edge" region. The red-edge point is defined as the absolute maximum of the first derivative in the range 690-750 nm and can be found

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Submitted for review in September 2010 as manuscript number IET 8774; approved for publication by the Information & Electrical Technologies Division of ASABE in June 2012.

The authors are **Huihui Zhang**, Research Associate, USDA-ARS Water Management Research Unit, Parlier, California; **Yubin Lan, ASABE Member,** Agricultural Engineer, **Charles P. Suh,** Research Entomologist, and **John K. Westbrook,** Research Meteorologist, USDA-ARS Areawide Pest Management Research Unit, College Station, Texas; **Ronald Lacey, ASABE Member,** Professor, Department of Biological and Agricultural Engineering, Texas A&M University, College Station, Texas; and **W. Clint Hoffmann, ASABE Member,** Agricultural Engineer, USDA-ARS Areawide Pest Management Research Unit, College Station, Texas. **Corresponding author:** Yubin Lan, USDA-ARS, 2771 F&B Road, College Station, TX 77845; phone: 979-260-3759; e-mail: yubin.lan@ars.usda.gov.

by plotting the first derivative of the reflectance spectrum and then identifying the highest peak manually (Horler et al., 1983; Fillella and Peñuelas, 1994). Demetriades-Shah et al. (1990) proposed the use of first and second derivative spectra in canopy measurements since these essentially eliminate the effects of soil background. Many researchers also have related the red-edge position to chlorophyll concentration, biomass, and leaf area index estimation (Curran et al., 1991; Danson and Plummer, 1995; Mutanga and Skidmore, 2007).

Several studies have used hyperspectral measurements in support of crop management, such as crop type identification, plant nutrition deficiency assessment, crop stress or damaged detection, yield estimation, and growth status evaluation. 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. Zhao et al. (2005a) evaluated the hyperspectral vegetative indices for discrimination of cotton nitrogen stress and growth stage. Zhao et al. (2005b) investigated the effects of nitrogen deficiency on grain sorghum growth and leaf hyperspectral reflectance properties. They reported that nitrogen deficiency increased leaf reflectance at 555 and 715 nm, but their experiments were conducted under outdoor potculture conditions. Plant et al. (2000) investigated the relationships between remotely sensed reflectance data and cotton growth and yield. Muhammed (2005) used hyperspectral data to discriminate between healthy and diseased plants in a spring wheat crop that suffered from fungal infestation. Koger et al. (2003) determined the potential for wavelet-based analysis of hyperspectral reflectance signals for detecting the presence of early-season pitted morning glory when intermixed with soybean and soil. Hyperspectral reflectance data were analyzed with a variety of methods for differentiating soybean, soil, and six weed species commonly found in Mississippi agricultural fields (Gray et al., 2009). Zhang et al. (2011) characterized the spatial variation of a vegetation index derived from hyperspectral reflectance measurements within a soybean field.

In this study, four common agricultural crops (cotton, corn, soybean, and sorghum) were planted in two blocks with different types of soil. The objective of this study was to investigate the spectral properties of four crop types at different growth stages in different types of soil and distinguish cotton from the other crop types at different growth stages with hyperspectral data.

Materials and Methods

Study Site

The study site was located at the Texas AgriLife Research Farm (30° 31′ 19″ N, 96° 23′ 52″ W) in Burleson County, Texas. Dominant soil types in the field include a Belky clay (fine, mixed, active, thermic Entic Hapluderts) and a Ships clay (very-fine, mixed, active, thermic Chromic Hapluderts). The field was divided into two blocks, which were called block BaA and block ShA. Four agricultural crops (cotton, corn, soybean, and grain sorghum) were planted and managed in each block during 2009 using conventional production practices for the area (table 1). Within each block, there were six rows of each crop with a row spacing of 1 m and rows oriented in the east-west direction.

Table 1. Crop types with respective planting dates in 2009, Texas AgriLife Research Farm, Burleson County, Texas.

