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Spectral reflectance curves to distinguish soybean from common cocklebur (*Xanthium strumarium*) and sicklepod (*Cassia obtusifolia*) grown with varying soil moisture

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Experiments were conducted to examine the use of spectral reflectance curves for discriminating between plant species across moisture levels. Weed species and soybean were grown at three moisture levels, and spectral reflectance data and leaf water potential were collected every other day after the imposition of moisture stress at 8 wk after planting. Moisture stress did not reduce the ability to discriminate between species. As moisture stress increased, it became easier to distinguish between species, regardless of analysis technique. Signature amplitudes of the top five bands, discrete wavelet transforms, and multiple indices were promising analysis techniques. Discriminant models created from data set of 1 yr and validated on additional data sets provided, on average, approximately 80% accurate classification among weeds and crop. This suggests that these models are relatively robust and could potentially be used across environmental conditions in field scenarios.

Nomenclature: Soybean, *Glycine max* (L.) Merr.

Key words: Leaf water potential, spectral reflectance curves, NDVI, RVI, SAVI, DVI, NDVIg, IPVI, MSI.

Producers could save time and money while decreasing the amount of pesticide released into the environment by applying herbicides site specifically. Weeds most often do not grow uniformly across the field but rather grow in aggregated patches (Cardina et al. 1997). To manage weed populations site specifically, fields must be sampled relatively intensively. The degree to which fields must be sampled for site-specific herbicide application to be effective is currently cost- and time prohibitive (Clay et al. 1999). Remote sensing is a tool that can be used to help identify weed infestations. The accuracy with which ground, aerial, and satellite sensors can measure targets in the field is constantly increasing (Thenkabail 2002). For this technology to be valuable in a variety of circumstances and locations, it is necessary to discriminate between weeds and crop under a variety of conditions. The degree to which moisture stress influences our ability to discriminate among weed species and the crop is relatively unknown.

Considerable research has been conducted on the use of remote sensing to monitor moisture content of vegetation (Ceccato et al. 2001; Curran et al. 2001; Danson et al. 1992; Gond et al. 1999; Hardy and Burgan 1999; Hunt and Rock 1989; Moran et al. 1994; Peñuelas et al. 1993; Steinmetz et al. 1990; Unganai and Kogan 1998). Remote sensing has also been used to assess the moisture status of vegetation to predict the likelihood and intensity of forest or rangeland fires (Roberts et al. 1993, 1997). Cohen (1991) used vegetation indices to estimate leaf water potential (LWP) and relative water content. The bands that comprised these indices were the Thematic Mapper (TM) bands. The bands that were most useful in identifying stress were TM5 (1.55 to 1.75 μm) and TM7 (2.08 to 2.35 μm). These bands were composed of broad portions of the electromagnetic spectrum. The indices created from these bands were suitable for use in predicting stress or accumulated effect of moisture deprivation; yet, they were not useful in diagnosing fluctuations in water content of vegetation. Although a majority of the indices published in the literature tend to focus on the visible region of the electromagnetic spectrum, Danson et al. (1992) suggest that the near infrared (NIR) and midinfrared region may also be useful to assess moisture status of vegetation. The particular region of the electromagnetic spectrum from which these portions of data are gathered to create the indices, as well as the bandwidths, will determine the usefulness of the indices created. For instance, Hardy and Burgan (1999) used the Normalized Difference Vegetation Index (NDVI) to assess the moisture status of a grassy site composed of wheatgrass (*Agropyron canium* L.), a shrub site composed of sagebrush (*Artemisia tridentate* Nutt.), and an open forest site composed of Douglas fir (*Pseudotsuga menziesii* Mirb.) and ponderosa pine (*Pinus ponderosa* Douglas ex. Lawson). No significant correlations were found between NDVI and vegetation moisture.

Rouse et al. (1973) and Tucker (1979) were pioneers in using portions of the electromagnetic spectrum in ratios such as NDVI (NIR − red)/(NIR + red) to assess vegetation health and vigor. Because of the tendency for healthy vegetation to absorb red light and reflect energy in the NIR, vigorous plants will have a high NDVI value. Conversely, as plant health declines, so does the ability to absorb red light and reflect NIR; this scenario results in low NDVI values signifying a decrease in plant vigor. A series of indices commonly found in the literature were compiled and used as classifiers (Table 1). Additional indices such as Soil-Adjusted Vegetation Index have been created that address issues such as minimizing soil background interference (Huete 1988). With this concept of tailoring an index to address a particular need, additional Drought Index of Normalized Observations indices (Figure 1; Table 2) were designed to

Table 1. Indices used for assessing vegetative health and status.[a]

Indices	Ratios[b]	References
RVI	(NIR/Red)	Jordan (1969)
NDVI	(NIR − Red)/(NIR + Red)	Rouse et al. (1973), Tucker (1979)
DVI	(NIR − Red)	Lillesand and Kiefer (1987), Richardson and Everitt (1992)
NDVIg	(NIR − Green)/(NIR + Green)	Gitelson et al. (1996)
IPVI	NIR/(NIR + Red)	Crippen (1990)
MSI	(TM5/TM4)	Hunt and Rock (1989)

