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Detection of pitted morningglory (*Ipomoea lacunosa*) by hyperspectral remote sensing. I. Effects of tillage and cover crop residue

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Field experiments were conducted to evaluate the potential of hyperspectral reflectance data collected with a hand-held spectroradiometer to discriminate soybean intermixed with pitted morningglory and weed-free soybean in conventional till and no-till plots containing rye, hairy vetch, or no cover crop residue. Pitted morningglory was in the cotyledon to six-leaf growth stage. Seven 50-nm spectral bands (one ultraviolet, two visible, four near-infrared) derived from each hyperspectral reflectance measurement were used as discrimination variables. Pitted morningglory plant size had more influence on discriminant capabilities than tillage or cover crop residue systems. Across all tillage and residue systems, discrimination accuracy was 71 to 95%, depending on the size of pitted morningglory plants at the time of data acquisition. The versatility of the seven 50-nm bands was tested by using a discriminant model developed for one experiment location to test discriminant capabilities for the other experiment, with discrimination accuracy across all tillage and residue systems of 55 to 73%, depending on pitted morningglory plant size.

Nomenclature: Hairy vetch, *Trifolium incarnatum* L.; pitted morningglory, *Ipomoea lacunosa* L. IPOLA; rye, *Secale cereale* L.; soybean, *Glycine max* (L.) Merr. 'Asgrow 4702RR'.

Key words: Conventional tillage, discriminant analysis, no tillage, remote sensing.

Weed populations are typically quite variable and spatially aggregated in fields (Cardina et al. 1997; Medlin et al. 2001; Van Groenendael 1988; Wiles et al. 1992). However, herbicides are often applied over entire fields to control weeds. By developing herbicide application maps based on remotely sensed data on weed distributions, herbicide(s) can be applied to only the weed patches and not entire fields. This would help to reduce herbicide usage, cost, time required for application, and off-site herbicide transfer (Cousens and Woolcock 1987).

Multispectral remote sensing has been used with some success for detecting weeds in row crops. Multispectral imagery has been used to discriminate late-season grass infestations in soybean (Koger et al. 2003). Multispectral remote sensing has also been used to discriminate experimental plots of cotton (*Gossypium hirsutum* L.), sorghum (*Sorghum bicolor* L.), johnsongrass [*Sorghum halepense* (L.) Pers.], and Palmer amaranth (*Amaranthus palmeri* S. Wats.) (Menges et al. 1985; Richardson et al. 1985). However, background soil reflectance inhibited its ability to discriminate the plots when plants were small in size, which is the time frame in which most weed control decisions are made. Pitted morningglory and sicklepod [*Senna obtusifolia* (L.) Irwin and Barnaby] infestations in soybean were detected by multispectral imagery with 90% accuracy when the weeds were 5 to 10 cm tall and at populations of at least 10 plants m^{-2} (Medlin et al. 2000). Detection accuracy, however, decreased as weed populations fell below 10 plants m^{-2} owing to an increase in soil background reflectance. Weed populations much lower than these often warrant herbicide treatment. Populations (sicklepod or pitted morningglory) of 1 plant m^{-2} are above the economic threshold and warrant treatment (Rankins et al. 1998).

Multispectral sensors often collect data for several (3 to 7) broad bands from the visible (380 to 720 nm) to near-infrared (720 to 1,300 nm) portions of the electromagnetic spectrum (380 to 3,000 nm). These portions of the spectrum are the most affected by soil background reflectance (Elvidge and Lyon 1985; Huete et al. 1985), thus limiting the usefulness of multispectral data for making accurate assessments of crop characteristics such as weed detection, water stress, nutrient levels, and phenology (Moran et al. 1994). These limitations have sparked new interest in the potential use of hyperspectral sensors, which collect more spectral bands (36 to $>$ 1,500) and often collect spectral information from a wider range of the electromagnetic spectrum than multispectral sensors (Thenkabail et al. 2000).

