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Detecting Late-Season Weed Infestations in Soybean (*Glycine max*)[1]

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Abstract: Field experiments were conducted in 1999 at Stoneville, MS, to determine the potential of multispectral imagery for late-season discrimination of weed-infested and weed-free soybean. Plant canopy composition for soybean and weeds was estimated after soybean or weed canopy closure. Weed canopy estimates ranged from 30 to 36% for all weed-infested soybean plots, and weeds present were browntop millet, barnyardgrass, and large crabgrass. In each experiment, data were collected for the green, red, and near-infrared (NIR) spectrums four times after canopy closure. The red and NIR bands were used to develop a normalized difference vegetation index (NDVI) for each plot, and all spectral bands and NDVI were used as classification features to discriminate between weed-infested and weed-free soybean. Spectral response for all bands and NDVI were often higher in weed-infested soybean than in weed-free soybean. Weed infestations were discriminated from weed-free soybean with at least 90% accuracy. Discriminant analysis models formed from one image were 78 to 90% accurate in discriminating weed infestations for other images obtained from the same and other experiments. Multispectral imagery has the potential for discriminating late-season weed infestations across a range of crop growth stages by using discriminant models developed from other imagery data sets.

Nomenclature: Barnyardgrass, *Echinochloa crus-galli* (L.) Beauv. #[3] ECHCG; browntop millet, *Brachiaria ramosa* (L.) Stapf # PANRA; large crabgrass, *Digitaria sanguinalis* (L.) Scop. # DIGSA; soybean, *Glycine max* (L.) Merr.

Additional index words: Discriminant analysis, multispectral, remote sensing, normalized difference vegetation index, weed detection.

Abbreviations: DGPS, differential global positioning system; exp., experiment; NDVI, normalized difference vegetation index; NIR, near infrared; POST, postemergence; PRE, preemergence.

INTRODUCTION

Weeds are often distributed spatially in an aggregated manner across fields (Goudy et al. 2001; Johnson et al. 1995; Medlin et al. 2000; Mortensen et al. 1998; Thornton et al. 1990; Van Groenendael 1988; Wiles et al. 1992). Several physical and chemical soil properties, such as pH (Buchanan et al. 1975; Weaver and Hamill 1985), nutrient levels (Banks et al. 1976; Medlin et al. 2001), organic matter content, and cation exchange capacity (Medlin et al. 2001), are believed to contribute to ''patchy'' weed distributions. Medlin et al. (2001) also found that topographic elevation influenced uneven distribution of weeds such as sicklepod [*Senna obtusifolia* (L.) Irwin and Barneby], pitted morningglory (*Ipomoea lacunosa* L.), and horsenettle (*Solanum carolinense* L.) across fields.

Herbicides are usually broadcast applied over entire fields, even though weed distribution is typically heterogeneous across fields. Applying herbicides where weeds do not occur results in unnecessary use of herbicide, costs associated with herbicide use, and time required for application, and an increased risk of herbicide movement to off-site areas (Cousens and Woolcock 1987; Felton et al. 1991; Swanton and Weise 1991; Thompson et al. 1991). Traditionally, intensive scouting has been the only means of providing information concerning weed distributions. However, scouting is labor and time intensive. Interest in using remote sensing for developing weed distribution maps has increased in recent years. The use of this technology has the potential to provide rapid assessments of weed distributions that can be used in treating only those portions of fields that contain weeds. This use would help to reduce herbicide costs

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[3] Letters following this symbol are a WSSA-approved computer code from *Composite List of Weeds*, Revised 1989. Available only on computer disk from WSSA, 810 East 10th Street, Lawrence KS 66044-8897.

and costs associated with herbicide use while still maintaining adequate weed control.