Crop	Variety	Planting Date
Corn	Integra INT9673VT3	March 24
Cotton	Deltapine DP174RF	April 16
Sorghum	DynaGro DG771B	April 15
Soybean	Asgrow O361380	March 24

Spectral Measurements and Analysis

Hyperspectral measurements were carried out from May to July during the 2009 growing season. Plant canopy spectra were collected with an ASD FieldSpec Handheld spectroradiometer (VNIR (325-1075 nm), Analytical Spectral Devices, Inc., Boulder, Colo.). Sunny days were chosen for the field tests, and all data were collected around solar noon. 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. The spectroradiometer was adjusted to ten scans per dark current, and the integration time was set at 217 ms. Spectral reflectance data, which were uncorrected for sun angle or atmospheric effects, were used for analysis in this study. The spectroradiometer was mounted on a tractor with a nadir-looking view at the top of the plant canopies. Because the field-of-view (FOV) of the sensor is an important factor in determining how much of the canopy will be viewed, the mounted height of the spectroradiometer was adjusted to maximize plant coverage and subsequently minimize soil background effects. For example, the average width of the cotton plants on May 27 was 0.357 m, so the sensor was placed about 0.8 m above the canopy with a 25° FOV. Measurements were taken at about a 4 m interval from the two middle rows for each crop. A total of 18 to 20 readings were taken for each crop within each block. The average reflectance of these readings was used to represent the mean reflectance of each crop type.

The spectral data ranged from a wavelength of 325 nm to 1075 nm with a sampling interval of 1.6 nm. The spectroradiometer output 512 continuous data points with each sample. The ViewSpec Pro software supplied by ASD was used to interpolate each sample into 1 nm intervals. This resulted in 751 individual wavebands for each sample. All 751 wavebands were presented as spectral signatures of crop types at different growth stages. Due to the scattering noises at the end of the spectral data, comparison of spectral reflectance from different crop types and the first derivatives of the spectra were based only on spectral data between 400 and 1000 nm. The data collection days and the corresponding growth stages are summarized in table 2.

Data Analysis

The spectral reflectance values at each of the 1 nm wavebands were analyzed with principal component analysis (PCA) to extract features prior to processing by discri-

Table 2. Hyperspectral measurement dates, days after planting (DAP), and respective stages of plant development for the 2009 growing season.[a]

Crop	May 7 (DAP)	May 27 (DAP)	June 11 (DAP)	July 16 (DAP)
Cotton	EV (21)	Early SQ (41)	SQ (56)	Boll/BM (91)
Corn	EV/V (44)	V/E (64)	DS (79)	HD (114)
Soybean	EV/V (44)	PD (64)	POD (79)	SD (91)
Sorghum	EV (22)	V (42)	BT (57)	BL (92)

[a] BL = black layer/mature, Boll/BM = bolls and blooming, BT = boot (head surrounded by flag leaf), DS = dough stage, E = ear developing, EV = early vegetative, HD = hard dent, PD = pod developing, POD = pod 3/16 inch at one of four upper nodes, SD = seeding/full seed, SQ = squaring, and V = vegetative.

minant analysis (DA). PCA is a multivariate technique used as a tool for reducing high-dimensional data. The information content contained in the original variables is projected onto a smaller number of principal components (PCs), which are linear combinations of those variables. The process of PCA returns PCA 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. In this case, PCA was used to reduce the dimensionality of the hyperspectral data to several bands that explain most of the variation among the original data. Principal component analysis was performed using the PRINCOMP procedure in SAS (SAS Institute, Inc., Cary, N.C.) in which a new principal component was created for each wavelength variable in the original data.

The DISCRIM procedure in SAS was applied on various numbers of derived PCs for classification. The DISCRIM procedure creates a discriminant function using a measure of generalized squared distance to classify each observation into groups. The discriminant function is based on either the individual within-group covariance matrices or the pooled covariance matrix and also takes into account the prior probabilities of the groups. Each observation is placed in the group from which it has the smallest generalized squared distance. The DISCRIM procedure also computes the posterior probability of an observation belonging to each group.

The generalized squared distance (d) function is:

$$d_t^2\left(x\right)=\left(x-m_t\right)' V_t^{-1}\left(x-m_t\right) \quad (1)$$

where x is a p-dimensional vector containing the quantitative variables of an observation, V_t is the pooled covariance matrix, t is a subscript to distinguish the groups, and m_t is the p-dimensional vector containing the variable means in group t.

