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Remote Sensing to Distinguish Soybean from Weeds After Herbicide Application[1]

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Abstract: Two experiments, one focusing on preemergence (PRE) herbicides and the other on postemergence (POST) herbicides, were conducted and repeated in time to examine the utility of hyperspectral remote sensing data for discriminating common cocklebur, hemp sesbania, pitted morningglory, sicklepod, and soybean after PRE and POST herbicide application. Discriminant models were created from combinations of multiple indices. The model created from the second experimental run's data set and validated on the first experimental run's data provided an average of 97% correct classification of soybean and an overall average classification accuracy of 65% for all species. These data suggest that these models are relatively robust and could potentially be used across a wide range of herbicide applications in field scenarios. From the data set pooled across time and experiment types, a single discriminant model was created with multiple indices that discriminated soybean from weeds 88%, on average, regardless of herbicide, rate, or species. Signature amplitudes, an additional classification technique, produced variable results with respect to discriminating soybean from weeds after herbicide application and discriminating between controls and plants to which herbicides were applied; thus, this was not an adequate classification technique.

Nomenclature: Common cocklebur, *Xanthium strumarium* L.; hemp sesbania, *Sesbania exaltata* (Raf.) Rydb. ex. A.W. Hill; pitted morningglory, *Ipomoea lacunosa* L.; sicklepod, *Sennna obtusifolia* (L.) Irwin and Barnaby; soybean, *Glycine max* (L.) Merr.

Additional index words: Acifluorfen, chlorimuron, hyperspectral imagery, imazaquin, indices, metribuzin, pendimethalin, ROC curve.

Abbreviations: CCC, canonical correlation coefficient; DAA, days after application; DINO, differential index of normalized observations; LDA, linear discriminant analysis; NDVI, normalized difference vegetation index; NIR, near-infrared; POST, postemergence; PRE, preemergence; ROC, receiver operator characteristics; SA, signature amplitudes; SCA, species classification accuracy; SDM, single discriminant model; SWIR, short-wave infrared.

INTRODUCTION

Because weeds grow in aggregated patches (Cardina et al. 1997), there exists the potential to apply herbicides site specifically to these weed patches as opposed to applying blanket herbicide applications across the entire field. This approach would save the producer time, water, and application expenses, as well as reduce the amount of pesticides released into the environment. Current techniques used in site-specific weed management require that fields must be sampled relatively intensively. The degree to which fields must be sampled for site-specific herbicides to be effective is currently cost- and time-prohibitive (Medlin 1999). Ultimately, maps of weed populations could be developed to interface with computerized decision support systems to provide site-specific recommendations for treating each threshold-level weed infestation with the most economical and efficacious herbicide (Medlin and Shaw 2000). Remote sensing can potentially be used to identify these weed infestations. The accuracy with which ground, aerial, and satellite systems can measure targets in the field is constantly increasing (P. Thenkabail, unpublished data). However, detection of threshold-level populations of small, controllable weeds will be difficult because of the

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small weed size required for control and elimination of weed interference before yield loss. Various research projects are currently evaluating ground-based and aerial remote sensing techniques for weed detection and classification (Gray et al. 2002; Koger et al. 2002). Identifying varying weed spectra at specific field locations could be perfectly suited for integration with global positioning system–geographic information technology to develop georeferenced maps of herbicide treatment regimes (Luschei et al. 2001; Van Wychen 2002).

For this technology to be robust and useful to producers, it is necessary to discriminate between weeds and crop under a variety of conditions. Herbicides may be applied to soybean preemergence (PRE) or postemergence (POST) (or both). Should a herbicide fail to completely control the weed population because of lack of an activating rainfall (Johnson 2000), inadequate foliar coverage (Hartzler 1999), rainfall washing the herbicide off immediately after application (Kendig and Johnson 2002), or general ineffectiveness of the herbicide on problem species (Mitich and Smith 1989; York and Culpepper 2002), weeds would remain in the field, potentially affecting yield or harvestability. Remote sensing could be used to identify the weeds that were not effectively controlled with initial herbicide applications, and follow-up applications could be made to control the problem (Singh et al. 1991; Wilson 1992; York and Culpepper 2002). Site-specific herbicide applications could then control the remaining weed populations. To date, the degree to which herbicide injury from a previous application influences discrimination between weed species and soybean is not documented. The objective of this research was to determine whether herbicide injury from a previous application interferes with using remotely sensed data to discriminate between weeds and crop.