Researchers have envisioned linking weed distribution maps generated via remote sensing, differential global positioning systems (DGPS), and site-specific herbicide applicators for targeting herbicide inputs only to those areas in the field that contain weed densities above economic thresholds (Christensen et al. 1999; Thornton et al. 1990). However, early-season detection of small weeds, which is the time frame in which weed control is most crucial for minimizing impact on crop yield (Barrentine 1974; Bloomberg et al. 1982), is faced with several challenges. Background reflectance of soil and vegetation often interferes with detection capabilities of small, early-season weeds (Bausch 1993; Medlin et al. 2000). Medlin et al. (2000) found that these factors influenced the ability to discriminate 5- to 10-cm-tall weeds intermixed with early-season soybean. Another challenge is that reflectance properties for small crops and weeds growing in association with one another may not differ substantially (Franz et al. 1991). Another potential challenge is the fact that little is known about the impact that soil roughness and background reflectance from crop residues in different tillage systems have on weed detection capabilities. Daughtry et al. (1995) found that reflectance of plant residues and soil typically differ, and often vary, in different tillage systems.

Even though accurate detection of small, early-season weeds with remote sensing may be hampered by physical or physiological factors, the technology has tremendous capabilities for detecting late-season weed infestations. Remote sensing has been used to distinguish various troublesome weeds in rangeland systems after closure of vegetation canopy (Balough and Bookhout 1989; Everitt et al. 1991, 1992, 1993, 1995, 1996; Lass et al. 1996; Peters et al. 1992). Richardson et al. (1985) as well as Menges et al. (1985) used multispectral video imagery to differentiate homogenous plots of cotton (*Gossypium hirsutum* L.), cantaloupe (*Cucumis melo* L.), Palmer amaranth (*Amaranthus palmeri* S. Wats.), johnsongrass [*Sorghum halepense* (L.) Pers.], and sorghum [*Sorghum bicolor* (L.) Moench.]. These species were successfully differentiated late in the growing season, when plants were mature and the soil surface was completely covered. However, trying to differentiate these species from bare soil early in the growing season was difficult.

Reduction in the use of prophylactic preemergence (PRE) herbicides with residual activity and a shift toward total postemergence (POST) herbicide weed control programs also may result in an increased need for remotely sensed detection of late-season weed infestations. Weed control programs consisting of total POST, nonresidual herbicides may provide less effective, full-season weed control and result in more late-season weeds than residual PRE plus POST herbicide programs (Vangessel et al. 2000, 2001). Ever-increasing adoption of herbicide-resistant crops such as glyphosate-resistant soybean, whose standard herbicide program often consists of total POST application of a nonresidual, nonselective herbicide (glyphosate), also may result in increased occurrence of late-season weed populations in some cases. This is especially true for weeds that are capable of germinating well into the growing season, such as barnyardgrass (Keeley and Thullen 1989), fall panicum (*Panicum dichotomiflorum* Michx.) (Vangessel et al. 2000), and common cocklebur (*Xanthium strumarium* L.) (Bloomberg et al. 1982).

Late-season weed detection may prove to be a useful tool in mapping where late-season weed infestations occur, and in turn where weed seed rain and seed banks are the greatest in fields. Late-season weed infestation maps can be used to predict where control methods should be directed the following year so as to control weeds effectively and efficiently and reduce the weed seed bank. Weed infestations can be relatively stable from year to year (Wilson and Brain 1991). Development of weed distribution maps based on late-season remote sensing imagery should be free of background soil reflectance and crop residues, which often hinder early-season weed detection capabilities. The objective of this research was to evaluate the potential of remote sensing for detection of late-season weed infestations in soybean.

MATERIALS AND METHODS

This research was conducted in conjunction with two existing soybean experiments that were initiated in the fall of 1998 at the USDA-ARS, Southern Weed Science Research Unit, near Stoneville, MS. The soil type was a Dundee silt loam (fine-silty, mixed, thermic, Aeric Ochraqualfs), with pH of 6.4 and 6.3 and organic matter contents of 1.6 and 1.1% for experiments 1 and 2 (exp. 1 and exp. 2), respectively. Each experiment was arranged in a randomized complete block with a split–split-plot arrangement of treatments. Each treatment was replicated four times. Sub-subplot size was 4.5 by 12 m. The main-plot factor for exp. 1 was cover crop residue, with main plots of no cover crop, 'Elbon' rye (*Secale cereale* L.), and crimson clover (*Trifolium incarnatum* L.). Rye and crimson clover seed were drilled at 84 and