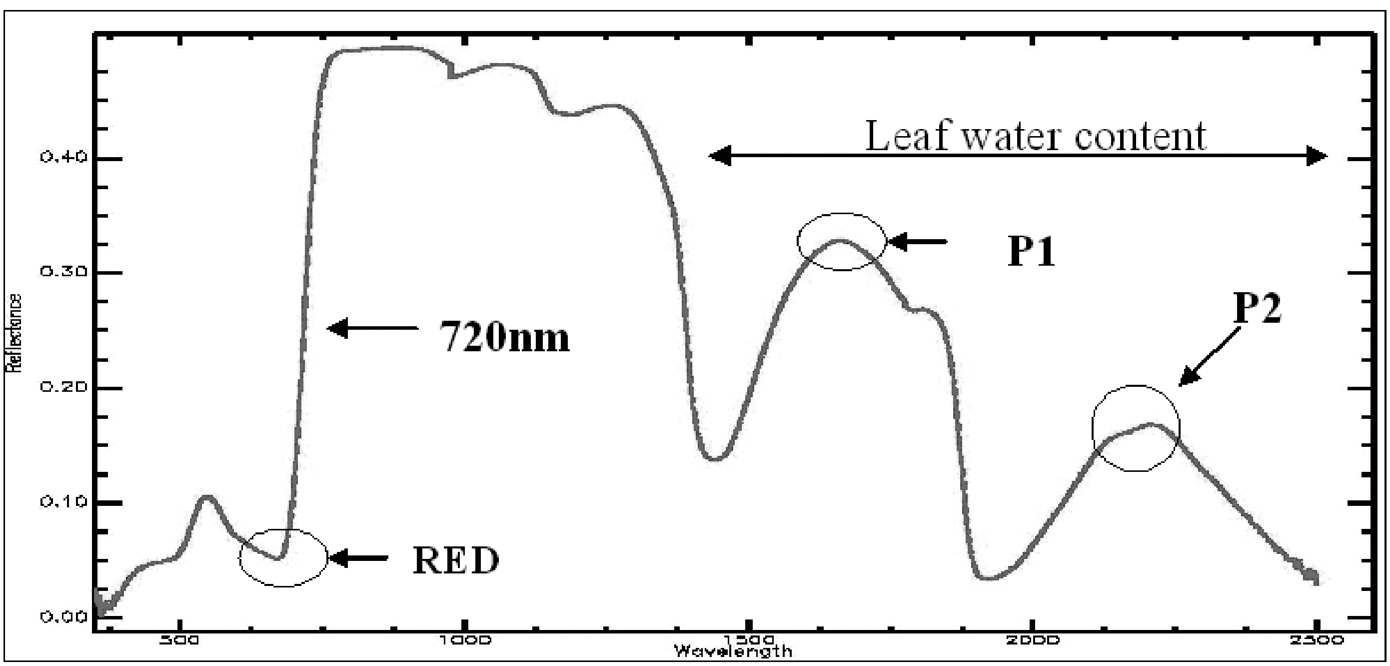
[a] Abbreviations: DVI, Difference Vegetation Index; IPVI, Infrared Percentage Vegetation Index; MSI, Moisture Stress Index; NDVI, Normalized Difference Vegetation Index; NDVIg, NDVI green; RVI, Ratio Vegetation Index; TM, Thematic Mapper.

[b] Green, 545 to 555 nm; red, 670 to 680 nm; NIR, 835 to 845 nm; TM4, 760 to 900 nm; and TM5, 1,550 to 1,750 nm.

maximize differences apparent in specific regions of the electromagnetic spectrum between moisture-stressed treatments and well watered controls. Other studies have also suggested that the short-wave infrared (1,400 to 2,500 nm) is largely influenced by plant water status (Gausman 1985; Tucker 1980).

Not only is the type of vegetation index chosen to evaluate the data important, the selection of leaves and the differences in maturity among those leaves is also significant (Patakas and Noitsakis 2001). Allen et al. (1998) suggest that environmental factors other than wind and temperature may contribute to the leaf water status of the plant. For example, elevated CO_2 causes stomatal conductance decreases, thereby increasing overall LWP of soybean. Peñuelas et al. (1993) noted that spectral signals signifying drought stress were more evident at the canopy level than at the leaf level. The highest correlation coefficients among the water status indices were observed in the species that lost cell wall elasticity in response to drought stress, suggesting that leaf architecture and structural effects caused by the canopy orientation may strongly influence ability to detect moisture status.

Not only will remote sensing be used to distinguish between species within a constant moisture level but also will be used across a range of moisture conditions in fields with variable elevation and soil textures. There is spatial variability with respect to moisture status within a field, as well as temporal variability. A rainfall event could drastically change the moisture status within a field, as could irrigation. If remote sensing can be used to distinguish between weeds and crops across a variety of moisture levels, this could be an important first step in demonstrating the usefulness of remote sensing in weed discrimination across environmental conditions.