MATERIALS AND METHODS

Two experiments, each replicated three times and repeated during late August and June of 2001, were conducted outdoors at the R. Rodney Foil Plant Science Research Center at Mississippi State, MS. The first experiment focused on PRE herbicides and was conducted in a randomized complete block design with a 3 by 4 by 5 factorial arrangement of treatments, with herbicide, rate, and species as factors. The following weed species were chosen because they commonly appear on producer's farms in Mississippi: common cocklebur, hemp sesbania, pitted morningglory, and sicklepod. Soybean (cultivar 'Hutcheson') was also included. All the plants in both experiments were grown in 3.8-L pots containing a Bosket fine sandy loam from the Delta Research and Extension Center, Stoneville, MS. Seeds were sown in excess and thinned to one plant per pot. Plants were watered as needed and fertilized weekly with approximately 230 ml of fertilizer solution[3] containing the following concentration of nutrients and micronutrients: N, 584 mg/L; P, 502 mg/L; K, 486 mg/L; Fe, 5.8 mg/L; Cu, 2.7 mg/L; Zn, 2.33 mg/L; Mn, 1.94 mg/L; B, 0.777 mg/L; and Mo, 0.0019 mg/L. The three PRE herbicides included imazaquin, metribuzin, and pendimethalin. After planting, herbicides were applied with a CO_2-pressurized backpack sprayer in 140 L/ha at 160 kPa. All herbicides were applied at 0.5×, 0.25×, and 0.125× rates of their lowest recommended use rates, which were: imazaquin, 105 g ae/ha; metribuzin, 280 g ai/ha; and pendimethalin, 560 g ai/ha (Ahrens 1994). These rates were chosen to target a range of herbicide application in which plants would be injured but not entirely killed.

The second experiment focused on POST herbicides and was also conducted in a randomized complete block design with a 2 by 4 by 5 factorial arrangement of treatments, with the same species as the PRE experiment. Acifluorfen and chlorimuron were applied at the five- to seven-leaf stage. The herbicides were also applied with a CO_2-pressurized backpack sprayer in 140 L/ha at 160 kPa. All herbicides were applied at 0.5×, 0.25×, 0.125×, and 0.0× of the lowest use rates: acifluorfen, 140 g ai/ha and chlorimuron, 8.8 g ai/ha (Ahrens 1994). All treatments included a 1.0% (v/v) nonionic surfactant.[4]

Hyperspectral data were generated from individual leaves. Leaves were specifically chosen from similar maturity levels across species to control for differences caused by leaf age or maturity. For soybean and hemp sesbania, the second and third unfurled leaves down from the top of the plant were measured. For common cocklebur, pitted morningglory, and sicklepod, the third and fourth unfurled leaves down from the top of the plant were measured.

Hyperspectral reflectance data were collected with a handheld spectroradiometer[5] at 1, 5, 6, 8, and 9 d after application (DAA) for the POST experiments and at 28, 30, and 34 DAA for the PRE experiments. An active light source (tungsten filament) was used to minimize

[3] Miracle-Gro Plant Food, Stern's Miracle-Gro, Box 888, Port Washington, NY 11050.

[4] Latron, AG-98, Rhom and Haas, 100 Independence Hall, West Philadelphia, PA 19106.