Table 1. Soybean growth stage, soybean and grass heights, and grass canopy estimates in weed-infested soybean and soybean growth stage and height in weed-free soybean at the time of image acquisition for experiment 1.[a,b]

Image-acquisition date	Weed-infested soybean				Weed-free soybean[c]	
	Soybean growth stage[d]	Soybean height	Grass height	Grass composition	Soybean growth stage[d]	Soybean height
		cm	cm	%		cm
August 11	R3	78	67	32	R3	82
August 19	R3–R4	82	68	36	R3–R4	90
August 28	R4	91	74	35	R4	96
September 9	R4–R5	94	75	30	R4–R5	98

[a] Data were pooled over cover crop residue and tillage treatments for each image-acquisition date.

[b] Images were acquired after soybean or grass (weed infested) and soybean (weed free) canopy closure.

[c] Plots were treated with flumetsulam (0.06 kg ai/ha) plus metolachlor (2.31 kg ai/ha) preemergence and bentazon (0.56 kg ai/ha) plus acifluorfen (0.3 kg ai/ha) plus clethodim (0.14 kg ai/ha) postemergence.

[d] Abbreviations: R3, soybean pods 5 mm in length on one of the four uppermost nodes; R4, seed pods 3 cm in length; R5, seed development, with seed approximately 3 mm in length.

25 kg/ha in 19-cm-wide rows. The subplot factor was tillage with no-till and conventional till treatments. The main-plot factor for exp. 2 was soybean row spacing, with spacings of 19, 57, and 94 cm. The subplot factor was no cover crop or rye (84 kg/ha) cover crop residue. Sub-subplots for each experiment were (1) no herbicide, (2) 0.06 kg ai/ha flumetsulam plus 2.31 kg ai/ha metolachlor applied PRE, (3) 0.56 kg ai/ha bentazon plus 0.3 kg ai/ha acifluorfen plus 0.14 kg ai/ha clethodim applied POST, and (4) 0.06 kg/ha flumetsulam plus 2.31 kg/ha metolachlor applied PRE and 0.56 kg/ha bentazon plus 0.3 kg/ha acifluorfen plus 0.14 kg/ha clethodim applied POST. Rye plots were seeded in October 1998 and desiccated with 1.1 kg ai/ha paraquat on April 21, 1999. All plots were planted with ‘DP 3588’ soybean on April 30, 1999. Soybean row spacing for exp. 1 was 57 cm. Because of soybean stand failure, exp. 1 was replanted on May 15, after existing soybean was desiccated with 1.1 kg/ha paraquat.

Percent composition of soybean and weeds in the canopy was visually estimated after canopy closure in no-herbicide plots and in plots treated with PRE plus POST herbicides in both experiments on August 11, 18, and 28 and September 9, 1999. Weed populations in plots treated with only PRE or POST herbicides were extremely variable; therefore, data were not collected from these plots. Plots treated with PRE plus POST herbicides were essentially free of weeds when images were acquired and will be referenced as ‘‘weed free.’’ Grasses comprised most of the vegetative canopy occupied by weeds in the no-herbicide (weed-infested) plots. Because grasses present in the weed-infested soybean plots were intermixed extensively, vegetative canopy estimates for browntop millet, barnyardgrass, and large crabgrass were summed together for each weed-infested plot. Soybean growth stage and height and grass height and estimated canopy composition data are listed in Tables 1 (exp. 1) and 2 (exp. 2).

Within 2 d of estimation of weeds and crops, multispectral imagery was collected with an aerial Real-time

Table 2. Soybean growth stage, soybean and grass heights, and grass canopy estimates in weed-infested soybean and soybean growth stage and height in weed-free soybean at the time of image-acquisition for experiment 2.[a,b]

Image-acquisition date	Weed-infested soybean				Weed-free soybean[c]	
	Soybean growth stage[d]	Soybean height	Grass height	Grass composition	Soybean growth stage[d]	Soybean height
		cm	cm	%		cm
August 11	R4	85	71	33	R4	91
August 19	R4	91	76	30	R4	96
August 28	R4–R5	93	88	32	R4–R5	101
September 9	R5	99	76	31	R5	98

[a] Data were pooled over soybean row spacing and cover crop residue treatments for each image-acquisition date.