Hyperspectral sensors often collect spectral data from the visible to the mid- to thermal-infrared (1,300 to 3,000 nm) portions of the electromagnetic spectrum (Thenkabail et al. 2000). Additionally, hyperspectral data are often collected from narrower bands than multispectral data, thus resulting in a finer spectral resolution for the collected bands. By dividing the electromagnetic spectrum into more distinct narrow bands, more data are available for making assessments of crop and weed characteristics. Hyperspectral data have been used successfully to estimate rice (*Oryza sativa* L.) yield (Shibayama and Akiyama 1991), photosynthetic and stomatal conductance in loblolly pine (*Pinus taeda* L.) and slash pine (*Pinus elliottii* Engelm.) canopies (Carter 1998), and physiological status of plants (Penuelas et al. 1993). Little is known about the potential use of hyperspectral data for early-season weed detection in row crops.

TABLE 1. Biomass of cover crop residue in different tillage and residue systems at Starkville and Stoneville.

Pitted morningglory growth stage	No-till			Till		
	No cover crop	Rye cover crop	Hairy vetch cover crop	No cover crop	Rye cover crop	Hairy vetch cover crop
no. of leaves	kg ha^{-1}					
Starkville						
Cotyledon–2	45	1,610	70	25	425	40
2–4	35	1,310	50	20	320	15
4–6	25	925	40	10	270	10
Stoneville						
Cotyledon–2	75	5,600	100	75	580	30
2–4	70	4,895	80	60	400	25
4–6	35	4,160	65	45	380	30

There is little known about the influence of plant residue and background soil reflectance in no-till and conventional tillage systems on weed detection capabilities. Daughtry et al. (1995) found cover crop residue, along with soil background reflectance, to interfere with reflectance of crop and weed vegetation, which can influence weed detection in crops. Wheat (*Triticum aestivum* L.) plants were differentiated from standing wheat stubble, bare soil, and incorporated wheat stubble by spectral data collected with a handheld hyperspectral radiometer that corresponded to LANDSAT multispectral bands (Aase and Tanaka 1984). However, these plots were weed free, so inferences regarding differentiation of weeds from crop by remote sensing were not possible.

With this in mind, the objective of this research was to identify and evaluate a select number of bands from hyperspectral data derived over a wide range of the electromagnetic spectrum (350 to 2,500 nm) for discriminating soybean intermixed with pitted morningglory and weed-free soybean across a wide range of pitted morningglory growth stages and background soil reflectance environments. It is more economically feasible to develop a weed detection sensor for a variety of tillage and residue systems rather than one limited to one or a few types of tillage–residue systems. Also, information regarding type of tillage and residue system may not always be known, so a sensor capable of detecting weeds across a range of environments would be more useful than one good for only a select few environments. Pitted morningglory was the only weed species evaluated in this research because it is a troublesome weed species in row crop production and so that the reflectance measurements for weeds in each weed-infested plot could be consistent and maintained more easily than that for a conglomerate of weed species.

Materials and Methods

Experiment Procedures

Field experiments were conducted in 2001 at the USDA-ARS Southern Weed Science Research Unit, Stoneville, MS, and the Plant Science Research Center, Starkville, MS. The soil types were a Dundee silt loam (fine-silty, mixed, thermic, Aeric Ochraqualf) with a pH of 6.3 and 1.1% organic matter at Stoneville and a Marietta fine sandy loam (fine-loamy, mixed, thermic, siliceous Aquic Fluventic Eutrochrept) with a pH of 6.0 and 1.4% organic matter at Starkville. Each experiment was arranged in a randomized complete block with a split–split plot factorial arrangement of treatments. Each treatment was replicated four times. Sub-subplot size was 4.5 by 12.0 m. The main plot factor was cover crop residue. Residues of native vegetation, 'Maton' rye, and hairy vetch were evaluated in till and no-till subplots. The absence or presence of pitted morningglory at a specific density was the sub-subplot factor and was evaluated in each residue by tillage combination.