The posterior probability of x belonging to group t is:

$$p\left(t \mid x\right)=\exp\left[-0.5D_t^2\left(x\right)\right] \Big/ \sum_u \exp\left[-0.5D_u^2\left(x\right)\right] \quad (2)$$

The DISCRIM procedure divided the data into two subsets. One subset was used to develop a calibration model, and the other was used to validate the model. The leave-one-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

The average height of corn plants was more than 2.7 m on DAP 79, which exceeded the height of the frame of the ground-based system described by Lan et al. (2009). Consequently, the reflectance spectra of corn plants were only available at their early vegetative and vegetative stages.

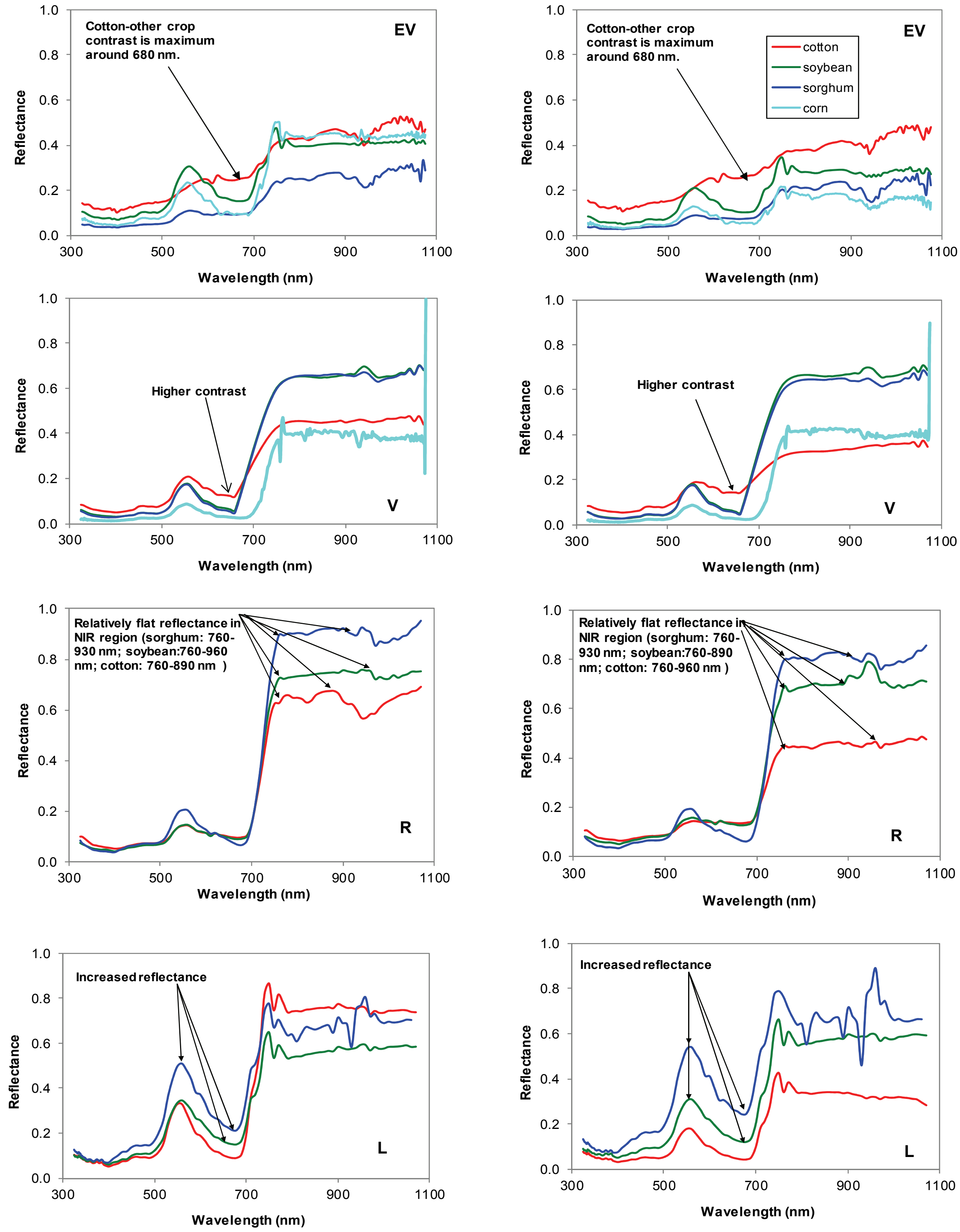
Figures 1a and 1b show the mean spectral reflectance across the 325 to 1075 nm wavelength band for these four crops in two blocks at their early vegetative, vegetative, reproductive, and late growth stages of development. All the spectra had two peaks in the green and NIR regions except for cotton and sorghum at the early vegetative growth stage. The maximum contrast of the reflectance value of cotton to those of other crops was near the 680 nm wavelength. The highest reflectance in the NIR region was observed at the reproductive stage, which was cotton at squaring, soybean at pod formation, and sorghum at boot. The average reflectance of each crop in block BaA was higher than of those in block ShA. There was considerable variation in the reflectance spectra of sorghum during the late growth stage. Contributing factors could be the leaf and canopy structures of the sorghum plants and the considerable movement of the plant canopies when the tractor was driving through the rows. Moreover, the seeds of sorghum plants were fully mature, and it is likely that the sensor measured reflectance not only from leaves but also from dark kernels.

