Weed Science, 52:788–796. 2004

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

W. Brien Henry
Corresponding author. USDA-ARS, 40335 County Road GG, Central Great Plains Research Station, Akron, CO 80720; brien.henry@ars.usda.gov

David R. Shaw
Kambham R. Reddy
Department of Plant and Soil Sciences, Mississippi State University, Mississippi State, MS 39762

Lori M. Bruce
Hrishikesh D. Tamhankar
Department of Electrical and Computer Engineering, Mississippi State University, Mississippi State, MS 39762

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]

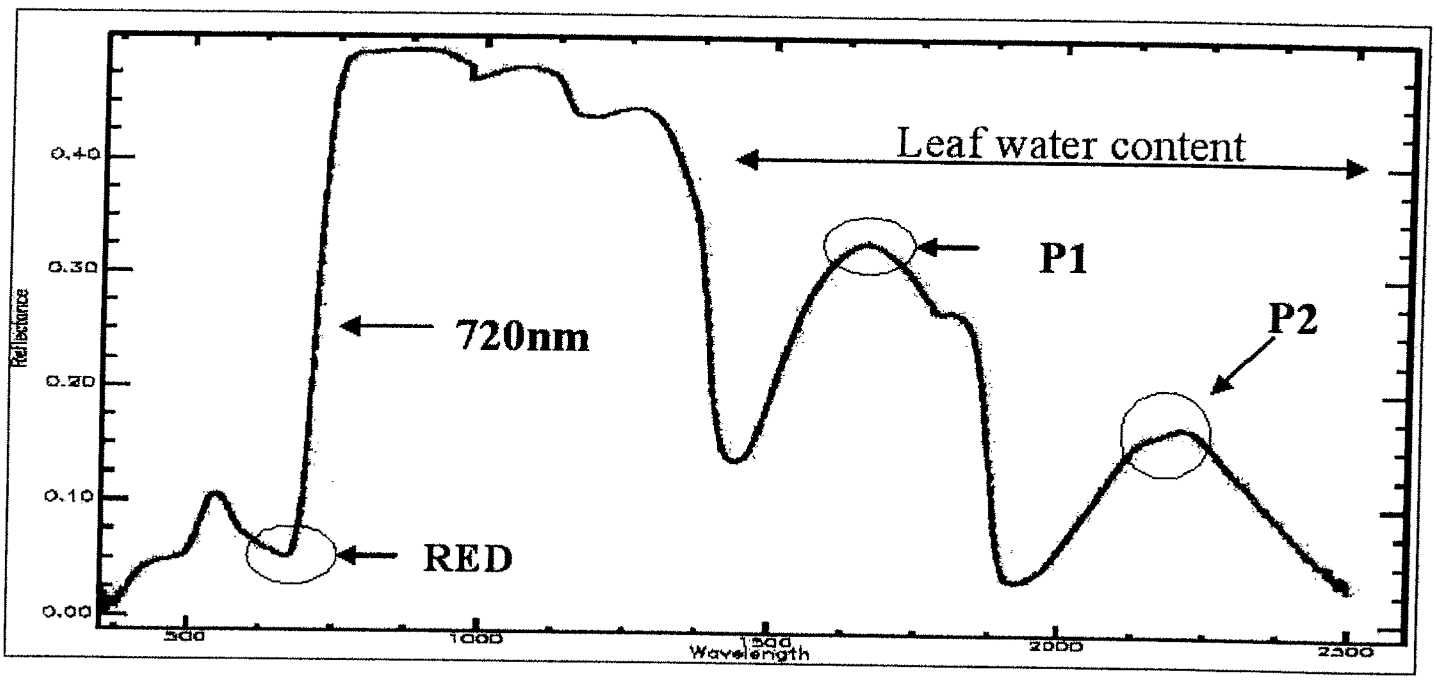
Indices	Ratios[b]	References
RVI	(NIR/Red)	Jordan (1969)
NDVI	(NIR − Red)/(NIR + Red)	Rouse et al. (1973), Tucker (1979)
DVI	(NIR − Red)	Lillesand and Kiefer (1987), Richardson and Everitt (1992)
NDVIg	(NIR − Green)/(NIR + Green)	Gitelson et al. (1996)
IPVI	NIR/(NIR + Red)	Crippen (1990)
MSI	(TM5/TM4)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