[b] Images were acquired after soybean or grass (weed infested) and soybean (weed free) canopy closure.

[c] Plots were treated with flumetsulam (0.06 kg ai/ha) plus metolachlor (2.31 kg ai/ha) preemergence and bentazon (0.56 kg ai/ha) plus acifluorfen (0.3 kg ai/ha) plus clethodim (0.14 kg ai/ha) postemergence.

[d] Abbreviations: R3, soybean pods 5 mm in length on one of the four uppermost nodes; R4, seed pods 3 cm in length; R5, seed development, with seed approximately 3 mm in length.

Digital Airborne Camera System sensor that contained a lens with 12.5-mm focal length, using charged-couple devices in a two-dimensional detector array. All images are 8-bit image pixels, and narrow–band-pass filters collected spectral response data for the visible green (540 $\pm$ 5 nm), red (695 $\pm$ 5 nm), and near-infrared (NIR) (840 $\pm$ 5 nm) spectral bands. Spectral data for each band were quantified in radiance ($W/m^2/sr$) measured at the sensor for each pixel and ranged from 0 to 255, with a value of 255 being the brightest reflectance value possible. Imagery was collected at an altitude of 1.8 km to allow for 1-m spatial resolution. Images were geometrically corrected to geographic coordinates (latitude and longitude) using the geodetic datum of World Geodetic System 84, with ground control points obtained using a DGPS unit. DGPS coordinates for the center of each plot were determined so that an area of 3-m^2 could be sampled from the plot center. To account for the 1-m accuracy of the DGPS and minute errors associated with image processing, spectral data for each 1-m^2 pixel within each sampling area were averaged for each spectral band. Red and NIR spectral data from each plot were used to develop a normalized difference vegetation index (NDVI) (NIR $-$ red and NIR $+$ red) (Rouse et al. 1973).

Spectral (green, red, and NIR) and NDVI data across tillage, cover crop residue, and row-spacing factors were analyzed according to the split plot experimental design. However, these factors had no effect on spectral or NDVI data. Thus, data for weed-infested and weed-free plots were pooled across these factors and analyzed as a randomized complete block design for each experiment, resulting in 24 blocks within each experiment. Spectral and NDVI data were subjected to analysis of variance, and means were separated at the 5% level of significance by Fisher's protected LSD test. The best variables (spectral bands and NDVI) for discriminating weed-infested and weed-free soybean were selected based on an *F* test ($P < 0.15$) for each variable within stepwise discriminant analysis (Franz et al. 1991). Discriminant analysis techniques were used to determine the potential for differentiating between weed-infested and weed-free soybean within each experiment and to evaluate the effectiveness of using discriminant models developed from one data set based on classification of other sets. All analysis procedures were conducted in SAS,[4] and cross-validation summaries of discriminant classification tests were reported in all results.

[4] SAS version 8.01, SAS Institute, Inc., Cary, NC 27513-2414.

RESULTS AND DISCUSSION

Tillage, cover crop residue, and soybean row spacing had no effect ($P > 0.05$) on spectral response in the green, red, and NIR spectrums (data not shown). Therefore, spectral data (green, red, NIR, and NDVI) were pooled across tillage, cover crop residue, and row-spacing factors for each weed-infested and weed-free soybean plot of each experiment, resulting in 24 weed-infested and 24 weed-free soybean for each experiment. Late-season grass canopy estimates for weed-infested soybean plots varied $<$ 7% across the four image-collection dates, with estimates ranging from 30 to 36% in exp. 1 (Table 1) and 30 to 33% in exp. 2 (Table 2).

