Discriminating among Cotton Cultivars with Varying Leaf Characteristics Using Hyperspectral Radiometry

H. Zhang, L. L. Hinze, Y. Lan, J. K. Westbrook, W. Clint Hoffmann

Abstract. *There is a rapidly growing interest in methods for automatic plant identification in agricultural research. Cotton (*Gossypium *spp.) is a crop well-suited to precision agriculture and its inherent goals of increasing yields while minimizing environmental impacts. Ten cotton (*G. hirsutum *and* G. barbadense*) cultivars with differing leaf characteristics were evaluated in a greenhouse environment. Hyperspectral data collected with a handheld spectroradiometer were used to distinguish among the cultivars. The features extracted by principal component analysis and stepwise selection approaches were used for discriminant analysis. The best discrimination accuracy by selected wavelengths was 90.4% for* G. hirsutum *cultivars, 100% for* G. barbadense *cultivars, and 91.6% for pooled cultivars of the two species. Spectral wavelengths at 550 and 760 nm were most relevant to the discrimination between these two cotton species. Two vegetation indices, NDVI and PRI, were also investigated for any significant differences across cotton cultivars. The results demonstrated that hyperspectral radiometry has good potential for discrimination of* G. hirsutum *and* G. barbadense *cotton cultivars in early stages of growth.*

Keywords. *Cotton cultivar discrimination, Glands, Hyperspectral, Leaf pigment, Pubescence.*

Cotton (*Gossypium* spp.) is a commercially cultivated crop grown primarily for its fiber but also for valuable products derived from its seed, including cottonseed oil and cottonseed meal. The majority of cotton grown is of either the *G. hirsutum* or the *G. barbadense* species. *G. hirsutum* is the most common species of cotton, accounting for approximately 90% of world production. *G. barbadense*, also known as Egyptian or Pima cotton, is grown on a more limited scale and is recognized for its high-quality fiber (Hague et al., 2009).

Cotton is well-suited to precision agriculture and its inherent goals of increasing yields while minimizing environmental impacts (McKinion et al., 2001). Precision agriculture applications using remote sensing have been steadily increasing in recent years. There has been a rapidly growing interest in cost- and time-effective methods for automatic identification of various crop types in precision agriculture (Rao et al., 2007; Tyystjarvi et al., 2011). The ability to detect different crop types at the species and cultivar level is important to enhance implementation of precision agriculture practices. Especially in larger fields with hundreds of acres, several cultivars are likely to be planted. Due to genetics and environment, each cultivar may vary in growth rate and yield potential. Cultivars may also have different requirements for inputs (fertilizer, insecticides, herbicides, etc.). Therefore, being able to identify cultivars automatically would allow the farmer to use precision agriculture practices to apply those inputs needed by a specific cultivar at a specific time.

Hyperspectral remote sensing devices have enhanced the spectral characterization of agricultural crops. 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 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, soybeans, and cotton. Hyperspectral reflectance data were analyzed with a variety of methods to differentiate the soybean crop from the reflectance data of the soil and six weed species commonly found in Mississippi agricultural fields (Gray et al., 2009). The possibilities of hyperspectral remote sensing for the extraction of information relevant to agricultural crops demand detailed understanding of spectral signatures in terms of position of feature specific absorption bands, shape of the spectrum, spectral variability, and similarity of various types of vegetative species (Rao et al., 2007). Rao et al. (2007) developed a spectral library for identification and classification of three cultivars each from rice, chili, and cotton using data from Hyperion images and *in situ* hyperspectral measurements.

Spectral reflectance properties based on the absorption of light at a specific wavelength are associated with specific plant characteristics. Leaf pigments and tissues are known to affect reflectance in different wavelengths. For healthy crops, spectral reflectance in the visible wavelengths (400-700 nm) is low because of the high absorption of light en-

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ergy by chlorophyll. In contrast, reflectance in the near-infrared (NIR) wavelengths (700-1300 nm) is high because of the multiple light-scattering mechanisms of different leaf tissues (Taiz and Zeiger, 2006). Specifically, marked differences in reflectance of pigmented cotton leaves (green, dark red, and yellow-green) have been reported (Gausman, 1982). Leaf structures such as trichomes, pubescence (hairs), and glaucousness (thick wax layer) have been observed to have either minimal or marked effects on spectral reflectance measurements in different species (Holmes and Keiller, 2002, Sims and Gamon, 2002). Neither of these studies of leaf structures included *Gossypium* in the range of species evaluated.