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

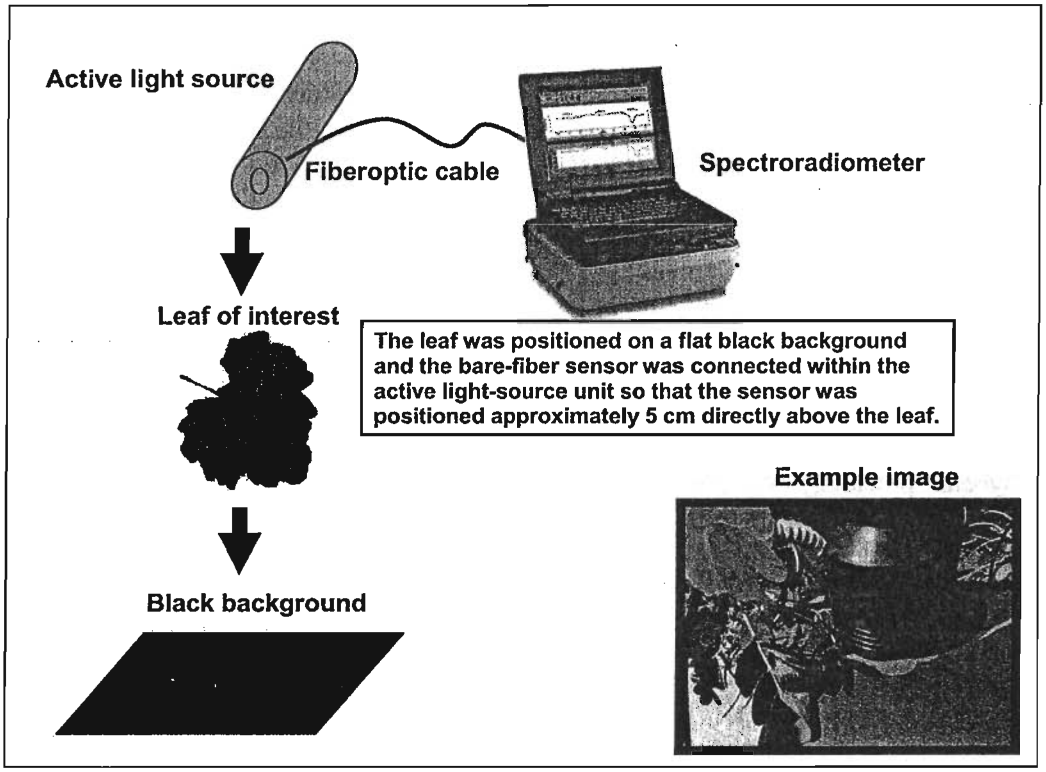

Figure 1. Data collection used an active light source for measuring individual leaves positioned on a black background.

the variability inherent with the use of a passive light source. One reflectance measurement was taken per leaf using a 25° bare-fiber field-of-view fiber optic cable (Figure 1). A black circular aperture restricted the area the sensor could measure to a diameter of approximately 3 cm. This circular, 3-cm window was placed on the upper leaf surface, directly in the center of the common cocklebur and morningglory leaves, the bottom center of the middle leaf of the soybean leaflet, and the middle of the topmost leaf of the sicklepod and hemp sesbania leaflets. 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. The bare-fiber sensor was connected within the active light source unit so the sensor was positioned directly above the leaf to eliminate background effects.

These hyperspectral reflectance measurements were collected between the spectral range of 350 and 2,500 nm. This methodology resulted in 2,151 individual spectral bands for each hyperspectral reflectance curve, with a bandwidth of 1.4 nm between 350 and 1,050 nm and 1.0 nm between 1,000 and 2,500 nm. Hyperspectral responses potentially suggesting herbicide injury were analyzed, and pertinent features were extracted using indices and signature amplitudes (SA). Visual injury ratings were also taken three times throughout each experiment.

Multiple indices were used as features in traditional statistical classification procedures (Tables 1 and 2). These procedures were conducted with stepwise discriminant analysis procedure[6] using crossvalidation (leave-one-out testing) in all instances. Rouse et al. (1973) and Tucker (1979) were pioneers in using portions of the electromagnetic spectrum, particularly in the red and near-infrared (NIR) regions, in ratios such as normalized difference vegetation index (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 NDVI value closer to 1. Conversely, as plant health declines, so too 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). Reviews of the strengths and weaknesses of these indices can be found in numerous reviews (e.g., Lillesand and Kiefer 1987).

Additional indices such as soil-adjusted vegetation in-

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

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

Index	Ratio[b]	Reference
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: RVI, ratio vegetation index; NDVI, normalized difference vegetation index; DVI, difference vegetation index; NDVIg, NDVI green; IPVI, infrared percentage vegetation index; MSI, moisture stress index; NIR, near-infrared; Tm, thematic mapper.

[b] Green = 545–555 nm; red = 670–680 nm; NIR = 835–845 nm; Tm4 = 760–900 nm; Tm5 = 1,550–1,750 nm.

dex 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 differential index of normalized observations (DINO) indices (Table 2; Figure 2) were constructed from regions of the electromagnetic spectrum that would potentially maximize the differences in reflectance caused by moisture stress, herbicide injury, or differential water use with respect to species. Carter et al. (2000) suggest that the region between 690 and 720 nm is particularly sensitive for stress detection in a wide variety of vascular plants. Because reflectance in the 720-nm region is prone to be affected by stress, it was included in several of the DINO indices. In addition, in several of the DINO indices, reflectance values were squared to increase the relative differences. Several studies have also suggested that the short-wave infrared (SWIR) (1,400 to 2,500 nm) is largely influenced by plant water status (Gausman 1985; Tucker 1980); therefore, because herbicide injury has the potential to damage plant cells and thus influence the leaf water potential of a plant, peak 1 (P1 = average 1,631 to 1,641 nm), an average of the reflectance across a 10-nm range, and peak 2 (P2 = average 2,215 to 2,225 nm) were chosen as representatives from this region and included in the construction of the DINO indices. Not only were the "best" (areas of this region in which reflectance was most distinctly different between treatments) portions of SWIR region considered in construction of these indices but also the "worst" (areas obscured by moisture bands) portions as well. Although an area around 1,400 nm appeared to provide consistent separability between treatments, if an airplane or satellite platform were used to obtain the data, indices created from wavelengths around 1,400 nm would be obscured by a moisture band and would be rendered useless.