Spectral Data for Weed-Infested and Weed-Free Soybean. Spectral response for the green, red, and NIR bands were higher in weed-infested soybean than in weed-free soybean of exp. 1 for the August 11, 18, and 28 images (Table 3). These results are similar to those of Richardson et al. (1985), who found spectral response in the red and NIR bands to be higher for weeds (johnsongrass) than for crops (cotton and sorghum). Green and red spectral responses in our study also were higher in weed-infested soybean than in weed-free soybean for the September 9 image. NDVI values were higher for weed-infested soybean than for weed-free soybean in the September 9 image.

For exp. 2, spectral response for the red and NIR bands were higher for weed-infested soybean than for weed-free soybean for the August 11, 18, and 28 images (Table 3). However, by the latest image-collection date (September 9), there was no difference in red and NIR spectral response or NDVI for weed-infested and weed-free soybean plots. The lack of differences in spectral response by September 9 may be attributed to substantial crop and grass senescence. Soybean and grass leaves were turning yellow in color by the time the last images were acquired (September 9).

Substantial differences in late-season spectral response for the various spectral bands and NDVI may prove to be beneficial when trying to differentiate weed-infested soybean from weed-free soybean. However, it appears that spectral data should be recorded before plants begin to senesce late in the growing season because differences in spectral-response data were still prevalent in exp. 1 by September 9 (Table 3), when soybean was highly vegetative (green). On the other hand, spectral response for the red and NIR bands and NDVI were not different between weed-infested and weed-free soybean when soybean began to lose color and defoliate in exp. 2 by September 9. Substantial differences in spectral respons-

Table 3. Mean values for green, red, near-infrared (NIR), and normalized difference vegetation index (NDVI) variables for images of weed-infested and weed-free soybean of experiments 1 and 2.[a–c]

Image-acquisition date	Weed level[f]	Experiment 1[d]				Experiment 2[e]			
		Green	Red	NIR	NDVI	Green	Red	NIR	NDVI
		Spectral response[g]							
August 11	Weed infested	95 a	93 a	175 a	0.31 a	93 a	96 a	180 a	0.34 a
	Weed free	78 b	84 b	165 b	0.32 a	90 a	85 b	166 b	0.33 a
	P value	0.002	0.0035	0.002	0.128	0.651	0.005	0.002	0.321
August 19	Weed infested	112 a	100 a	190 a	0.31 a	119 a	111 a	180 a	0.23 a
	Weed free	93 b	86 b	169 b	0.32 a	113 b	95 b	153 b	0.23 a
	P value	0.003	0.0021	0.0034	0.0923	0.035	0.0025	0.0015	0.905
August 28	Weed infested	101 a	92 a	172 a	0.30 a	105 a	103 a	139 a	0.15 a
	Weed free	84 b	83 b	150 b	0.29 a	98 b	90 b	110 b	0.10 b
	P value	0.015	0.024	0.0012	0.193	0.0024	0.0051	0.016	0.0084
September 9	Weed infested	124 a	79 a	189 a	0.41 a	112 a	96 a	129 a	0.15 a
	Weed free	111 b	78 a	163 b	0.35 b	103 b	90 a	128 a	0.17 a
	P value	0.0078	0.689	0.027	0.0314	0.0048	0.0941	0.851	0.743

[a] Spectral response was 540 ± 5 nm for green, 695 ± 5 nm for red, and 840 ± 5 nm for NIR spectrums.

[b] Green, red, and NIR spectral data were obtained with an airborne camera system, and NDVI was derived according to the function NIR − red/NIR + red.

[c] Mean values followed by the same letter within a column and image-acquisition date are not significantly different according to Fisher's protected LSD test at P = 0.05.

[d] Data were pooled over cover crop residue and tillage treatments for each image-acquisition date.

[e] Data were pooled over soybean row spacing and cover crop residue treatments for each image-acquisition date.

[f] Weed-infested plots were treated with flumetsulam (0.06 kg ai/ha) plus metolachlor (2.31 kg ai/ha) preemergence and bentazon (0.56 kg ai/ha) plus acifluorfen (0.3 kg ai/ha) plus clethodim (0.14 kg ai/ha) postemergence.