The application of hyperspectral remote sensing data for vegetation discrimination has been documented in several studies (Goel et al., 2003; Karimi et al., 2005; Irisarri et al., 2009). Many vegetation indices (VI) have been developed from spectral data based on simple mathematical formulas, such as ratios or differences between the reflectance at given wavelengths. The normalized difference vegetative index (NDVI) (Rouse et al., 1973) is a commonly used indicator of crop health in agricultural applications (Sembiring et al., 1998; Thenkabail et al., 2000; Zhao et al., 2005; Freeman et al., 2007). The normalized difference vegetation index is calculated as: NDVI = (NIR – Red) / (NIR + Red), where Red and NIR are the spectral reflectance measurements acquired in the red and near-infrared wavelengths, respectively. The photochemical reflectance index (PRI) is calculated as: PRI = (R531 - R570) / (R531 + R570), where R531 and R570 are the reflectance values at the 531 nm and 570 nm wavelengths, and was good at estimating photosynthetic radiation-use efficiency (Peñuelas et al., 1995).

The objectives of this study were to assess the potential of using hyperspectral remote sensing data to identify *G. hirsutum* and *G. barbadense* cultivars in the presence of varying leaf characteristics (pigmentation, pubescence, and glanding) and to determine the spectral wavelengths that were most relevant to the discrimination at canopy level in a greenhouse environment.

Materials and Methods

Experimental Plants

Ten cotton cultivars were grown in pots in two greenhouses. In one greenhouse, five *G. hirsutum* cultivars were grown (group 1). These cultivars included Paymaster Tejas (PMTejas, a cultivated type with normal leaves), Paymaster HS26 (PMHS26, a cultivated type with normal leaves), Stoneville 506 (STV506, a cultivated type with normal leaves), TM-1 (TM1, the genetic standard for *G. hirsutum* with normal leaves), and the cross albescent × Deridder Red (F4, an experimental type with variegated white, green, and pink pigmented leaves). In a second greenhouse, five *G. barbadense* cultivars were grown (group 2). These cultivars included 3-79 (3_79, the genetic standard for *G. barbadense* with normal leaves), Pima S-6 (PIMAS6, a cultivated type with normal leaves), pilose (T1T1, a mutant with soft silvery hair (pubescence) on leaves), red (R1R1, a mutant with dark red pigmented leaves), and glandless (GL3GL3, a mutant lacking the normal conspicuous black glands on leaves). The cultivars presented a range of leaf phenotypes (pigment, pubescence, and glanding characteristics) potentially affecting spectral reflectance measurements.

Three cultivars (PMTejas, PMHS26, and STV506) were planted in pots in the greenhouse during fall 2008. The remaining seven cultivars were "stumped" (cut back, dug up, potted, and placed in the greenhouse) from plants growing in the field during summer 2009. Plants already in the greenhouse were cut back at approximately the same time (mid-August) as stumped plants came into the greenhouse from the field. Reflectance readings were taken at three broadly defined growth stages: flowering, boll development, and open boll. Ideally, it takes approximately 50 days for a boll to "open" after pollination occurs during flowering (Ritchie et al., 2004). Cotton plants are indeterminate and continue to grow and produce flowers until terminated. Readings were taken when more than 50% of the plant was flowering, maturing bolls, or opening bolls to harvest. Even though there was a range of cultivars, including some non-commercial mutant types, all cultivars met the minimum requirement for growth stages when measured. Five plants per cultivar were measured to have adequate replication within cultivars.

Both greenhouses were set up for similar environmental conditions. The experiments were maintained at 27°C/21°C day/night temperature regimes with no supplemental light except for solar light. Automatic fertigation was used to apply fertilizer through a drip irrigation system. Fourteen parts per million of nitrogen (ppm N) from a 15-16-17 (nitrogen-phosphorous-potassium) fertilizer formulation was applied to the plants through the irrigation system. Approximately one-third of a gallon of the fertilizer solution was applied to each pot once a day.