Table 2. Differential indices of normalized observations (DINO) including regions of the electromagnetic spectrum between 1,400 and 2,500 nm.

Index	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] P1 = peak 1, average (1,631–1,641 nm); P2 = peak 2, average (2,215–2,225 nm); red, average (670–680 nm); 720 = 720 nm.

Reflectance data were analyzed within each experimental data set, between experimental data sets, and finally, within an all-encompassing, pooled data set comprising data from all experiments.

The second analysis technique used SA from a subset of the spectral bands as features. Data were pooled across experimental runs and were analyzed within both PRE and POST experiment types. 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) based on discriminant capability. Receiver operator characteristics (ROC) analysis was used to determine the efficacy of each band as a potential classification feature. ROC analysis was originally used to measure the accuracy with which radar analysts identified aircraft. The correct identification of an aircraft was weighed against the frequency that either something that was not an aircraft was identified as such (false positive) or that an aircraft was not correctly identified (false negative). 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 area under the ROC curve was then used as a design parameter for choosing

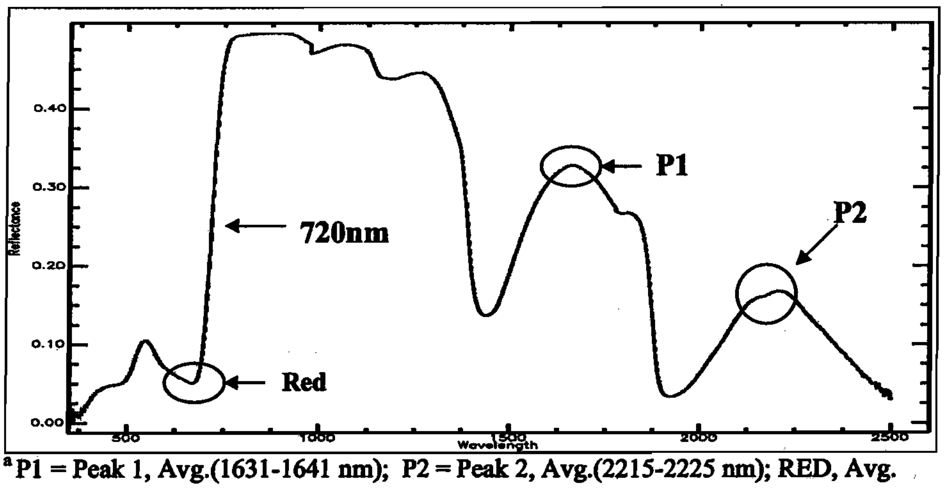

Figure 2. Differential indices of normalized observations (DINO) indices were constructed from multiple regions[a] of the electromagnetic spectrum including the range between 1,400 and 2,500 nm.

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

Linear discriminant analysis (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, 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 within both the PRE and POST experiments.

RESULTS AND DISCUSSION

Discriminant models, constructed from combinations of multiple indices, were used to classify species. With this analysis technique, all species were combined into a large data set, soybean grouped with the four weeds, and unique discriminant models were created to distinguish soybean from weeds. Table 3 presents classification accuracies of multiple, unique discriminant models, each developed within a particular set of circumstances. An example of this was a model created to classify all plants that were sprayed with imazaquin during the first

Table 3. Multiple discriminant models created with combinations of indices were generated within each experiment type, herbicide, and experiment number to produce species classification accuracies.

Experiment type[a]	Herbicide	Experiment number[b]	Soybean	Pitted morningglory	Sicklepod	Common cocklebur	Hemp sesbania	Overall
			%					
PRE	Imazaquin	1	92	66	80	80	79	79
PRE	Metribuzin	1	84	64	76	68	67	72
PRE	Pendimethalin	1	83	74	83	71	91	80
PRE	Imazaquin	2	87	81	87	76	91	84
PRE	Metribuzin	2	98	70	77	78	90	82
PRE	Pendimethalin	2	83	76	91	61	81	78
POST	Acifluorfen	1	91	70	78	70	74	76
POST	Chlorimuron	1	94	63	83	80	79	80
POST	Acifluorfen	2	86	86	60	78	89	80
POST	Chlorimuron	2	97	78	75	65	86	80

[a] Abbreviations: PRE, preemergence; POST, postemergence.