[a]P1 = Peak 1 = Avg.(1631-1641 nm), P2 = Peak 2 = Avg.(2215-2225 nm),

RED = Avg.(670-680 nm), 720 = 720 nm.

Figure 1. Drought indices of normalized observations were compiled from multiple regions[a] of the electromagnetic spectrum including drought-sensitive areas between 1,500 and 2,500 nm.

TABLE 2. Drought indices of normalized observations (DINO) composed of drought sensitive regions of the electromagnetic spectrum.

Indices	Portions of the spectrum[a]
DINO1	(P1 − RED)/(P1 + RED)
DINO2	(P2 − RED)/(P2 + RED)
DINO3	(P1 + P2)/RED
DINO4	$(P1/RED)^2$
DINO5	$(P1 + P2)^2/RED$
DINO6	$((P1 + P2)^2 - 720)/((P1 + P2)^2 + 720)$
DINO7	$(P1 + P2)^2/720$
DINO8	$(10 \times P2)^2/720$
DINO9	$((P2)^2 - 720)/((P2)^2 + 720)$
DINO10	$((5 \times P2)^2 - 720)/((5 \times P2)^2 + 720)$
DINO11	P2
DINO12	(P2 − 720)/(P2 + 720)

[a] Abbreviations: P1, Peak 1 = average (1,631 to 1,641 nm); P2, Peak 2 = average (2,215 to 2,225 nm); RED, average (670 to 680 nm); 720, 720 nm.

There has yet to be any research focusing on the ability to discriminate between weeds and crop across moisture levels. This is an important and very applied question that should be addressed so that remote sensing technologies may be used in field applications to successfully discriminate between weeds and crops under a variety of environmental conditions. The objective of this research was to determine whether spectral reflectance curves could be used to distinguish between plant species under a variety of moisture levels.

Materials and Methods

Plant Culture

This research was conducted during the summers of 2000 and 2001, outdoors at the R. Rodney Foil Plant Science Research Center at Mississippi State, MS. The experiment was conducted in a randomized complete block design with a 3 by 3 factorial arrangement of treatments, with species and moisture level as factors. There were 11 rows of 12-L pots. The 1st and 11th rows were border rows. The nine remaining rows consisted of 17 pots per row. Pots on either end of a row were also border pots. The remaining 15 pots per row consisted of 5 pots each of the following: common cocklebur (*Xanthium strumarium* L.), sicklepod (*Cassia obtusifolia* L.), and soybean (cultivar 'Hutcheson'). All species were grown in masonry sand-filled 12-L pots. All species were sown in excess and thinned to two plants per pot. Planting date in both years was mid-July. Throughout the first 8 wk, plants were grown under ideal nutrient and moisture conditions. Plants were fertilized and irrigated simultaneously with a computer-regulated drip-irrigation system. The nutrient medium consisted of half-strength Hoagland's solution (Hoagland and Arnon 1950).

Moisture Treatments

After the eighth week, moisture stress was induced by decreasing the time, and subsequently the amount, that plants were watered. There were three moisture regimes. The plants receiving no moisture stress (moisture level III, 100%) were watered three times daily for a total of 45 min and 2.25 L. The plants in the second water-stress treatment (moisture level II, 60%) were watered a total of 27 min and 1.35 L daily. The plants in the first water-stress treatment (moisture level I, 40%) were watered a total of 18 min and 0.9 L daily. The moisture treatments were selected on the basis of on a preliminary study with soybean that resulted in midday LWPs in the following three ranges: − 0.9 to − 1.5 MPa for moisture level III, − 1.5 to − 2.0 MPa for moisture level II, and more than − 2.0 MPa for moisture level I (K. R. Reddy, unpublished data).

Spectral Data Acquisition

Spectral reflectance data were generated at approximately 2-d intervals from September 10, 2000, 1 d after stress (DAS), through October 2, 2000. Spectral reflectance curves and LWP data were generated for an individual leaf from three plants of each species (three in 2000 and two in 2001) per moisture level (three) per replication (three). In 2000, there were 81 separate samples per given sampling date; in 2001, there were 54 samples per sampling date. Data from 2000 at 7 DAS is absent from the analysis because a malfunction in the spectroradiometer resulted in unusable data. In 2001, data were collected September 20, 1 DAS, through September 30, 10 DAS. Soybean data were not collected in 2001 because of an infestation of a downy mildew fungus [*Peronospora manshurica* (Naum.) Syd. ex. Gaum.]. Growth of this fungus was enhanced by particularly wet growing conditions in 2001. The fungus was identified, and an application of chlorothalonil (4.8 kg ai ha^{-1}) was made in an effort to control it; however, its lifecycle had already progressed to a point at which small chlorotic lesions were present on the soybean leaves.