[g] Quantization of measurable radiance ($W/m^2/sr$).

es between the two experiments were probably due to exp. 2 being planted 2 wk after exp. 1, resulting in different vegetative growth stages for soybean between the two experiments when images were acquired.

Relative Importance of Classification Variables. As the number of selected classification variables (green, red, NIR, and NDVI) according to stepwise discriminant analysis increased, the average squared canonical correlation (ASCC) value also increased. The ASCC is an accumulative measure of the variation accounted for by each selected classification variable. Typically, as the ASCC value approaches 1 for selected variables, discrimination capabilities of the linear discriminant function improve when compared with ASCC values closer to 0 (Johnson 1998). When three or more classification variables were selected by the stepwise discriminant function, ASCC values were typically greater than 0.66 (Tables 4 and 5). The green, red, and NIR bands had a composite ASCC value of 0.77 for the August 11 collection date of exp. 1. The August 28 and the September 9 collection dates of exp. 2 had composite ASCC values of 0.67 (NDVI, green, and red) and 0.68 (green, red, NIR, and NDVI), respectively. However, there were instances where two or fewer classification variables were selected by the stepwise discriminant procedure and resulted in ASCC values of greater than 0.5. The ASCC values were 0.55 and 0.59 for the August 28 collection date of exp. 1 and the August 19 collection date of exp. 2, respectively (Tables 4 and 5).

The green spectral band proved to be the most consistent classification variable selected in stepwise discriminant analysis. The green band was selected as an important classification variable in all the four exp. 1 collection dates and in three of the four collection dates of exp. 2. It also was the sole classification variable selected for the August 28 collection date of exp. 1. However, even though the green spectral band was the most consistently selected, it was not always the largest contributor to the ASCC value. The degree of variability accounted for by the green band was minimal for some images when compared with other classification variables, with the green variable accounting for 0.02 and 0.03 of the total 0.45 and 0.67 ASCC values for the August 19 (exp. 1) and August 28 (exp. 2) collection dates, respectively (Tables 4 and 5).

Even though the stepwise discriminant procedure provided a good indication of which variables had the best discrimination capabilities, it may be beneficial to use all classification variables in developing linear discriminant functions for classification purposes. The use of all available bands as classification variables is especially true for multispectral remote sensing data, where typically only three to five spectral bands are available for developing discriminant models. Additionally, using the step-

Table 4. Statistics of the stepwise discriminant analysis of classification variables (green, red, NIR, and NDVI) used for discriminating weed-infested and weed-free soybean from each image of experiment 1.[a]

Image-acquisition date	Classification variable entered into discriminant model	Model entrance number[b]	Statistics			
			Partial R^2	F value	Probability $> F$[c]	Average squared canonical correlation[d]
August 11	Green	1	0.65	84.43	< 0.0001	0.64
	Red	2	0.29	18.93	< 0.0001	0.75
	NIR	3	0.10	5.1	0.0289	0.77
August 19	Red	1	0.43	34.62	< 0.0001	0.43
	Green	2	0.05	2.45	0.1248	0.45
August 28	Green	1	0.56	59.5	< 0.0001	0.55
September 9	Green	1	0.53	52.29	< 0.0001	0.53
	NDVI	2	0.15	7.88	0.0074	0.61

[a] Abbreviations: NIR, near-infrared; NDVI, normalized difference vegetation index.

[b] Variable entered into discriminant model according to the amount of variability accounted for by that variable, with the first variable accounting for more variation that the second variable.

[c] Variables entered into discriminant model at the P = 0.15 level.

[d] Accumulative measure of the variation accounted for by selected classification variables.

wise discriminant procedure to select among variables that are potentially collinear, such as NDVI and the red and NIR variables used to derive NDVI, may lead to the elimination of important discriminant variables. As in the case of this research, there was a strong linear relationship between the NDVI variable and those variables (red and NIR) used to derive NDVI. A negative relationship ($r = -0.70$ to -0.96) existed between NDVI and the red variable across both experiments and all images, whereas a positive relationship ($r = 0.68$ to 0.97) existed between NDVI and the NIR variable (data not shown). The stepwise discriminant function may prove to be more useful for selecting a number of pertinent spectral bands from hyperspectral remote sensing data, where there may be over 2000 spectral bands available for discriminating weed-infested crop from weed-free crop.