Data Acquisition

All spectral measurements were collected between 13:00 and 14:00 h on cloud-free days to avoid the influence of illumination changes on the spectral responses. Within each greenhouse, the plants were moved to a uniform setting for measurements. The five cotton cultivars in each greenhouse were analyzed separately for spectral characteristics. For each plant, spectra readings were collected from five different upper-layer leaves using a FieldSpec handheld spectroradiometer (Analytical Spectral Devices, Inc., Boulder, Colo.). Table 1 gives the sampling protocol for the two groups of cotton cultivars. The FieldSpec spectroradiometer measures radiation at wavelengths ranging from 325 to 1075 nm with a sampling interval of 1.6 nm and an angular field-of-view of 25°. Since the reflectance property of the crop canopy is affected by the spatial distribution of vegetated and non-vegetated areas, the spectroradiometer was placed at a height of approximately 10 cm with a nadir-looking view above the surfaces of upper layer leaves to reduce the non-vegetated area that the sensor might view. The effects of the orientation of the leaves were ignored. The instrument optimization and white reference measurements were performed prior to each measurement according to Castro-Esau et al. (2006). The white reference was collected with a Spectralon white panel until a straight 100% reflectance line appeared. Spectral reflectance data were exported into a spreadsheet for further analyses.

Data Analysis

Reduction of spectral data dimension and smoothing of the spectral data were performed to allow rapid computer analysis and avoid noise associated with specific bands. The moving average method was used to smooth the original spectrum to reduce the random noise induced by the instrument internal factors, and then the pretreated spectrum was normalized by the maximum reflectance value of each spectrum. The normalized reflectance values were averaged to fifty 10 nm wavebands with an effective working region of 400 to 900 nm.

Table 1. Protocol for sampling two groups of cotton cultivars with a FieldSpec handheld spectroradiometer.

Sampling Date	Cotton Growth Stage	No. of Samples	
		Group 1	Group 2
16 Nov. 2009	Flowering	125	125
16 Dec. 2009	Boll development	125	125
10 Jan. 2010	Open boll	125	125

The final spectral reflectance values at each of the 10 nm wavebands were then analyzed with two techniques for feature extraction: principal component analysis (PCA) and stepwise selection. PCA is a multivariate technique used as a tool for reducing multidimensional data. The variance contained in the original variables was projected onto a smaller number of principal components (PCs), which are linear combinations of those variables. The PCs that explained more than 1% of the variance were selected as the inputs for discriminant analysis. PCA 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 stepwise selection of the STEPDISC procedure in SAS was used to select the wavelengths that were most likely to be associated with the differences in the reflectance data of different cotton cultivars. When given a group of variables, this procedure reduced the data set to those variables that maximized between-group variability while minimizing within-group variability. F-tests were conducted to differentiate between groups with variables that were significant.

After the principal components and wavelengths were selected, their discriminant capability was analyzed using the DISCRIM procedure in SAS. The pooled covariance matrix and prior probability parameters were used to develop the discriminant function. The DISCRIM procedure divided the data into two subsets. One subset was used to develop the 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.

Analysis of variance (ANOVA) tests were performed using the GLM procedure in SAS on the VIs calculated with spectral data to detect significant differences in VIs across cotton cultivars. Duncan's multiple range tests were used for multiple comparisons between the VIs of cultivars. The reflectance values at the 680 nm and 800 nm wavelengths were used to calculate the NDVI (Castro-Esau et al., 2006). The reflectance values at the 530 nm and 570 nm wavelengths were used to calculate the PRI.

Results and Discussion

Normalized Reflectance Spectra

The average normalized reflectance spectra taken on 16 November 2009 are shown in figure 1 for the *G. hirsutum* cotton cultivars (PMTejas, PMHS26, STV506, TM1, and F4) and in figure 2 for the *G. barbadense* cotton cultivars (3_79, PIMAS6, T1T1, R1R1, and GL3GL3). The differences among the spectra of various cultivars could be seen clearly in the visible regions (400-700 nm). The reflectance spectra show light absorption between 400 to 500 nm and 660 to 680 nm, with a peak around 550 nm. Most of these spectra differences were caused by absorption of blue and red light and reflection of green light. The reflectance values of F4 and R1R1 in the green region were substantially lower than others since their leaves were not green. F4 had variegated white, green, and pink pigmented leaves, while R1R1 leaves had dark red pigmentation due to higher levels of anthocyanins. The increased pubescence of T1T1 also caused a notable difference in the reflectance spectra. The higher reflectance values for T1T1 at 680 nm correspond with the higher reflectance values observed for hairy versus hairless leaves as measured in *Campanula elationides* and *Kalanchoe tomentosa* (Holmes and Keiller, 2002).