Reflectance data were generated between the hours of 11:00 A.M. and 1:00 P.M. at 2-d intervals. Data were generated from individual leaves. Individual leaves were chosen so that canopy, leaf angle, and background effects from soil would be negated. Leaves were specifically chosen from similar maturity levels across species to control differences caused by leaf age or maturity. For soybean, the second and third unfurled leaves from the top of the plant were measured. For common cocklebur and sicklepod, the third and fourth unfurled leaves from the top of the plant were measured.

Spectral reflectance data were collected with a hand-held, portable spectroradiometer.[1] An active light source (tungsten filament) was used to minimize the variability inherent with the use of a passive light source. A passive light source such as sunlight could be influenced by time of day and environmental conditions such as clouds or haze. One measurement was taken per leaf using a 25° bare-fiber field-of-view fiber optic cable. The reflectance of individual leaves, or leaflets in the case of sicklepod and soybean, was recorded with the leaf positioned on a flat, foam, black background (Figure 2). The bare-fiber sensor was connected within the active light source unit such that the sensor was positioned directly above the leaf. A black circular aperture restricted the area that the sensor could measure to a diameter of approximately 3 cm. This circular, 3-cm window was placed on the upper surface, directly in the center of the common cocklebur leaf, the bottom-center of the middle leaf of the soybean leaflet, and the middle of the top-most leaf of the sicklepod leaflet. A black background positioned directly be-

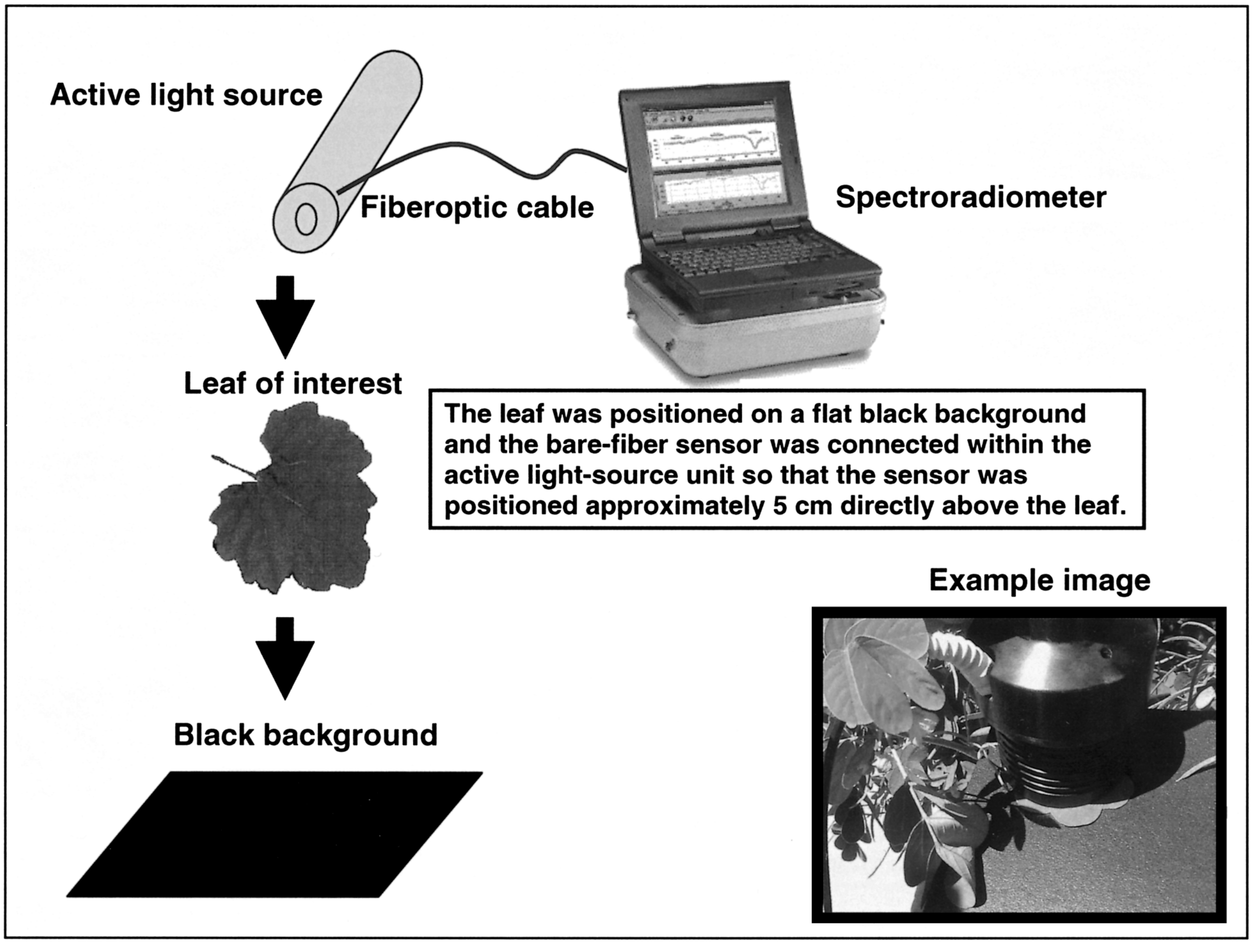


FIGURE 2. Data collection used an active light source for measuring individual leaves positioned on a black background.