Discrimination of Weed-Infested and Weed-Free Soybean. The green, red, and NIR spectral bands and NDVI were used in developing linear discriminant models for both the experiments and all the image-collection dates. For each experiment and image-collection date, the overall average ability to discriminate weed-infested soybean from weed-free soybean was 90% or greater, regardless of experiment, soybean growth stage, and grass canopy composition at the time of image acquisition (Table 6). The consistency in correct classification across the different image-collection dates was important because soybean growth stage late in the season did not influence

Table 5. Statistics of the stepwise discriminant analysis of classification variables (green, red, NIR, and NDVI) used for discriminating weed-infested and weed-free soybean from each image of experiment 2.[a]

Image-acquisition date	Classification variable entered into discriminant model	Model entrance number[b]	Statistics			
			Partial R^2	F value	Probability $> F$[c]	Average squared canonical correlation[d]
August 11	NDVI	1	0.69	101.9	< 0.0001	0.69
	Green	2	0.19	10.34	0.0024	0.75
August 19	NIR	1	0.59	70.3	< 0.0001	0.59
August 28	NDVI	1	0.61	69.43	< 0.0001	0.61
	Green	2	0.09	4.87	0.0325	0.64
	Red	3	0.077	3.54	0.0666	0.67
September 9	Green	1	0.21	11.7	0.0013	0.21
	NIR	2	0.1583	8.46	0.0056	0.33
	Red	3	0.26	15.39	0.0003	0.51
	NDVI	4	0.37	24.81	< 0.0001	0.68

[a] Abbreviations: NIR, near-infrared; NDVI, normalized difference vegetation index.

[b] Variable entered into discriminant model according to the amount of variability accounted for by that variable, with the first variable accounting for more variation than next variable.

[c] Variables entered into discriminant model at the P = 0.15 level.

[d] Accumulative measure of the variation accounted for by selected classification variables.

Table 6. Correct classification accuracy of weed-infested and weed-free soybean of experiments 1 and 2 using green, red, and near-infrared spectral bands and normalized difference vegetation index as classification variables in linear discriminant analysis.

Image-acquisition date	Experiment 1			Experiment 2		
	Weed infested	Weed free[a]	Average accuracy[b]	Weed infested	Weed free[a]	Average accuracy[b]
	% correct classification					
August 11	92	96	94	96	96	96
August 19	88	92	90	84	100	92
August 28	88	92	90	87	100	94
September 9	88	92	90	85	96	91

[a] Plots treated with flumetsulam (0.06 kg ai/ha) plus metolachlor (2.31 kg ai/ha) preemergence and bentazon (0.56 kg ai/ha) plus acifluorfen (0.3 kg ai/ha) plus clethodim (0.14 kg ai/ha) postemergence.

[b] Average classification accuracy of weed-infested and weed-free plots within each image-acquisition date and experiment.

discrimination capabilities. The use of multispectral images for late-season weed detection may prove to be a useful tool because images can be collected over a wide window of time while still maintaining high levels of detection accuracy. Another benefit is that weed control decisions based on late-season images will typically be made in the following seasons. Thus, image-processing time is not critical, and image delivery could be more economical.

The correct discrimination of weed-infested soybean was very high, with 88 to 92% correct classification for exp. 1 and 85 to 96% for exp. 2 across all the images (Table 6). Weed-free soybean was rarely mistaken for weed-infested soybean, with 92 to 96% and 96 to 100% correct classification of weed-free soybean in exp. 1 and exp. 2, respectively. Correct classification of weed-infested and weed-free soybean consistently reduces the risk of misclassifying weed patches, and in turn the likelihood of not identifying weed patches in images that may be used for developing herbicide-application maps for the following growing season.