Feature Extraction

PCA procedures were carried out to reduce the fifty 10 nm average wavelengths into a few principal components. The first three or four principal components (PC1 to PC4) explained more than 98% of the variability for all cotton groups. Figure 3 shows loadings for the first four principal components from PCA for group 1 and 2 sampled on 16 No-

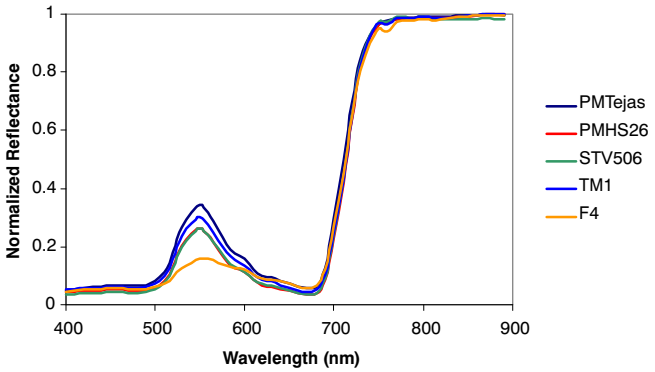

Figure 1. Average normalized reflectance spectra taken on 16 November 2009 of *G. hirsutum* cotton cultivars (group 1): PMTejas, PMHS26, STV506, TM1 and F4.

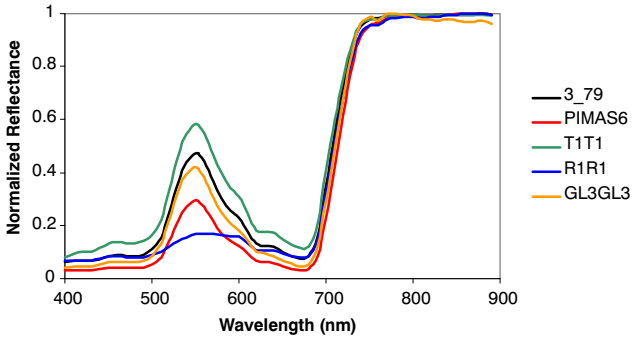

Figure 2. Average normalized reflectance spectra taken on 16 November 2009 of *G. barbadense* cotton cultivars (group 2): 3_79, PIMAS6, T1T1, R1R1 and GL3GL3.

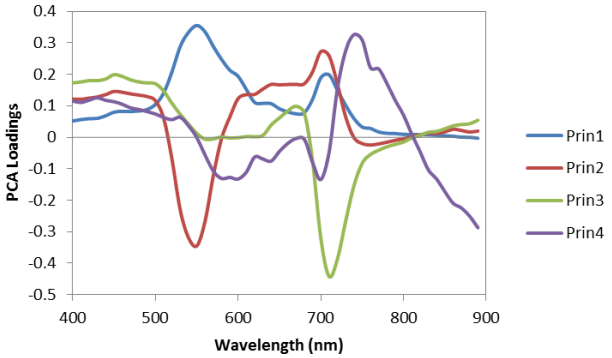

Figure 3. The first four principal component loadings from PCA for groups 1 and 2 sampled on 16 November 2009.

Table 2. Selected wavelengths, listed in order of significance, as determined by the STEPDISC procedure for each classification group and sampling date.