neath the leaf was used to eliminate background effects. Once reflectance of the leaf was measured, this leaf was removed from the plant and the LWP measurements were measured with a pressure chamber.[2] Leaf area was also recorded with a leaf area meter[3] on several sampling dates throughout the experiment. Green weight and oven-dry weight were both recorded, and nutrient analyses were also performed at the beginning (September 10), middle (September 17), and end (October 2) of the 2000 experiment.

These spectral reflectance measurements were collected in the spectral range of 350 to 2,500 nm. This resulted in 2,151 individual spectral bands for each spectral reflectance curve, with a bandwidth of 1.4 nm between 350 and 1,000 nm and 1.0 nm between 1,050 and 2,500 nm. Spectral responses potentially suggesting moisture stress were analyzed and pertinent features were extracted using indices, signature amplitudes (SA), and wavelet transforms.

Spectral Data Analysis

Spectral reflectance data were analyzed with SA, discrete wavelet transforms (DWT) (both with and without linear discriminant analysis [LDA]), and indices to determine the utility of these analysis techniques for discriminating between species grown at no moisture stress (100% moisture), moderate moisture stress (60% moisture), and high moisture stress (40% moisture).

Nutrient analyses were performed three times: early (September 9 to 10), middle (September 17), and late (October 2) throughout the summer of 2000. Across species, none of the nutrient analyses were found to be positively or negatively correlated beyond 0.62 with LWP (data not shown).

SA analysis uses a subset of the spectral bands as features. Because 2,151 reflectance values are available to be used as classification features, it is computationally efficient to select a subset of bands (top five bands) on the basis of discriminant capability. Receiver operator characteristics (ROC) analysis was used to determine the efficacy of each band as a potential classification feature. ROC analysis used in this study assumes that the two classes' features have Gaussian distributions. The area under the ROC curve ranges from 0.5 to 1.0, with 0.5 representing features not useful in classification (exact overlap of the two classes' distribution curves) and 1.0 corresponding to ideal classification features (no overlap between distribution curves) (Hanley and McNeil 1982). The second of these three techniques included extracting DWT from the hyperspectral response data and using these as classification features. Recently, the energies of the DWT coefficients have been used as classification features (Huang et al. 2001). However, in this study, classification features are a subset of the DWT coefficients.

The area under the ROC curve was used as a design parameter for choosing a subset of spectral bands to use as classification features. The reflectance values for the top five bands (largest area under the ROC curve) of the original