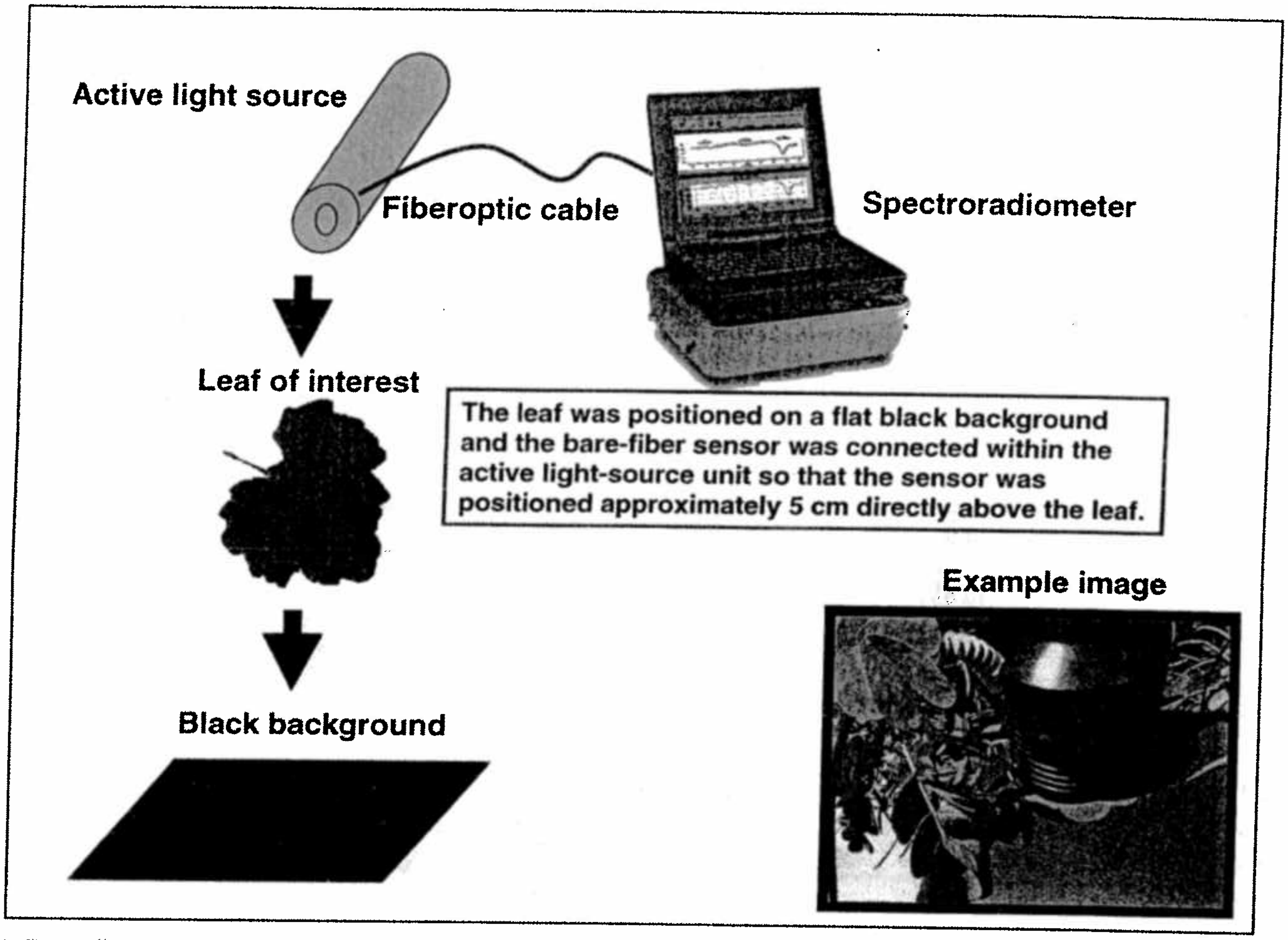


FIGURE 2. Data collection used an active light source for measuring individual leaves positioned on a black background.

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

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 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.

Literature Cited

Allen, L. H. Jr., R. R. Valle, J. W. Jones, and P. H. Jones. 1998. Soybean leaf water potential responses to carbon dioxide and drought. Agron. J. 90:375–383.