Cotton Group	Sampling Date	Wavelengths (nm)
1	16 November 2009	760, 750, 730, 550, 520, 400, 810, 650, 530, 560
	16 December 2009	810, 770, 780, 830, 760, 550, 580, 530, 430, 720
	10 January 2010	660, 720, 800, 710, 740, 760, 550, 520, 570, 810, 850
2	16 November 2009	870, 550, 560, 760, 750, 770, 810, 530, 880, 520
	16 December 2009	860, 830, 550, 590, 580, 400, 720, 620, 530, 810
	10 January 2010	890, 870, 760, 810, 780, 860, 840, 730, 550, 710, 530, 750
1 and 2	16 November 2009	550, 570, 830, 840, 890, 750, 760, 740, 720, 710
	16 December 2009	830, 860, 550, 580, 760, 880, 800, 890, 770, 780, 500, 570
	10 January 2010	820, 840, 730, 640, 760, 550, 590, 710, 860, 650

vember 2009. PC1 was mostly dominated by larger-magnitude positive loadings around the 550 and 710 nm wavelengths; PC2 had larger-magnitude positive loadings in the red region (600- 700 nm) and larger negative loadings around 550 nm; PC3 was primarily dominated by larger-magnitude positive loadings in the blue region and negative loading around 710 nm; and PC4 had larger-magnitude positive loadings in the NIR region around 740 nm. Thenkabail et al. (2004) reported that the first five PCs provide the highest factor loadings for classification of crops and weeds. Thenkabail et al. (2004) also documented that PC2 was dominated by the red region for crops and weeds, similar to the results observed in the present study.

The STEPDISC procedures were applied to three classification problems: *G. hirsutum* cotton cultivars, *G. barbadense* cotton cultivars, and pooled cultivars. Given 50 wavelengths as variables for each classification problem, the STEPDISC procedure performed a stepwise discriminant analysis to select a subset of wavelengths that contributed most to the discrimination. The selected wavelengths, listed in order of significance as determined using the STEPDISC procedure, are given in table 2. The selected wavelengths for the *G. hirsutum* cotton cultivars, *G. barbadense* cotton cultivars, and pooled cultivars were assessed for their frequency of occurrence. The highest frequency of occurrence was found for 550, 760, and 810 nm for the *G. hirsutum* cultivars; 530, 550, and 810 nm for the *G. barbadense* cultivars; and 550 and 760 nm for the pooled cultivars. The wavelengths found in all data sets covered the green region (520-560 nm), red region (620-650 nm), red-edge region (710-750 nm), and NIR region (760, 770, 800, and 810 nm) of the reflectance spectrum.

Discriminant Analysis

The DISCRIM models were applied to the different numbers of wavelengths observed in each group and sampling date based on their order of entry in the stepwise procedure. A summary of the calibration and cross-validation classifications for a set of principal components by PCA is given in table 3, and a summary for the selected wavelengths from the STEPDISC procedure is shown in table 4. Higher classification accuracy, as determined by lower misclassification rates for cross-validation, was acquired when using the selected wavelengths rather than the principal components. In the case of discriminating the *G. hirsutum* cotton cultivars, the best results were obtained by using 9, 10, and 11 wavelengths at each subsequent sampling date, with an accuracy of 90.4%, 89.6%, and 76.8%, respectively. For the *G. barbadense* cotton cultivars, 7, 10 and 10 wavelengths were used to obtain an accuracy of 100%, 98.4%, and 92.4%, respectively. For the pooled cultivars, 10, 12, and 10 wavelengths were used to obtain an accuracy of 91.6%, 90%, and 74.4%, respectively, at each sampling date.

Table 3. Summary of misclassification matrices obtained from the DISCRIM procedure using the set of principal components from PCA.

Sampling Date	No. of PCs	Explained Variance (%)	Percent Misclassified	
			Calibration	Cross-Validation
Cotton group 1				
16 Nov. 2009	4	99	26.4	35.2
16 Dec. 2009	4	98.5	20	25.6
10 Jan. 2010	4	98.8	27.2	40
Cotton group 2				
16 Nov. 2009	3	99	14.4	18.4
16 Dec. 2009	4	99	2.4	5.6
10 Jan. 2010	4	98.7	21.6	31.2
Cotton groups 1 and 2				
16 Nov. 2009	3	98.6	32.4	40
16 Dec. 2009	4	98.7	14	20.4
10 Jan. 2010	4	98.3	41.2	50.8

Table 4. Summary of misclassification matrices obtained from the DISCRIM procedure using selected wavelengths as determined using the STEPDISC procedure.