[b] Both experiments, PRE and POST, were repeated during the summer of 2001; 1 = first experimental run, 2 = second experimental run.

Table 4. Discriminant models generated across herbicide rates using multiple indices produced classification accuracies using a model generated from one data set to classify the other data set.

Linear discriminant model		Experiment		
Constructed from[a]	Tested on[b]	type[c]	Soybean	Overall[d]
			%	
Experiment 1	Experiment 2	PRE	70	73
Experiment 2	Experiment 1	PRE	94	71
Experiment 1	Experiment 2	POST	89	60
Experiment 2	Experiment 1	POST	100	58

[a] Data set from which a discriminant model was created using multiple indices.

[b] Data set on which a discriminant model created from another experiment's data was tested.

[c] Abbreviations: PRE, preemergence; POST, postemergence.

[d] Overall classification accuracy data include all species: soybean, pitted morningglory, sicklepod, common cocklebur, and hemp sesbania.

experimental run (Table 3). In this instance, soybean was discriminated 92% from weeds, and overall species classification accuracy (SCA) was 79%. Using separate discriminant models, each created to analyze data generated under a specific set of circumstances, soybean classification accuracies ranged from 83 to 98% (Table 3).

The next step in data analysis was to determine how well these data pooled, with respect to the herbicide applied, PRE and POST, and also with respect to time and experimental data set (Table 4). The ability to correctly discriminate soybean from weeds with models developed from one data set and validated on another data set should determine the robustness of these models. Soybean classification accuracies ranged from 70% with a model constructed from the data generated in the first PRE experiment and tested on the second PRE experiment to 100% with a model constructed from data generated in the second POST experiment and tested on the first POST experiment (Table 4). Classification accuracies, using models developed from one experiment validated on the other experiment, remained relatively high, suggesting that data were consistent across experiments; therefore, data sets were pooled. Similar analyses were then performed on the one large data set.

Discriminant models were again generated within each specific set of conditions (Table 5). For instance, a unique model was generated to analyze all plants to which a 1/2× application of acifluorfen was made. Under these circumstances, this model discriminated soybean 93%. Soybean classification accuracies ranged from 80 to 97% using multiple models to discriminate within a variety of herbicide and rate combinations. Soybean was not classified as well after pendimethalin application; this was probably due to slight soybean injury from this herbicide. The controls, to which there were no herbicides applied, generated 82% classification accuracies across species. Discriminating soybean from weeds without herbicide treatment was most difficult; healthy vegetation had more similar reflectance characteristics.

It is impractical to take these analysis techniques to the field and expect to generate multiple discriminant models dependent on specific situations and herbicide applications. Ideally, from this one large data set, a single, robust, discriminant model could be created and used under a variety of circumstances. Table 6 displays the classification accuracies of this model. The single

Table 5. Species classification accuracies by herbicide and rate using multiple discriminant models, each generated from subsets[a] of the entire data set.

Herbicide	Rate	Soybean	Pitted morningglory	Sicklepod	Common cocklebur	Hemp sesbania	Overall
		%					
Acifluorfen	1/2	93	67	70	75	79	77
	1/4	83	71	64	63	67	70
	1/8	93	70	62	67	79	74
Chlorimuron	1/2	97	60	71	69	63	72
	1/4	93	55	71	55	73	70
	1/8	97	64	71	53	82	74
Imazaquin	1/2	98	50	78	74	79	76
	1/4	93	72	84	64	82	79
	1/8	84	76	92	79	79	82
Metribuzin	1/2	95	59	87	86	81	82
	1/4	90	79	77	57	67	74
	1/8	83	71	78	64	83	76
Pendimethalin	1/2	80	83	81	50	81	75
	1/4	80	63	83	75	70	74
	1/8	80	81	94	72	89	83
None	0	82	66	81	74	80	77

[a] A unique discriminant model was created to classify data within each combination of herbicide and rate; for example, a discriminant model was created to discriminate among all species to which a 1/2× rate of acifluorfen was applied.

Table 6. Species classification accuracies by herbicide and rate using a single discriminant model generated from the entire data set.