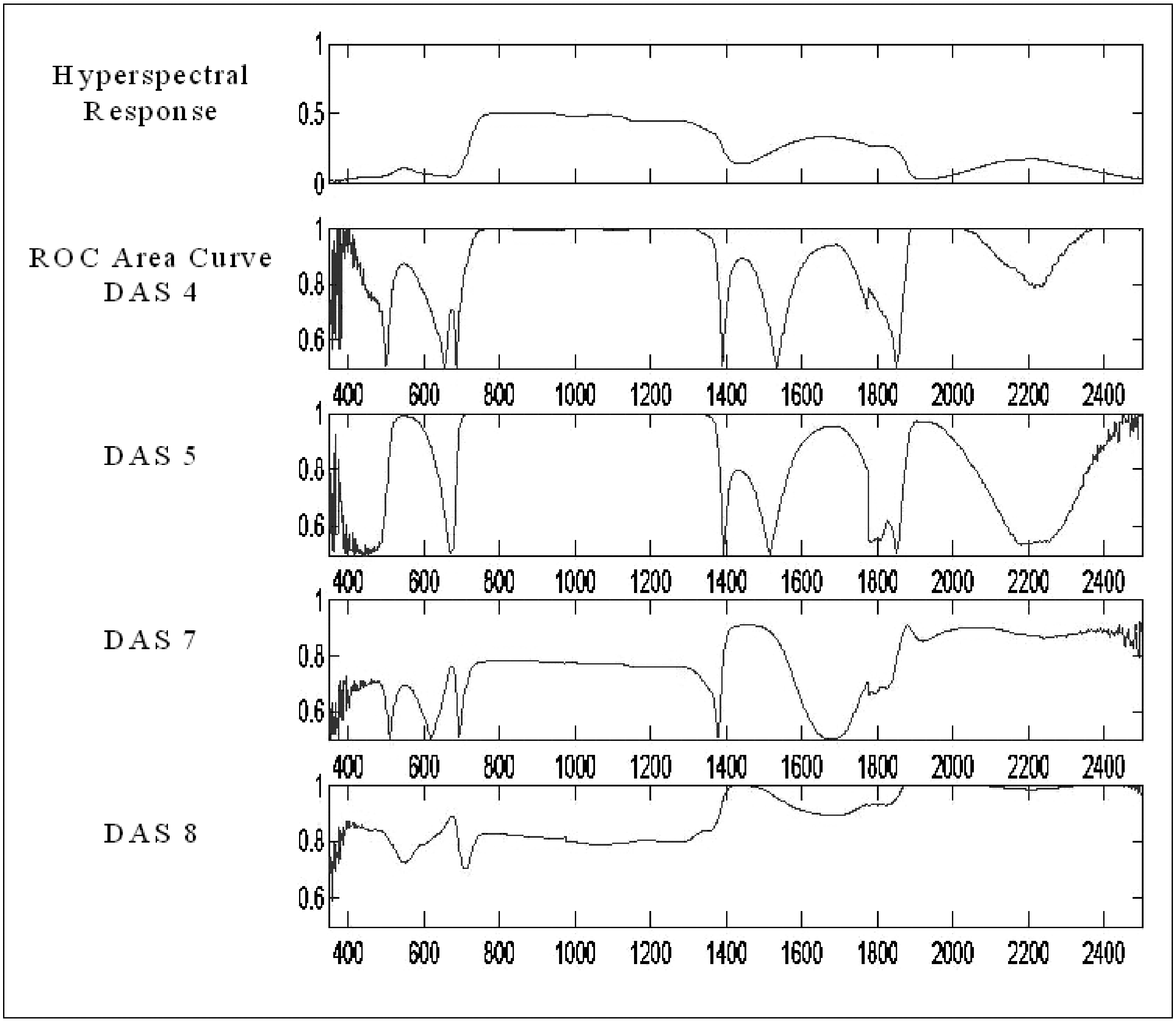


FIGURE 3. Examples of a hyperspectral vegetation response and receiver operator characteristics (ROC) curve analysis. ROC curve analysis indicates the regions of the hyperspectral response that are the best (values approaching one) for discriminating treatments. Hyperspectral data were used to generate ROC curves to discriminate between moderate- and no-stress treatments at 4, 5, 7, and 8 d after the imposition of moisture stress.

data set of 2,151 bands were used as features. The extracted feature for each spectral response is a 1- by 5-vector. This technique was a univariate analysis technique so that only one band is considered at a time as a potential feature. This method was used because of its relative simplicity.

LDA was used to increase classification accuracy. LDA increases the class separability by linearly combining the available features to form an optimum single scalar value (Duda et al. 2001). Therefore, the original 1- by 5-feature vector is eventually reduced to a 1- by 1-feature vector. Finally, the 1- by 1-feature vector was input into a maximum-likelihood classifier to determine the appropriate classification. It is important to note that the ROC analysis, the LDA analysis, and the maximum-likelihood decision boundaries require training data. To fully use all the experimental data collected in this study, the classification system was trained and tested using cross-validation analysis.

Figure 3 demonstrates a soybean hyperspectral vegetation response, as well as the area under the ROC curve as a function of the spectral band. The two classes used to generate these ROC curve analyses were soybean and common cocklebur grown at high moisture stress.

The second type of feature investigated in this study was based on the DWT of the hyperspectral curve. The DWT coefficients were computed for a 10-level wavelet decomposition using the Haar function as the mother wavelet. The DWT decomposes a signal into a number of detailed coefficients and approximation coefficients, depending on the desired level of decomposition (Graps 1995). Multiple mother wavelets and wavelet bases are available for use in decompositions and may be selected accordingly depending on the application (Burrus et al. 1998; Koger 2001; Leon 2001). The Haar wavelet was a good choice for image processing because of its simplicity and fast computational algorithm.

The DWT coefficients obtained from the Haar decom-

Table 3. Signature amplitude 2000 classification accuracies between soybean and weed species across moisture levels using maximum likelihood with ROC[a] curve analysis.

Moisture[b]	DAS[c]	Soybean vs. common cocklebur: Soybean	Common cocklebur	Overall	Soybean vs. sicklepod: Soybean	Sicklepod	Overall
		%					
HS	1	100	100	100	100	100	100
	3	100	100	100	100	89	94
	5	88	89	88	100	100	100
	7	89	100	94	100	100	100
	8	100	100	100	89	100	94
MS	1	100	100	100	100	100	100
	3	100	100	100	100	100	100
	5	88	89	88	100	89	94
	7	100	89	94	100	100	100
	8	88	89	88	100	89	94
NS	1	78	78	78	78	50	65
	3	100	100	100	100	89	94
	5	100	78	88	100	89	94
	7	100	100	100	100	78	88
	8	100	89	94	89	89	89

[a] Abbreviation: ROC, receiver operator characteristics.
[b] Moisture: HS, high stress (40% moisture); MS, moderate stress (60% moisture); NS, no stress (100% moisture).
[c] Abbreviation: DAS, days after stress, number of days after the imposition of moisture stress.

position were then subjected to ROC analysis, and five coefficients with the largest area under the ROC curve were chosen. LDA was then applied to form the optimum scalar feature. This scalar was then input into a maximum-likelihood classifier. Cross-validation was used for the system training and testing.