Sampling Date	No. of Wavelengths	Percent Misclassified	
		Calibration	Cross-Validation
Cotton group 1			
16 Nov. 2009	9	0	9.6
16 Dec. 2009	10	0	10.4
10 Jan. 2010	11	0	23.2
Cotton group 2			
16 Nov. 2009	7	0	0
16 Dec. 2009	10	0	1.6
10 Jan. 2010	10	4	7.6
Cotton groups 1 and 2			
16 Nov. 2009	10	0	8.4
16 Dec. 2009	12	0	10
10 Jan. 2010	10	1.6	25.6

The best misclassification matrices for cross-validation using the selected wavelengths from the STEPDISC procedure are given in table 5 for the *G. hirsutum* cotton cultivars, *G. barbadense* cotton cultivars, and pooled cultivars. The values in the table provide the number of correctly classified cases (values on the diagonal) and misclassified cases (values above or below the diagonal) for the three classification problems. The three best results are shown, and they were from the data sets taken on 16 November 2009, when the cotton plants were in their flowering stage of growth. These results indicate that hyperspectral radiometry has good potential for discrimination of the *G. hirsutum* and *G. barbadense* cotton cultivars at an early stage of growth.

Vegetation Indices

Cultivars had a significant effect on NDVI and PRI for both cotton species at all growth stages. Table 6 presents the

Table 5. Misclassification matrices of cross-validation data for *G. hirsutum*, *G. barbadense*, and pooled cotton cultivars from reflectance spectra obtained during flowering (16 November 2009).

	From Cultivar	Classified as					Total
		F4	PMHS26	PMTejas	STV506	TM1	
G. hirsutum	F4	25	0	0	0	0	25
	PMHS26	0	21	2	1	1	25
	PMTejas	0	0	25	0	0	25
	STV506	0	0	0	25	0	25
	TM1	0	0	0	0	25	25
	Total	25	21	27	26	26	125
	From Cultivar	Classified as					Total
		3_79	GL3GL3	PIMAS6	R1R1	T1T1	
G. barbadense	3_79	25	0	0	0	0	25
	GL3GL3	0	25	0	0	0	25
	PIMAS6	0	0	25	0	0	25
	R1R1	0	0	0	25	0	25
	T1T1	0	0	0	0	25	25
	Total	25	25	25	25	25	125

	From Cultivar	Classified as									Total
		PMTejas	R1R1	STV506	T1T1	TM1	3_79	F4	GL3GL3	PIMAS6	PMHS26	
Pooled cultivars	PMTejas	24	0	1	0	0	0	0	0	0	0	25
	R1R1	0	25	0	0	0	0	0	0	0	0	25
	STV506	0	0	22	0	3	0	0	0	0	0	25
	T1T1	0	0	0	25	0	0	0	0	0	0	25
	TM1	0	0	1	0	24	0	0	0	0	0	25
	3_79	0	0	0	0	0	25	0	0	0	0	25
	F4	0	0	0	0	0	0	25	0	0	0	25
	GL3GL3	0	0	0	0	0	0	0	25	0	0	25
	PIMAS6	0	0	0	0	0	2	0	0	23	0	25
	PMHS26	2	0	0	0	4	0	0	0	0	19	25
	Total	26	25	24	25	31	27	25	25	23	19	250

Table 6. Means and significant differences from an ANOVA test on two VIs for ten cotton cultivars ($p < 0.05$).[a]