Herbicide	Rate	Soybean	Pitted morningglory	Sicklepod	Common cocklebur	Hemp sesbania	Overall
		%					
Acifluorfen	1/2	93	67	48	54	64	66
	1/4	87	82	64	33	83	70
	1/8	90	63	45	57	68	64
Chlorimuron	1/2	100	73	39	92	63	74
	1/4	90	66	43	79	50	67
	1/8	97	79	32	80	71	72
Imazaquin	1/2	86	54	67	71	91	76
	1/4	91	79	74	52	82	77
	1/8	87	76	97	61	85	83
Metribuzin	1/2	79	59	90	61	94	76
	1/4	88	74	74	43	94	74
	1/8	78	56	89	78	86	77
Pendimethalin	1/2	85	83	83	65	75	79
	1/4	85	66	86	61	83	76
	1/8	98	72	94	56	72	79
None	0	83	65	80	63	80	76

discriminant model (SDM) was generated from the entire data set, which included all herbicides, rates (including controls), and species. The SDM was used to classify species within herbicide and rate. Soybean classification accuracies ranged from 83 to 100% (Table 6). SDM was able to correctly discriminate soybean from the four weed species 88%, on average, across herbicide and rate. The significance of this model is that a single, robust model created from multiple indices can be used to discriminate soybean from weeds, regardless of herbicide application. Sicklepod was effectively controlled by the POST herbicide applications, thus its classification was not confused with the healthy soybean. It typically was misclassified with common cocklebur treated with acifluorfen. Untreated pitted morningglory was most often misclassified as soybean. Soybean, when misclassified, did not show a clear trend toward any single weed species.

The number of indices included in the SDM affects both how well the model accounts for the variability inherent in the system, the canonical correlation coefficient (CCC), a measure of this variability, and the overall SCA (Table 7). The stepwise procedure first excluded only NDVI from the 18 different indices used to create the SDM. A model comprising the 17 remaining indices generated 74% overall SCA with a 0.41 CCC (Table 7). As indices accounting for the least variability in the system were sequentially removed, the CCC declined from 0.41 to 0.15 and overall SCA declined from 74 to 43%. Although the overall SCA declined from 74 to 43% because fewer indices were used to generate a model, it is of interest to note that soybean classification remained 81% or higher, regardless of the number of indices used to create the model. If only one index, DINO8, which comprises just two regions of the electromagnetic spectrum (Table 2), was used to classify species, soybean was correctly discriminated 85% (Table 7). If the objective of this research were to correctly determine all species included in the study, this would necessitate including additional indices to increase overall SCA; however, because the goal of this research was to distinguish between soybean and weed species, using a single index, DINO8, was sufficient. Soybean was correctly classified 86% using a model created with 17 indices and 85% using a model created with a single index. The percentage of weeds misclassified as soybean should also be considered. The one species that was consistently misclassified as soybean was pitted morningglory. The model created with 17 indices mistakenly classified pitted morningglory as soybean 11%, whereas the model created with only one index mistakenly classified pitted morningglory as soybean 18% (data not shown). Some indices were quite important for individual species, e.g., inclusion of the NDVIgreen for discrimination of sicklepod and soybean.

If it were necessary to increase overall SCA, additional indices could be included in the construction of the model. To increase the overall SCA to 70% or greater and increase the CCC from 0.15 to 0.36, six regions of the electromagnetic spectrum were needed to build an additional seven indices: green, 545 to 555 nm; red, 670 to 680 nm; NIR, 835 to 845 nm; P1, 1,631 to 1,641; P2, 2,215 to 2,225 (Tables 1, 2, and 7). The objectives of the research or the availability of data within these regions could dictate the computational complexity and the necessity of including additional indices.

Table 7. Indices contributing to species classification accuracy and the CCC associated with them.[a]

		Species classification accuracy					
Index removed[b]	CCC	Soybean	Pitted morningglory	Common cocklebur	Sicklepod	Hemp sesbania	Overall
NDVI	0.41	86	68	73	63	78	74
DINO3	0.41	86	68	73	63	79	74
RVI	0.41	85	67	73	63	79	73
DINO4	0.41	85	67	74	63	79	73
DINO5	0.40	85	67	74	62	78	73
MSI	0.39	85	67	77	58	78	73
DINO6	0.38	85	66	78	60	77	73
DINO7	0.37	87	63	76	59	76	72
DINO2	0.37	87	61	74	60	78	72
DINO12	0.36	86	58	74	63	80	72
DINO1	0.36	84	57	74	60	79	71
DINO11	0.34	82	54	72	57	78	69
DINO9	0.33	82	52	72	58	78	68
IPVI	0.30	81	47	73	56	72	66
NDVIg	0.27	82	49	68	18	69	57
DINO10	0.23	84	41	65	17	68	55
DVI	0.15	85	48	52	5	24	43
DINO8 = final index remaining							

[a] Abbreviations: NDVI, normalized difference vegetation index; DINO, differential index of normalized observations; RVI, ratio vegetation index; MSI, moisture stress index; IPVI, infrared percentage vegetation index; NDVIg, NDVI green; DVI, difference vegetation index.