Figures 2a to 2d illustrate the mean spectral reflectance of each crop in two blocks at four growth stages, respectively. Each spectrum curve represents the average of all the measurements for each crop at that stage. The reflectance spectra of corn at the vegetative stage and of soybean and sorghum at the vegetative and late stages in both blocks were similar. In other cases, the spectral reflectance values of crops in block BaA were higher than those in block ShA. We also noticed that the reflectance of sorghum in the green and red regions increased at the late growth stage.

FIRST DERIVATIVE OF REFLECTANCE SPECTRA

Figure 3 represents the first derivative of reflectance spectra of cotton, soybean, and sorghum in two blocks at the vegetative, reproductive, and late stages, respectively. The first derivative of reflectance spectra of corn is only available for the vegetative stage and is not plotted in the figure.

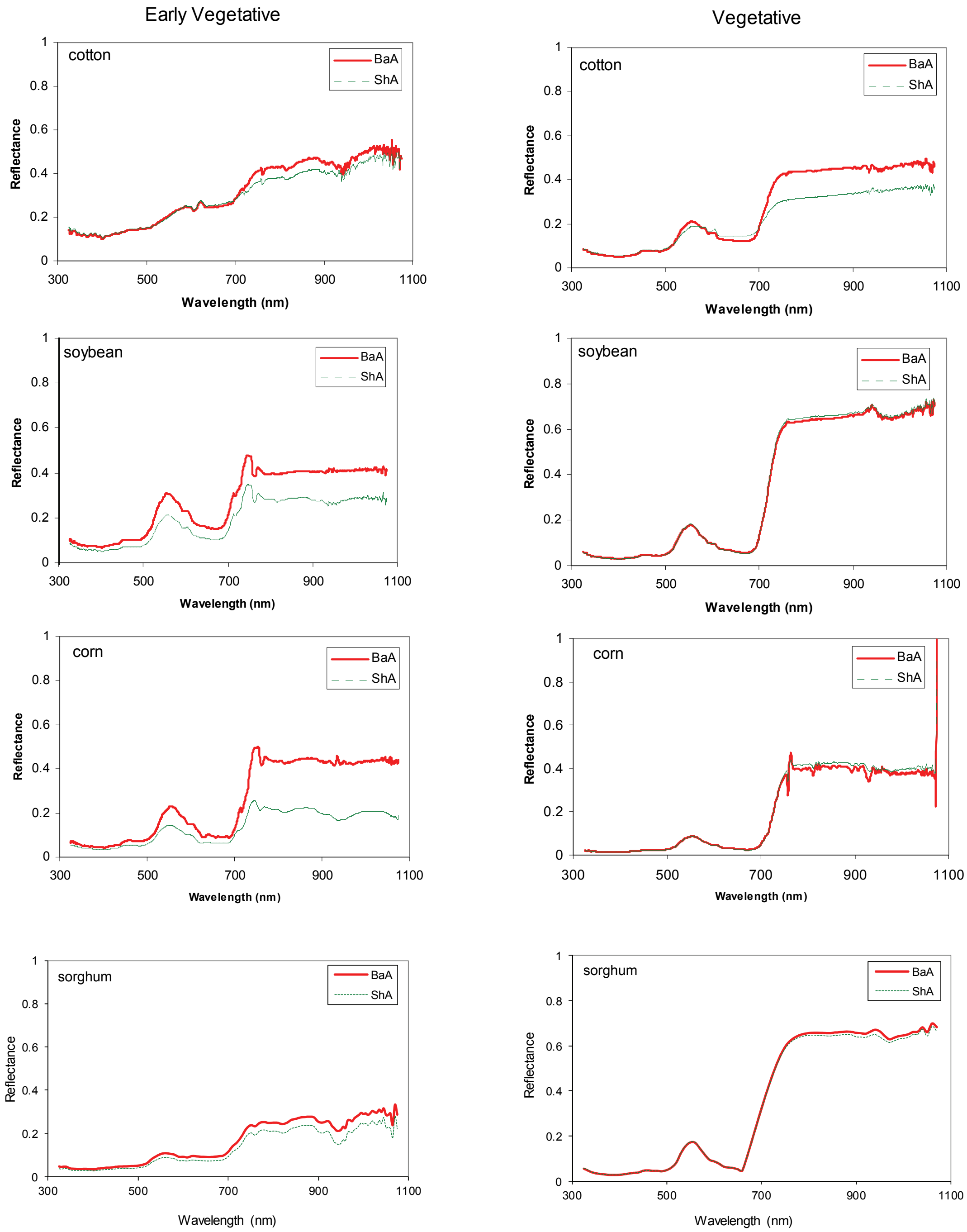
Cotton, soybean, and sorghum can be distinguished from each other by the red-edge points of the spectra at the vegetative and reproductive stages. In block BaA, the red-edge points were found at 710 nm, 726 nm, 720 nm, and 728 nm for cotton, corn, soybean, and sorghum, respectively, at the vegetative stage; the red-edge points were found at 718 nm,