	G. hirsutum			*G. barbadense*		
Sampling Date	Cultivar	NDVI	PRI	Cultivar	NDVI	PRI
16 November 2009	PMTejas	0.877 b	-0.016 b	3_79	0.847 b	-0.006 b
	PMHS26	0.921 ab	-0.032 cd	PIMAS6	0.932 a	-0.017 c
	STV506	0.924 a	-0.021 bc	T1T1	0.785 c	-0.008 b
	TM1	0.9 ab	-0.039 d	R1R1	0.849 b	0.082 a
	F4	0.877 b	0.072 a	GL3GL3	0.9 a	-0.04 d
16 December 2009	PMTejas	0.89 a	-0.045 bc	3_79	0.877 ab	-0.039 b
	PMHS26	0.863 abc	-0.053 c	PIMAS6	0.882 a	-0.035 b
	STV506	0.871 abc	-0.051 bc	T1T1	0.871 ab	-0.038 b
	TM1	0.886 ab	-0.037 b	R1R1	0.873 ab	0.012 a
	F4	0.85 c	0.045 a	GL3GL3	0.854 b	-0.04 b
10 January 2010	PMTejas	0.87 a	-0.039 b	3_79	0.901 a	-0.055 c
	PMHS26	0.89 a	-0.05 b	PIMAS6	0.892 a	-0.04 b
	STV506	0.892 a	-0.04 b	T1T1	0.851 b	-0.045 b
	TM1	0.892 a	-0.05 b	R1R1	0.897 a	-0.025 a
	F4	0.65 b	0.11 a	GL3GL3	0.839 b	-0.04 b

[a] Within a column, means followed by different letters are significantly different at p = 0.05 according to Duncan's t-test.

differences among means using Duncan's multiple range tests for the VIs. Among the *G. hirsutum* cultivars, the cultivar F4 had the lowest NDVI and highest and only positive values for PRI on each sampling date. Healthy plants have a high NDVI value because of their high reflectance of infrared light and relatively low reflectance of red light. The variegated white, green, and pink leaves of the F4 cultivar may be interpreted in the VIs as reduced vigor since healthy plants generally have green leaves. At the flowering stage, there were more significant differences in PRI values among the five cultivars. The PRI index is a measure of photosynthetic efficiency. When photosynthesis is most effective (low light intensities), PRI has a high value, while at high light intensities (excess light), PRI has a low (negative) value (Barton and North, 2001). All *G. hirsutum* cultivars were grown in the same greenhouse; therefore, light intensity was consistent across these cultivars. The high PRI values for cultivar F4 would indicate that this cultivar made the most effective use of available light and had the most photosynthetic activity. At the harvest stage, only the VIs of cultivar F4 were significant-

ly different from the other four cultivars, while the VIs of the other four cultivars showed no differences. The VIs at the flowering stage were generally higher than those at the boll development and the harvest stages.

Considerable leaf variability was observed among the *G. barbadense* cultivars: the leaves of cultivars 3_79 and PIMAS6 had normal green pigment, T1T1 had green pigment with silvery color due to pubescence, R1R1 had red pigmentation, and the leaves of GL3GL3 were normally pigmented but lacking the conspicuous black glands seen on 3_79 and PIMAS6. Having the same normal green pigment leaf phenotype, cultivars 3_79 and PIMAS6 are expected not to differ. However, they do differ in NDVI during flowering and in PRI values during the open boll stage. Similar to the *G. hirsutum* cultivars, most differences among cultivars for NDVI and PRI were seen in the flowering stage. During the flowering and open boll stages, PRI was better able to discriminate among cultivars than NDVI. The red leaves of R1R1 provided the greatest discrimination and the highest PRI values across all three growth stages. The PRI values of cultivar GL3GL3 did not change throughout the growing stages.

CONCLUSIONS

From this research, we can conclude that spectral wavelengths at 550 and 760 nm were most relevant to the discrimination among cotton cultivars of *G. hirsutum* and *G. barbadense* with unique leaf characteristics. Fifty wavelengths were reduced to the first four PCs. The best discrimination accuracy by PCs across sampling dates was 74.4%, 94.4%, and 79.6% for the *G. hirsutum*, *G. barbadense*, and pooled cultivars, respectively. The best discrimination accuracy by a total of 10 to 12 selected wavelengths by stepwise discriminant analysis across sampling dates was 90.4%, 100%, and 91.6% for the *G. hirsutum*, *G. barbadense*, and pooled cultivars, respectively. The results of ANOVA tests on VIs showed that neither NDVI nor PRI could be used effectively to distinguish among all cotton cultivars. These indices were best able to detect differences among cultivars during flowering. PRI could be used to separate cotton cultivar F4 from other cultivars in the *G. hirsutum* group and to distinguish cultivar R1R1 in the *G. barbadense* group during all stages of growth. These results show that hyperspectral radiometry has good potential for discrimination of the *G. hirsutum* and *G. barbadense* cotton cultivars at the early stage of growth.

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