[b] Indices were sequentially removed from the model beginning with indices that contributed least to explaining the variability inherent in the system until only one index remained.

Table 8. Signature amplitudes used to discriminate between both soybean and weed species to which a 1/2× rate of preemergence herbicide was applied.

		Classification accuracy		
Herbicide	DAA[a]	Soybean	Weed	Overall
		%		
			Common cocklebur	
Pendimethalin	28	100	92	96
	30	83	83	83
	34	50	50	50
Metribuzin	28	70	70	70
	30	40	80	67
	34	75	50	63
Imazaquin	28	82	83	82
	30	88	75	81
	34	50	50	50
			Hemp sesbania	
Pendimethalin	28	92	92	92
	30	33	50	44
	34	83	83	83
Metribuzin	28	70	67	69
	30	40	50	45
	34	50	0	25
Imazaquin	28	91	83	87
	30	75	75	75
	34	50	83	67
			Sicklepod	
Pendimethalin	28	83	83	83
	30	33	55	47
	34	67	83	75
Metribuzin	28	70	80	75
	30	60	40	47
	34	100	67	80
Imazaquin	28	91	100	95
	30	88	83	85
	34	33	67	50

[a] Abbreviation: DAA, days after application.

SA analysis was also used to discriminate weeds from soybean after PRE herbicide application. SA results were generated from one large PRE data set created by pooling both runs of the experiment. Results were variable, with overall classification accuracies fluctuating between 38 and 100% (Table 8). In general, regardless of herbicide, rate, or weed species, as DAA increased from 28 to 34, discriminating weeds from soybean became more difficult and classification accuracies declined across herbicide, rates, and species, from 82 to 57%, respectively (data not shown). Herbicide injury facilitated the discrimination of soybean from weeds. From an applied perspective, for the 1/2× rate, if classification accuracies were averaged across weed species and herbicides, it was possible to discriminate weeds from soybean on average 83% at 28 DAA (Table 8). Weeds normally emerge within approximately 1 wk of the PRE herbicide application. This would provide approximately a 3-wk window in which to use remote sensing to effectively discriminate between weeds and soybean. This would be the most crucial time to identify weeds for a producer. Challenges would include the small size of the weed with respect to the soil background. Pixel mixing and variability caused by soil composition and moisture level must be addressed with respect to field data. The promising conclusion from these data is that reflectance, analyzed with SA techniques, even if influenced by PRE herbicide application, can be used to discriminate between weeds and soybean.

Table 9. Signature amplitudes were used to discriminate between both soybean and weed species to which a 1/2× rate of postmergence herbicide was applied.

Herbicide	DAA[a]	Classification accuracy		
		Soybean	Weed	Overall
		%		
			Common cocklebur	
Acifluorfen	1	83	67	75
	5	67	83	75
	6	67	50	58
	8	50	67	58
	9	50	50	50
Chlorimuron	1	50	50	50
	5	100	83	92
	6	17	25	20
	8	50	67	58
	9	33	25	30
			Hemp sesbania	
Acifluorfen	1	83	67	75
	5	67	83	75
	6	67	50	58
	8	50	67	58
	9	50	50	50
Chlorimuron	1	50	50	50
	5	100	83	92
	6	17	25	20
	8	50	67	58
			Pitted morningglory	
Acifluorfen	1	83	67	75
	5	67	83	75
	6	67	50	58
	8	50	67	58
	9	50	50	50
Chlorimuron	1	50	50	50
	5	100	83	92
	6	17	25	20
	8	50	67	58
			Sicklepod	
Acifluorfen	1	83	67	75
	5	67	83	75
	6	67	50	58
	8	50	67	58
	9	50	50	50
Chlorimuron	1	50	50	50
	5	100	83	92
	6	17	25	20
	8	50	67	58
	9	33	25	30

[a] Abbreviation: DAA, days after application.