(a) Block BaA

(b) Block ShA

Figure 1. Mean spectral reflectances of cotton, soybean, and sorghum measured at four growth stages and corn at early vegetative and vegetative stages in blocks (a) BaA and (b) ShA: EV = early vegetative stage, V = vegetative stage, R = reproductive stage, and L = late stage.

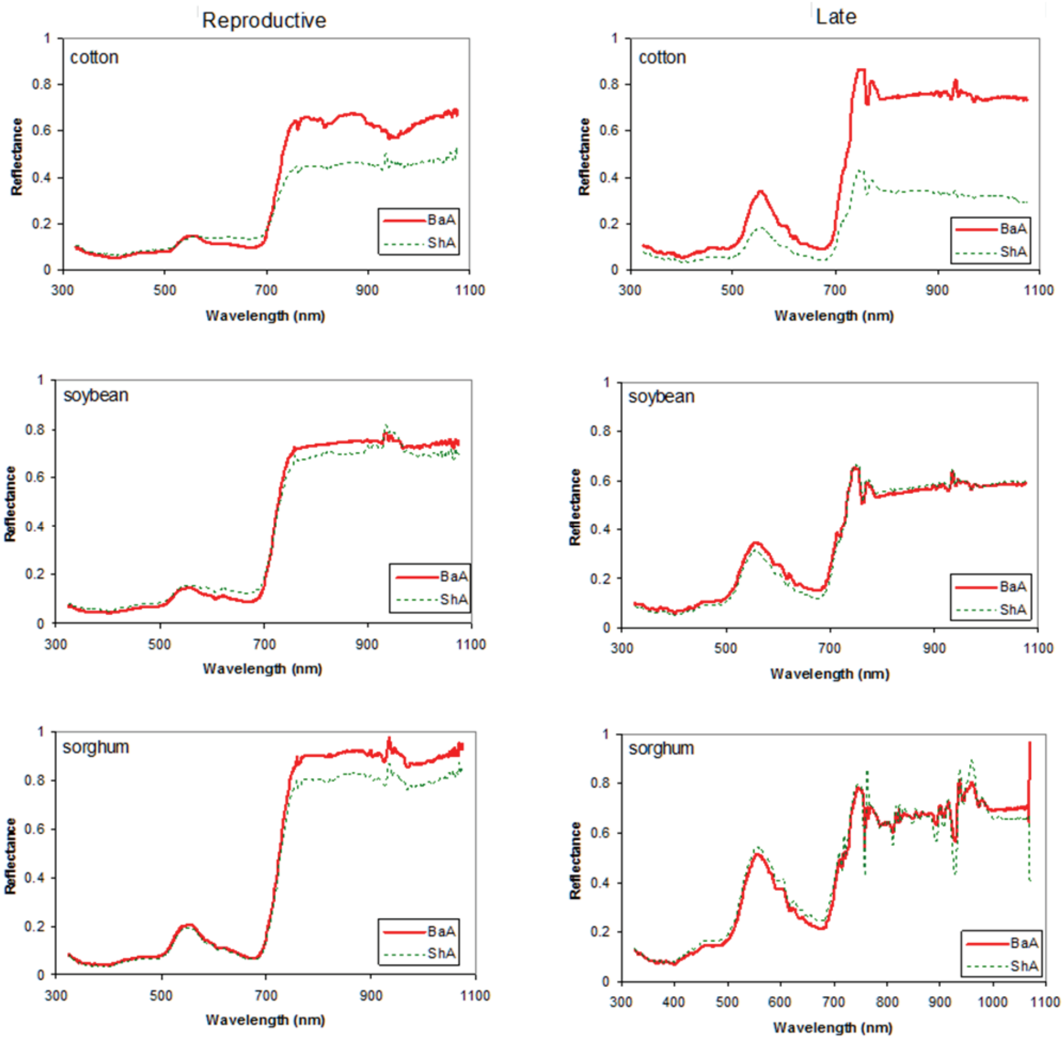


(a) Early vegetative stage **(b) Vegetative stage**

Figure 2. Reflectance of cotton, corn, soybean, and sorghum measured in blocks BaA and ShA at (a) early vegetative and (b) vegetative stage.

721 nm, and 730 nm for cotton, soybean, and sorghum, respectively, at the reproductive stage. The same wavelengths were found in block ShA except that 714 nm was found for cotton at the vegetative stage. The red-edge positions shifted to longer wavelengths with later crop development. This result is consistent with the findings of Railyan and Korobov (1993), who studied the red-edge structure of canopy reflectance spectra of triticale and concluded that the red-edge position varied according to the plant growth stage.

Two or more peaks were identified in the red-edge region at the late stage. Reflectance maxima were at 704 and 732 nm and at 702 and 732 nm for cotton in blocks BaA and ShA, respectively; at 704 and 735 nm for soybean in both blocks; and at 700 and 732 nm for sorghum in both blocks. Horler et al. (1983) reported that the first peak was attributed to the chlorophyll content in the leaves and the second peak was attributed to cellular scattering in the leaves. In our case, the reflectance spectra were measured at the plant canopy scale instead of individual leaves. The soybean plants were at seeding/full seed stage, and the leaves had started senescence. For sorghum plants, aside from the noise of the raw reflectance spectra, other factors



(c) Reproductive stage **(d) Late stage**

Figure 2 (continued). Reflectance of cotton, corn, soybean, and sorghum measured in blocks BaA and ShA at (c) reproductive and (d) late stage.

that may cause more peaks in the red-edge region need to be investigated in a future study.

PCA Feature Extraction

Principal component analysis procedures were undertaken on the spectral measurements for crops in block BaA. There were a total of four spectral datasets for four test days. Figure 4 gives the first three principal components, which explained 99% of the variation from PCA for the dataset on May 7, 2009. The corresponding wavelengths could be selected based on the minimum and maximum of PC loadings in the different spectral regions. For example, PC3 had peaks at the wavelengths of 557 nm and 747 nm.