Rye and hairy vetch seed were drilled at 90 and 45 kg ha^{-1}, respectively, in 19-cm-wide rows in mid-October of 2000. The following spring (mid-April), existing vegetation in all plots was desiccated with 1.1 kg ai ha^{-1} paraquat. After desiccation, the tillage plots were tilled with a disk harrow and a field cultivator to thoroughly incorporate the plant residue before soybean planting. Desiccated plant residue was left undisturbed in no-till plots. Glyphosate-resistant soybean cultivar 'Asgrow 4702 RR' was planted on May 8, 2001, at Starkville and May 11, 2001, at Stoneville in 57-cm-wide rows in all plots. At planting, additional flushes of weeds and cover crop regrowth in all plots were desiccated with paraquat (1.1 kg ha^{-1}). A 3.0- by 3.0-m plastic tarp was placed in the center of designated plots to establish pitted morningglory. Preemergence application of 2.25 kg ai ha^{-1} metolachlor plus 0.14 kg ai ha^{-1} imazaquin was done to control other weeds in all plots except the quadrat areas designated for pitted morningglory establishment. Tarps were then removed, and pitted morningglory seed, purchased from a local seed vendor,[1] was planted in nine 1.0-m^2 quadrats in the center of each soybean intermixed with pitted morningglory plot. Once emerged, pitted morningglory populations were thinned to 4 plants per 1.0-m^2 quadrat. This density was maintained throughout the duration of the experiment by hand weeding excess pitted morningglory and other weeds as needed. Because of excessive amounts of rye residue in the no-till–rye residue system at Stoneville (Table 1), no pitted morningglory emerged; thus, data were not collected from these plots. All weeds in plots not containing pitted morningglory (weed free) and weeds outside the center 3.0- by 3.0-m sampling area in soybean intermixed with pitted morningglory plots were controlled with 1.1 kg ai ha^{-1} glyphosate as needed. Soybean and pitted morningglory emergence at Starkville was poor because of dry conditions at time of planting. Thus, existing vegetation was killed with 1.1 kg ha^{-1} paraquat, and soybean

Table 2. Pitted morningglory and soybean growth stage, height, and ground cover estimates in soybean plus pitted morningglory and weed-free soybean plots at Starkville and Stoneville.[a]

Soybean plus pitted morningglory						Weed-free soybean		
Pitted morningglory			Soybean			Soybean		
Growth stage	Height	Ground cover	Growth stage[b]	Height	Ground cover	Growth stage[b]	Height	Ground cover
no. of leaves	cm	%	no. of leaves	cm	%	no. of leaves	cm	%
Starkville								
Coty.–2	5–8	25	2–3	5–15	28	2–3	7–14	32
2–4	5–10	30	3–4	9–16	30	3–4	12–16	34
4–6	8–12	38	4–6	22–29	36	4–6	23–27	39
Stoneville								
Coty.–2	2–8	22	2–4	7–18	35	2–4	8–16	37
2–4	2–15	35	3–6	9–20	40	3–6	10–22	45
4–6	5–20	35	5–8	15–25	51	5–9	13–28	58

[a] Abbreviation: Coty., cotyledon.
[b] Number of trifoliolate leaves.

and pitted morningglory seed were replanted on May 21 using the same procedures described previously.