The versatility of the developed linear discriminant models was evaluated by classifying weed-infested and weed-free soybean from one image by using models developed from another image for the same experiment. For exp. 1, the overall correct classification of weed-infested and weed-free soybean was 90% when classifying plots from the August 19 image on the basis of discriminant models developed from the August 11 image (Table 7). The overall average classification of plots from the September 9 image based on models from the August 28 image was 81%. However, when testing plots from the August 11 and September 9 images by using models developed from the September 9 and August 11

Table 7. Correct classification accuracy of weed-infested and weed-free soybean of experiments 1 and 2 using green, red, and near-infrared spectral bands and normalized difference vegetation index as classification variables in linear discriminant models fitted for other images and the other experiment.[a,b]

Data set used to develop discriminant model		Data set tested in linear discriminant analysis				
Exp.	Image acq. date	Exp.	Image acq. date	Weed infested	Weed free	Average accuracy[b]
				% correct classification		
1	August 11	1	August 19	94	86	90
1	August 28	1	September 9	84	78	81
1	September 9	1	August 11	55	48	51
1	August 11	1	September 9	100	38	71
2	August 11	2	August 19	100	84	92
2	August 28	2	September 9	84	96	90
2	September 9	2	August 11	75	55	65
2	August 11	2	September 9	73	79	75
2	August 11	1	August 11	86	74	80
2	September 9	1	September 9	79	86	83
1	August 11	2	August 11	75	80	78
1	September 9	2	September 9	80	80	80
2	September 9	1	August 11	88	25	56
2	August 11	1	September 9	24	70	47
1	September 9	2	August 11	44	66	55
1	August 11	2	September 9	58	54	56

[a] Abbreviations: Exp., experiment; acq., acquisition.

[b] Average classification accuracy of weed-infested and weed-free soybean within each experiment and image-acquisition date.

images, overall discrimination capabilities were reduced to 51 and 71% (Table 7), respectively. Differences in soybean growth stage between the two opposing images probably contributed to the reduced classification capabilities. On August 11, soybean plants were green and in the R3 (soybean pods 5 mm in length) growth stage, whereas soybean plants were beginning to senesce and were in the R4 to R5 growth stage (seed pods 3 cm in length to seed development) by September 9. For exp. 2, correct classification of weed-infested and weed-free soybean for the August 19 image was 100 and 84%, respectively, when using models developed with the August 11 image. The overall average correct classification for the system was 92%. Similar classification capabilities resulted from testing the September 9 image on the basis of discriminant models for the August 28 image, with 90% correct classification. However, as in results for exp. 1, the ability to discriminate weed-infested from weed-free soybean using models formed with the August 11 and September 9 images to test the September 9 and August 11 images was reduced to 65 and 75%, respectively. Substantial differences in soybean plant color and growth stage probably contributed to the reduction in discriminating capabilities.

Testing discrimination capabilities for the August 11 and September 9 images with discriminant models developed from the same image-collection date but in a different experiment resulted in 78% or better classification for all the scenarios tested (Table 7). However, discrimination capabilities were reduced when testing the August 11 and September 9 images of both the experiments with models developed from the September 9 and August 11 images of the other experiment. These tests resulted in 47 to 56% overall correct classification of weed-infested and weed-free plots for all the scenarios tested. As previously mentioned, for testing within experiments, differences in plant color and growth stage are believed to have contributed to reduced discriminating capabilities when classifying plots using discriminant models from the other experiments and images. Thus, crop growth stage between data sets should be similar so that accurate classification assessments of weed infestations can be made when using discriminant models from data sets other than the one being tested.

This research also spawns several questions that need further research. One question involves the potential for linking weed distribution maps on the basis of late-season images and factors such as soil properties. Medlin et al. (2001) found that spatial distribution of weeds such as sicklepod and pitted morningglory was related to soil pH and nutrient levels. Linking these two relationships may be helpful in understanding the often patchy distribution of weeds. Future research needs to be conducted on the potential for discriminating other weed species and to determine whether different weed canopy composition levels influence the ability to classify weed patches.

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