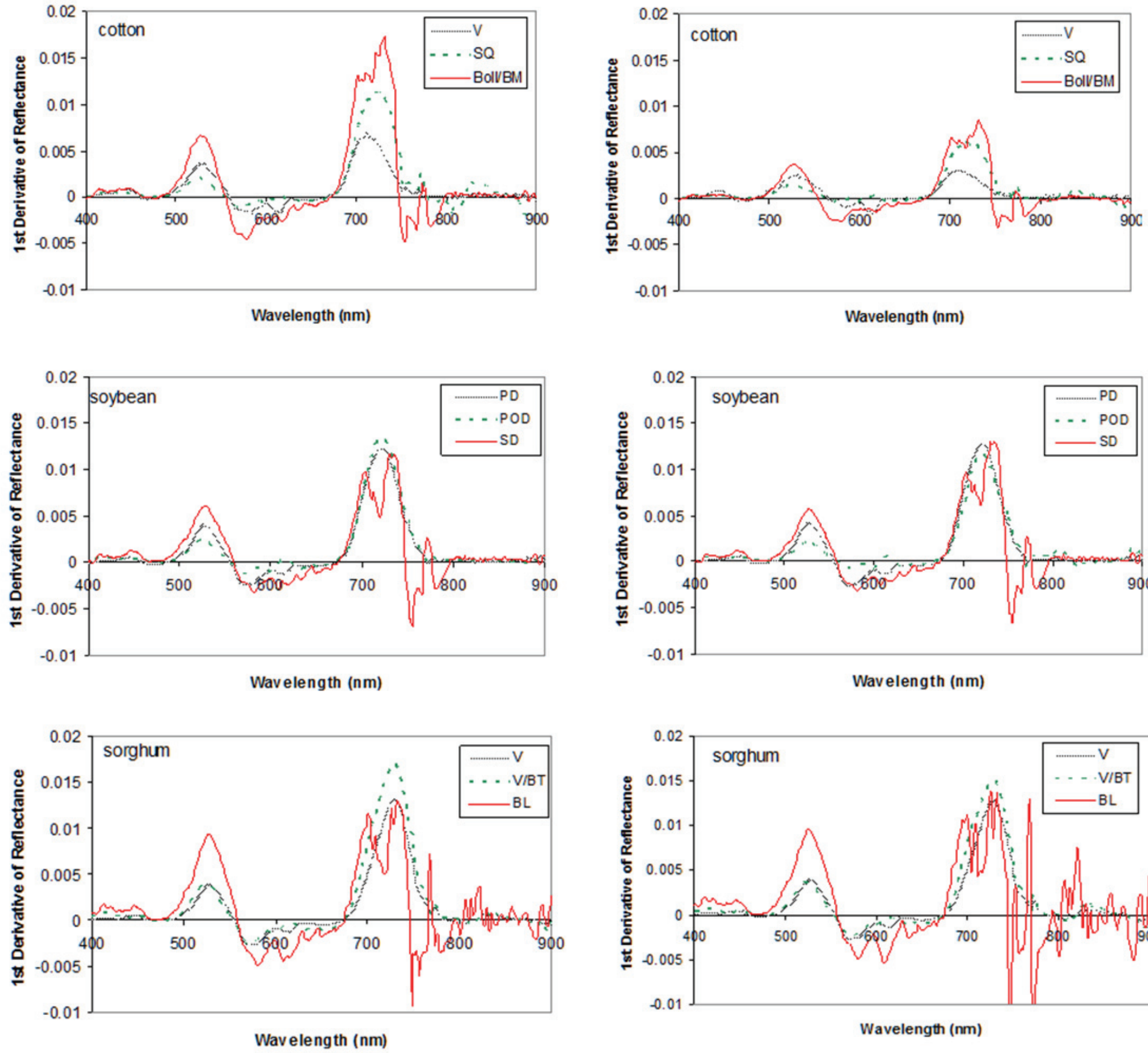
The selected wavelengths based on their PC loadings for all datasets and the proportion of variation explain by each principal component are summarized in table 3. The wavelengths selected by PCs varied for the four datasets, but most of them were within 548 to 556 nm, 679 to 682 nm, 756 to 764 nm, and 928 to 940 nm. These wavelengths carried significant information on the discrimination of crop types.

Discriminant Analysis

Classification results for the four datasets are reported in table 4. For four days, the DISCRIM procedure was able to identify the crop types during the calibration step with different numbers of PCs. For the May 27 and July 6 datasets, the accuracy of classification was 100% with three or four PCs in both the calibration and cross-validation steps. For the June 11 dataset, six PCs were used to get 100% accuracy of classification in the calibration and cross-validation steps. However, the May 7 dataset achieved a misclassification rate of 1.32% in cross-validation. The misclassified crop types from the four days datasets were corn vs. soybean on May 7, soybean vs. sorghum on May 27 and June 11, and cotton vs. soybean on July 6. Generally, the discriminant analysis was able to differentiate cotton from corn, soybean, and sorghum.