Hyperspectral Data Acquisition

Beginning when soybean plants had two to three true leaves and pitted morningglory was in the cotyledon to two-leaf growth stage, hyperspectral reflectance measurements were collected using a portable spectroradiometer.[2] Reflectance is the ratio of energy reflected off the target (i.e., plant and background soil–residue) to energy incident on the target, which was measured using a $BaSO_4$ white reference. Hyperspectral reflectance measurements were collected between 350 and 2,500 nm, resulting in 2,151 individual spectral bands for each hyperspectral reflectance measurement, with a bandwidth of 1.4 nm between 350 and 1,050 nm and 1.0 nm between 1,051 and 2,500 nm. Eight hyperspectral reflectance measurements were collected for soybean plus background soil–residue in each weed-free soybean plot. Eight measurements of soybean intermixed with pitted morningglory plus background soil–residue were also collected from each soybean intermixed with pitted morningglory plot. Hyperspectral measurements were collected using a 23° field-of-view optic, and the sensor was held 122 cm directly above the object of interest. This resulted in approximately 0.25-m spatial resolution for each hyperspectral measurement. The background reflectance of soil, residue, and soil intermixed with residue was included in each reflectance measurement. Hyperspectral reflectance data were collected at each location using the same procedures when pitted morningglory plants were in the two- to four-leaf and four- to six-leaf growth stages. Cover crop residue and native vegetation (no cover crop residue system) biomass estimates in each tillage system, growth stage and height of soybean and pitted morningglory, and percent visual ground cover estimates for pitted morningglory and soybean were also recorded (Tables 1 and 2) at each location when hyperspectral reflectance measurements were collected.

Data Analysis

Using the forward selection procedure in stepwise discriminant analysis (Franz et al. 1991), the 10 individual (1.0 or 1.4 nm) bands having the greatest power for discriminating soybean intermixed with pitted morningglory and weed-free soybean in each tillage, residue, and pitted morningglory growth stage combination were selected for each location (Table 3). Hyperspectral response measurements (350 to 2,500 nm) were divided into forty-three 50-nm bands. However, 50-nm bands in the mid-infrared portion centered at 1,375, 1,425, 1,825, 1,875, and 1,925 nm coincide with atmospheric water absorption bands, from which little energy is reflected from green vegetation because most energy is absorbed by water (Hatfield and Pinter 1993). Excessively hot daytime temperatures (34 ± 2 C) caused the sensor that collects data between 2,300 and 2,500 nm to overheat, causing reflected energy for the bands centered at 2,425 and 2,475 nm to be background noise from the sensor or stray light and not reflected energy from plant material (Goetz et al. 1983). Thus, the 50-nm bands centered at 1,375, 1,425, 1,825, 1,875, 1,925, 2,425, and 2,475 nm were not considered for the forward selection procedure in discriminant analysis. Dissecting extraneous portions of large hyperspectral data sets into reduced portions applicable for making crop-related inferences has been researched previously. Haertel and Landgrebe (1999) reduced 220-band airborne visible–infrared imaging spectrometer (AVIRIS) data into 5- to 30-band data sets used to classify tillage patterns of corn and soybean in Indiana. In their research, dissecting multidimensional hyperspectral data into reduced portions provided similar levels of classification accuracy as that of the entire sets, all the while reducing the entire data sets to smaller, more manageable sets.

The best 50-nm bands of a possible 36 for discriminating weed-free soybean and soybean intermixed with pitted morningglory were selected based on where the most individual (1.0 or 1.4 nm) bands, selected in the stepwise procedure, were located within the spectrum (Table 3). This stepwise discriminant-based selection procedure has also been used to identify bands from thermatic mapper simulator data that could be used to classify forest land-cover classes (Nelson et al. 1984). The seven selected 50-nm bands for each reflectance measurement were subjected to Fisher's linear discriminant analysis (Franz et al. 1991) to determine discrimination accuracy for soybean intermixed with pitted morning-

Table 3. The number of individual 1.0- or 1.4-nm bands selected within each 50-nm band for discriminating soybean intermixed with pitted morningglory and weed-free soybean in all tillage–residue systems and pitted morningglory growth stages at Starkville and Stoneville.

Center of each 50-nm spectral band	No. of individual bands selected[a]
375	45[b]
425	28[b]
475	8
525	9
575	20[b]
625	6
675	6
725	26[b]
775	10
825	7
875	7
925	28[b]
975	24[b]
1,025	6
1,075	7
1,125	22[b]
1,175	6
1,225	5
1,275	6
1,325	6
1,475	6
1,525	6
1,575	5
1,625	2
1,675	2
1,725	1
1,775	5
1,975	4
2,025	5
2,075	6
2,125	3
2,175	3
2,225	1
2,275	1
2,325	1
2,375	5

[a] Individual 1.0- and 1.4-nm bands selected with stepwise discriminant analysis at the $P = 0.15$ level of significance.