The third analysis technique was indices that were used as features in traditional statistical classification procedures. These analysis procedures were conducted with stepwise discriminant analysis procedure[4] using cross-validation (leave-one-out testing) in all instances.

Results and Discussion

Tables 3 and 4 present classification data using both SA and DWT across moisture levels in 2000. These data were collected 1 through 8 DAS. In 2000, SA, DWT, and indices were all effective tools to discriminate between species across all moisture levels, providing better than 80% discrimination between weeds and soybean, regardless of moisture level (Tables 3–5). In 2000 and 2001, as the moisture stress level increased from no stress to high stress, classification accuracies with indices combinations also increased from an av-

Table 4. Discrete wavelet transform 2000 classification accuracies between soybean and weed species across moisture levels using maximum likelihood with ROC[a] curve analysis.

Moisture[b]	DAS[c]	Soybean vs. common cocklebur: Soybean	Common cocklebur	Overall	Soybean vs. sicklepod: Soybean	Sicklepod	Overall
		%					
HS	1	89	78	83	100	89	94
	3	89	89	89	89	89	89
	5	100	89	94	75	78	77
	7	100	100	100	89	89	89
	8	100	100	100	89	100	94
MS	1	100	100	100	100	100	100
	3	89	89	89	78	67	72
	5	100	100	100	100	89	94
	7	89	78	83	100	89	94
	8	100	78	88	100	100	100
NS	1	89	100	94	78	63	71
	3	100	100	100	100	89	94
	5	75	22	47	75	89	82
	7	100	100	100	100	100	100
	8	100	89	94	78	89	83

[a] Abbreviation: ROC, receiver operator characteristics.
[b] Moisture: HS, high stress (40% moisture); MS, moderate stress (60% moisture); NS, no stress (100% moisture).
[c] Abbreviation: DAS, days after stress, number of days after the imposition of moisture stress.

TABLE 5. Species by species comparison of classification accuracies in 2000 and 2001 using combinations of indices.

Year	Moisture[a]	Species		
		%		
		Sicklepod	Soybean	Overall
2000	HS	99	98	98
	MS	97	99	98
	NS	93	97	95
2001	HS	—	—	—
	MS	—	—	—
	NS	—	—	—
		Common cocklebur	Soybean	Overall
2000	HS	92	89	91
	MS	94	89	92
	NS	96	94	95
2001	HS	—	—	—
	MS	—	—	—
	NS	—	—	—
		Common cocklebur	Sicklepod	Overall
2000	HS	90	93	91
	MS	87	84	86
	NS	89	86	87
2001	HS	98	89	93
	MS	100	100	100
	NS	100	100	100

[a] Moisture: HS, high stress (40% moisture); MS, moderate stress (60% moisture); NS, no stress (100% moisture).

TABLE 6. Species comparison within moisture levels using data pooled across 2000 and 2001 with a linear discriminant function created from multiple indices.

Moisture level	Species		
	%		
	Soybean	Common cocklebur	Overall
HS[a]	89	93	94
MS	96	93	95
NS	94	98	96
	Soybean	Sicklepod	Overall
HS	100	97	99
MS	99	96	97
NS	95	94	95
	Common cocklebur	Sicklepod	Overall
HS	94	92	93
MS	92	90	91
NS	94	89	91

[a] Moisture: HS, high stress (40% moisture); MS, moderate stress (60% moisture); NS, no stress (100% moisture).

erage of 82% across species to 90% or greater in all instances except one (Table 5). Similar trends were observed in the SA and DWT analyses. Classification accuracy also tended to increase with increasing moisture stress. SA provided more classification consistency than DWT by correctly discriminating common cocklebur from soybean 100% on over half of the sample dates. Sicklepod was discriminated correctly from soybean 100% of the time, twice as frequently with SA compared with DWT. In 2000 with the high-stress treatment, SA correctly discriminated common cocklebur from soybean with 100% accuracy on three of the five sample dates, with an overall accuracy of 96% across all sample dates (Table 3). Accuracy was still relatively high (92%) for the common cocklebur vs. soybean with no-stress treatment (92%). Similar trends were observed when SA was used to discriminate between sicklepod and soybean. In the 2000 high-stressed treatment, SA also correctly discriminated sicklepod from soybean with 100% accuracy on three of the five sample dates, with an overall accuracy of 99%. For the sicklepod vs. soybean with no stress, there were no instances that species were discriminated 100% of the time, but overall accuracy was 86% across all sample dates. Because SA produced consistent data in 2000, and compared with DWT they are computationally less demanding with respect to analysis and processing, it was the method of choice for 2001 analysis. In 2001, virtually all the species' discrimination accuracies were at least 89% using SA (data not shown), regardless of moisture level or analysis technique.