Burrus, S., R. Gopinath, and H. Guo. 1998. Introduction to Wavelets and Wavelet Transforms: A Primer. 1st ed. Upper Saddle River, New Jersey: Prentice-Hall. Pp. 6–7.

Cardina, J., G. A. Johnson, and D. H. Sparrow. 1997. The nature and consequences of weed spatial distribution. Weed Sci. 45:364–373.

Ceccato, P., S. Flasse, S. Tarantola, S. Jacquemoud, and J. M. Gregoire. 2001. Detecting vegetation leaf water content using reflectance in the optical domain. Remote Sens. Environ. 77:22–33.

Clay, S. A., G. J. Lems, D. E. Clay, F. Forcella, M. M. Ellsbury, and C. G. Carlson. 1999. Sampling weed spatial variability on a fieldwide scale. Weed Sci. 47:674–681.

Cohen, W. B. 1991. Response of vegetation indices to changes in tree measures of leaf water stress. Photogram. Eng. Remote Sens. 57:195–202.

Crippen, R. E. 1990. Calculating the vegetation index faster. Remote Sens. Environ. 34:71–73.

Curran, P. J., J. L. Dungan, and D. L. Peterson. 2001. Estimating the foliar biochemical concentration of leaves with reflectance spectrometry testing the Kokaly and Clark methodologies. Remote Sens. Environ. 76: 349–359.

Danson, F. M., M. D. Steven, T. J. Malthus, and J. A. Clark. 1992. High-spectral resolution data for determining leaf water content. Int. J. Remote Sens. 13:461–470.

Duda, R. O., P. E. Hart, and D. G. Stark. 2001. Pattern Classification. 2nd ed. New York: J. Wiley. Pp. 117–124.

Gausman, H. W. 1985. Plant Leaf Optical Properties in Visible and Near-Infrared Light. Graduate Studies. No. 29. Texas Technical University, Lubbock, TX: Texas Tech. Press. Pp. 1–78.

Gitelson, A., Y. Kaufman, and M. Merzlyak. 1996. Use of a green channel in remote sensing of global vegetation from EOS-MODIS. Remote Sens. Environ. 58:289–298.

Gond, V., D.G.G. DePury, F. Veroustraete, and R. Ceulemans. 1999. Seasonal variations in leaf area index, leaf chlorophyll, and water content; scaling-up to estimate fAPAR and carbon balance in a multiplayer, multispecies temperate forest. Tree Physiol. 19:673–679.

Graps, A. 1995. An introduction to wavelets. IEEE Comput. Sci. Eng. 2: 1–18.

Hanley, J. and B. McNeil. 1982. The meaning and use of the area under a receiver operating characteristics (ROC) curve. Diagn. Radiol. 143: 29–36.

Hardy, C. C. and R. E. Burgan. 1999. Evaluation of NDVI for monitoring live moisture in three vegetation types of the western U.S. Photogram. Eng. Remote Sens. 65:603–610.

Hoagland, D. H. and D. I. Arnon. 1950. The water-culture method for growing plants without soil. Calif Agric. Exp. Stn. Cir. 347:1–32.

Huang, Y., L. M. Bruce, J. Byrd, and B. Mask. 2001. Using wavelet transforms of hyperspectral reflectance curves for automated monitoring of *Imperata cylindrica* (cogongrass). Pages 2244–2246 *in* Proceedings of the IEEE Geoscience and Remote Sensing Symposium. Sydney, Australia. New York: IEEE.

Huete, A. R. 1988. A soil-adjusted vegetation index (SAVI). Remote Sens. Environ. 25:295–309.

Hunt, E. R. Jr. and B. N. Rock. 1989. Detection of changes in leaf water content using near- and middle-infrared reflectances. Remote Sens. Environ. 30:43–54.

Jordan, C. F. 1969. Derivation of leaf area index from quality of light on the forest floor. Ecol. 50:663–666.

Koger, C. H. 2001. Remote Sensing Weeds, Cover Crop Residue, and Tillage Practices in Soybean. Ph.D. dissertation. Mississippi State University, Mississippi State, MS. Pp. 120–140.

Leon, C. T. 2001. Crop Monitoring Utilizing Remote Sensing, Soil Parameters, and GPS Technologies. M.S. thesis. Mississippi State University, Mississippi State, MS. Pp. 27–84.