POST applications of acifluorfen and chlorimuron also resulted in variable classification accuracies when SA was used to classify weed vs. soybean. SA results were generated from one large POST data set created by pooling both runs of the experiment. Some trends were present; however, they were not consistent across rates, herbicides, and weed species. SA discriminated weeds from soybean 86% 1 DAA when acifluorfen was applied at the 1/2× rate (Table 9). As DAA increased, classification accuracy declined to 49% because the weeds were recovering from the initial injury of the herbicide application. It is interesting to note that classification accuracies were typically higher at 1 DAA for acifluorfen, a herbicide that acts quickly, usually within 1 to 2 d, exhibiting a burning symptomology. Conversely, for chlorimuron, a herbicide whose injury is typically visible at 3 to 5 DAA, the highest classification accuracies were usually at 5 DAA. Although these trends were not as evident at the lower rates (data not shown), there appears to be a relationship among mode of action, days to development of symptoms, and classification accuracies.

SA was also used to generate within-species comparisons between plants to which PRE herbicide was applied and control plants. These comparisons were made in an effort to quantify the degree to which herbicide application influences reflectance within species. The highest classification accuracies, 88% overall, occurred at 30 DAA with the 1/2× rate of metribuzin on hemp sesbania; however, the majority of classification accuracies were around 50%, which in a two-class system is the same as classification by random chance (data not shown). POST data were analyzed similarly. SA results were again variable with respect to day, rate, herbicide, and species. Classification accuracies between treated and controls ranged from 17 to 100%. These data suggest that either there is not much variability in spectral response after herbicide application or SA analysis was not an effective means of detecting this variability.

These results compare favorably to other studies that have investigated herbicide injury, albeit from other perspectives. Bloodworth et al. (2001) examined remotely sensed data for identifying glyphosate injury on conventional cotton (*Gossypium hirsutum* L.). Glyphosate treatments were classified correctly 65 to 66%, even in the absence of visual injury symptoms. Adcock et al. (1990) also used a spectroradiometer to standardize herbicide injury ratings. Correlation coefficients with the remotely sensed data were greater than or equal to 0.98, whereas visual injury estimates ranged from 0.69 to 0.96 and 0.74 to 0.94 for plots treated with glyphosate and paraquat, respectively.

These data also produced similar classification accuracies, approximately 85%, as previous studies on species separability, suggesting that herbicide injury does not decrease discriminatory capabilities between weeds and crop. LaMastus (2002) used wavelengths selected from stepwise discriminant analysis to classify common cocklebur, pitted morningglory, sicklepod, soybean, and bare soil 81% or better when using test plot data. Medlin and Shaw (2000) were able to correctly identify, with at least 75% accuracy, weed infestations of sicklepod, pitted morningglory, and horsenettle (*Solanum carolinense*

L.) in soybean fields. Foresters have used similar techniques to assess stand composition, with respect to species identification. Franklin et al. (2001) produced 75% or better classification accuracies among stand composition when incorporating texture and reflectance data in their analyses. Van Aardt and Wynne (2001) effectively used stepwise discriminant analysis (99 to 100%) to discriminate between pine and hardwood species. Species separability among three pine species ranged between 62 and 84%, and data most heavily influencing classification accuracies tended to come from the visible and the SWIR regions.

Potential weaknesses of these data analysis techniques may include a loss of consistency, when applied to field data that were acquired with a potentially more variable active light source. This potential weakness is not a function of the analysis techniques, per se, but rather a function of how the data were collected. How well these analysis techniques perform on data gathered under potentially more variable field conditions is unknown. Canopy structure, shading, and soil type may also contribute variability with respect to species classification, herbicide application, and herbicide injury. These data were generated from individual leaves pressed onto a flat, black background; in the field, a canopy of leaves to which herbicides were applied may appear differently. Other herbicides, in addition to the ones used in this research, may produce different injury symptoms. An example of this would be a phenoxy herbicide, 2,4-D, which causes a twisting symptomology. If a weed were twisted and the underside of the leaf were visible to a sensor above the canopy, the degree to which this type of injury might interfere with discriminating crop from weeds is not known. Indices, developed and identified in the present study, were quite consistent and able to discriminate between weeds and crop, regardless of scenario. Ideally, these analysis techniques would be robust enough to handle a variety of situation including various herbicides and species.

This analysis technique is now ready to be tested on field data. In theory, this model should continue to function equally well because more species are encountered in the field. With respect to the weeds included in this study, soybean was most frequently misclassified as pitted morningglory, which on visual inspection appears to have the most similar color and hue compared to soybean. Other leguminous species such as sicklepod and hemp sesbania did not present any misclassification difficulties.

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