To test the robustness or versatility of the discriminant functions generated from indices, a model developed from the 2000 data set was tested on a second data set (2001) with a PROC DISCRIM[4] procedure. Using the model generated from the 2000 data, species classification accuracies for the 2001 data were 98% overall, averaged across moisture levels. Classification accuracies declined to 60% when the 2001 data were used similarly to build a model to classify the 2000 data. The decrease in classification accuracies was caused by the misclassification of sicklepod as common cocklebur. This phenomenon occurred more frequently than the opposite scenario, common cocklebur misclassified as sicklepod. The misclassification of sicklepod as common cocklebur was influenced by moisture. The highest overall classification accuracy using the 2001 model to test the 2000 data was 68% and occurred in the high-stress treatment. Overall classification accuracies in the moderate- and no-stress treatments were considerably lower, at 52 and 60%, respectively.

Discriminant functions developed from the 2000 data applied to the 2001 data and from the 2001 data applied to the 2000 data discriminated species correctly approximately 80%, on average (data not shown). It is desirable to pool these two data sets and draw potentially broader inferences concerning the robustness of the discriminant capabilities of indices combinations. Using one large data set composed of all readings from 2000 and 2001, both weed species were individually compared with soybean (soybean vs. common cocklebur and soybean vs. sicklepod) and the two weed species (common cocklebur vs. sicklepod) were compared with each other (Table 6). Overall discriminant capabilities were 89% or better in all instances, regardless of moisture level (Table 6). The discriminant capabilities of the model were then tested within moisture levels. All three species were included in these analyses. In this instance, soybean was correctly discriminated from weed species 83% or better, regardless of moisture level (Table 7). Finally, and perhaps what could be considered most similar to what might be seen in the field, data were analyzed across moisture levels and species. Again, soybean was correctly discriminated from the weed species 89% (Table 7). These data suggest that moisture level, at least at the leaf level, does not decrease the ability of remote sensing to discriminate between weeds and soybean. The potential for discriminating weeds from soybean with hyperspectral data is promising and appears not to be diminished by changes in reflectance caused by

Table 7. Comparison of multiple species both within moisture levels and across moisture levels using pooled data from 2000 and 2001 with linear discriminant functions created from multiple indices.

Moisture[a]	Soybean	Common cocklebur	Sicklepod	Overall
	%			
	Within moisture level			
HS	94	86	91	91
MS	92	88	89	91
NS	83	90	85	86
	Across moisture levels			
All	89	90	89	89

[a] Moisture: HS, high stress (40% moisture); MS, moderate stress (60% moisture); NS, no stress (100% moisture).

varying leaf moisture levels. These data and conclusions concerning leaf reflectance set the groundwork for future research that should investigate the degree to which canopy architecture and wilting affect reflectance. They also demonstrate the promise for using remote sensing to correctly discriminate patches of weeds so that they may be treated site specifically.

In summary, moisture stress does not decrease the ability to discriminate between species. As moisture stress increased, it became easier to distinguish between species, regardless of analysis technique. SA (top five band) analysis was a promising technique because of its accuracy and computational simplicity. These data, when pooled and analyzed across years, suggest that moisture level, at least at the leaf level, does not decrease the ability of remote sensing to discriminate between weeds and soybean. The potential for discriminating weeds from soybean with hyperspectral data is promising and appears not to be diminished by changes in reflectance caused by varying leaf moisture status.

These data analysis techniques should now be applied to field data. From an applied perspective, regardless of analysis technique, soybean was correctly discriminated from weed species better than 85%, on average. It will be interesting to see how well these analysis techniques perform when applied to field data. Possible limitations in the application of these techniques would include pixel mixing, background interference from soil, variability in the intensity of sunlight, and canopy architecture effects. Limitations to this end would include early-season measurements in which vegetation (both weeds and soybean) covers only a small portion of the ground. It will be challenging to discriminate between weeds and soybean if only a small percentage of the image comprises vegetation. Soil will contribute substantially to the image, and the variability within soil types will become a component of the image-interpretation process that must be addressed. With the ever increasing spatial and spectral resolution and the computationally intense algorithms to discriminate pixel classes, there exists the potential for these analysis techniques to be beneficial to the producer. One of the promising findings from this research is that leaf-level reflectance can be used to separate soybean from weed species, regardless of moisture status of leaves.

Sources of Materials

[1] ASD FieldSpec Pro FR, Analytical Spectral Devices Inc., 5335 Sterling Drive, Boulder, CO 80301-2344.

[2] 3000 Plant Water Status Console, Soilmoisture Equipment, 801 South Kellogg Avenue, Goleta, CA 93117.

[3] LI-3100 Laboratory Area Meter, LI-COR Biosciences, 4421 Superior Street, Lincoln, NE 68504.

[4] SAS, SAS Institute Inc., SAS Campus Drive, Cary, NC 27513.

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