Conclusions

Field tests were carried out to investigate the spectral properties of cotton, corn, soybean, and grain sorghum crops at their different growth stages during the 2009 grow-



(a) Block BaA

(b) Block ShA

Figure 3. First derivative of the spectra of cotton, soybean, and sorghum at different stages in (a) block BaA and (b) block ShA: V = vegetative, SQ = squaring, Boll/BM = bolls and blooming, PD = pod developing, POD = pod 3/16 inch at one of four upper nodes, SD = seeding/full seed, V/BT = vegetative/boot, and BL = black layer/mature.

ing season. The spectral characteristics of crops at different growth stages were compared. Using the first derivative of the spectral data, the red-edge position of cotton was at a shorter wavelength than that of corn, soybean, and sorghum at the vegetative stage and soybean and sorghum at the reproductive stage. The red-edge points of cotton, soybean, and sorghum increased about 4 nm, 1 nm, and 2 nm, respectively, from the vegetative stage to the reproductive stage. Two or more peaks were observed from the first derivative of spectra, and the maxima were at 732 and 735 nm.

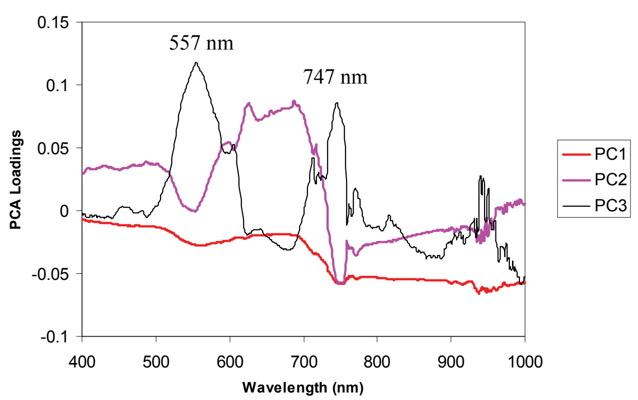


Figure 4. PC loadings of the first three principal components for spectral data on May 7, 2009.

Principal component analyses were successful in reducing the dimensionality of the hyperspectral data and identifying significant features from the original data. The discriminant analysis method was found to be able to differentiate cotton from the other crops at four critical growth stages with 100% accuracy of classification for all four dates. In light of these findings, spectral analysis of plants shows considerable promise as a method for discriminating cotton from other crop types.

Table 3. Selected wavelengths by principal component analysis.

Test Date (2009)	PC	Selected Wavelengths (nm)	Explained Variation (%)
May 7	PC1	554, 680	86.32
	PC2	516, 540, 688, 757	10.38
	PC3	557, 684, 747, 940	2.72
	PC4	607, 625, 759, 940	0.29
	PC5	556, 680, 720, 756, 940	0.18
	PC6	607, 625, 718, 892	0.02
May 27	PC1	550, 680, 758	90.93
	PC2	710, 754, 758, 764, 928	8.36
	PC3	516, 686, 728, 758, 764, 932	0.32
June 11	PC1	549, 550, 700, 760	93.72
	PC2	548, 690, 720, 780, 818, 872, 943	3.83
	PC3	549, 721, 762, 946, 818	1.65
	PC4	555, 679, 730, 816, 868, 928	0.55
	PC5	552, 682, 730, 928	0.13
	PC6	624, 759, 762, 778, 817, 867, 927, 936	0.04
July 6	PC1	552, 757, 762, 928, 960	76.9
	PC2	581, 695, 757, 762, 928, 960	20.79
	PC3	545, 621, 755, 762, 928, 960	1.63
	PC4	553, 710, 715, 753, 759, 919, 932	0.26

Table 4. Summary of misclassification matrices obtained from DISCRIM procedure.

Test Date (2009)	No. of PCs	Calibration (%)	Cross-Validation (%)	Misclassification
May 7	1	36.84	51.32	Corn vs. soybean
	2	21.05	22.37	
	3	2.63	3.95	
	4	1.32	2.63	
	5	2.63	2.63	
	6	0	1.32	
May 27	1	35.29	38.24	Soybean vs. sorghum
	2	5.05	1.47	
	3	0	0	
June 11	1	33.33	33.33	Soybean vs. sorghum
	2	12.5	14.58	
	3	10.42	16.7	
	4	0	4.17	
	5	0	2.08	
	6	0	0	
July 6	1	3.17	4.76	Cotton vs. soybean
	2	1.59	1.59	
	3	0	1.59	
	4	0	0	

Acknowledgements

This study was supported in part by grants from the Deployed War-Fighter Protection (DWFP) Research Program, funded by the U.S. Department of Defense through the Armed Forces Pest Management Board (AFPMB), and from Cotton Inc. (RCA No. 09-597). The authors express their sincere gratitude to Mr. Mike O'Neil and Mr. Charlie Harris for helping with the ground-based field tests.

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