[b] The 50-nm band selected as discrimination variable to discriminate soybean intermixed with pitted morningglory and weed-free soybean.

glory and weed-free soybean in each tillage and residue system and pitted morningglory growth stage. To test the versatility of the selected 50-nm bands at each growth stage, linear discriminant models developed for one experiment were applied to the data collected from the other experiment. All bands were selected at the $P = 0.15$ level of significance in the stepwise discriminant analysis procedure. All analysis procedures were conducted in SAS,[3] and cross-validation summaries of discrimination results were used in all scenarios.

Results and Discussion

Seven 50-nm bands (375, 425, 575, 725, 925, 975, and 1,125 nm) were selected to discriminate weed-free soybean and soybean intermixed with pitted morningglory in the different tillage and residue systems based on where the most individual (1.0 or 1.4 nm) bands were located in the electromagnetic spectrum (Table 3). Number of individual (1.0 or 1.4) bands selected from the seven selected 50-nm bands ranged from 20 to 45 compared with 1 to 10 individual bands for the remaining 28 50-nm bands. One 50-nm band was selected from the ultraviolet (30 to 400 nm), two from the visible (400 to 700 nm), and four from the near-infrared (700 to 1,300 nm) portion of the spectrum (Figure 1). Most energy in the ultraviolet and visible portions of the spectrum is absorbed by plants and used to drive photosynthesis processes. However, differences in leaf pigments, primarily chlorophylls, carotenoids, xanthophylls, and anthocyanins for these spectral regions have been used to differentiate plant species (Gates et al. 1965; Thenkabail et al. 2000). Differences in internal cellular structure have also been used to differentiate species by spectral characteristics (Thenkabail et al. 2000).

Discriminant Capabilities of 50-nm Bands across Tillage and Residue Systems

Soybean intermixed with pitted morningglory and weed-free soybean spectral data for the seven 50-nm bands were pooled across all tillage and residue systems for each pitted morningglory growth stage. Pitted morningglory and soybean growth stage affected discrimination capabilities more than tillage or cover crop residue because discriminant accuracy at both locations increased with increasing plant size of pitted morningglory and soybean (Table 2). Overall discrimination accuracy for soybean intermixed with pitted morningglory and weed-free soybean was 71 and 73% at Starkville and Stoneville at the cotyledon to two-leaf pitted morningglory growth stage, compared with 80 and 75% at the two- to four-leaf stage and 95 and 86% at the four- to six-leaf stage, respectively (Table 4). Increased discriminant capabilities with increasing plant size is possibly due to less soil–residue background reflectance with increasing plant size of pitted morningglory and crop maturity.

The discriminant model developed for the seven 50-nm spectral bands (discrimination variables) in one experiment was used to test discriminating capabilities across all tillage and residue systems in the other experiment. Overall, discriminant capabilities increased only slightly as pitted morningglory growth stage increased, with 55 and 57% correct discrimination of soybean intermixed with pitted morningglory and weed-free soybean at the cotyledon to two-leaf growth stage, compared with 62 to 73% by the four- to six-leaf stage (Table 4). Reduced discriminant capabilities when using discriminant models from one data set to test another may be due to substantial differences in residue biomass for the different systems at time of data acquisition at the two locations (Table 1). Versatility of a sensor used for weed detection across a range of environments (tillage and cover crop residue) may be determined by its ability to discriminate weeds from crop using discriminant models developed from other data sets. Information regarding tillage system and the presence of cover crop residue may be available in some cases. Therefore, investigation of weed discriminant capabilities when information regarding the type of tillage and residue system is available may further reveal the diversity and usefulness of the seven 50-nm bands for weed discrimination.

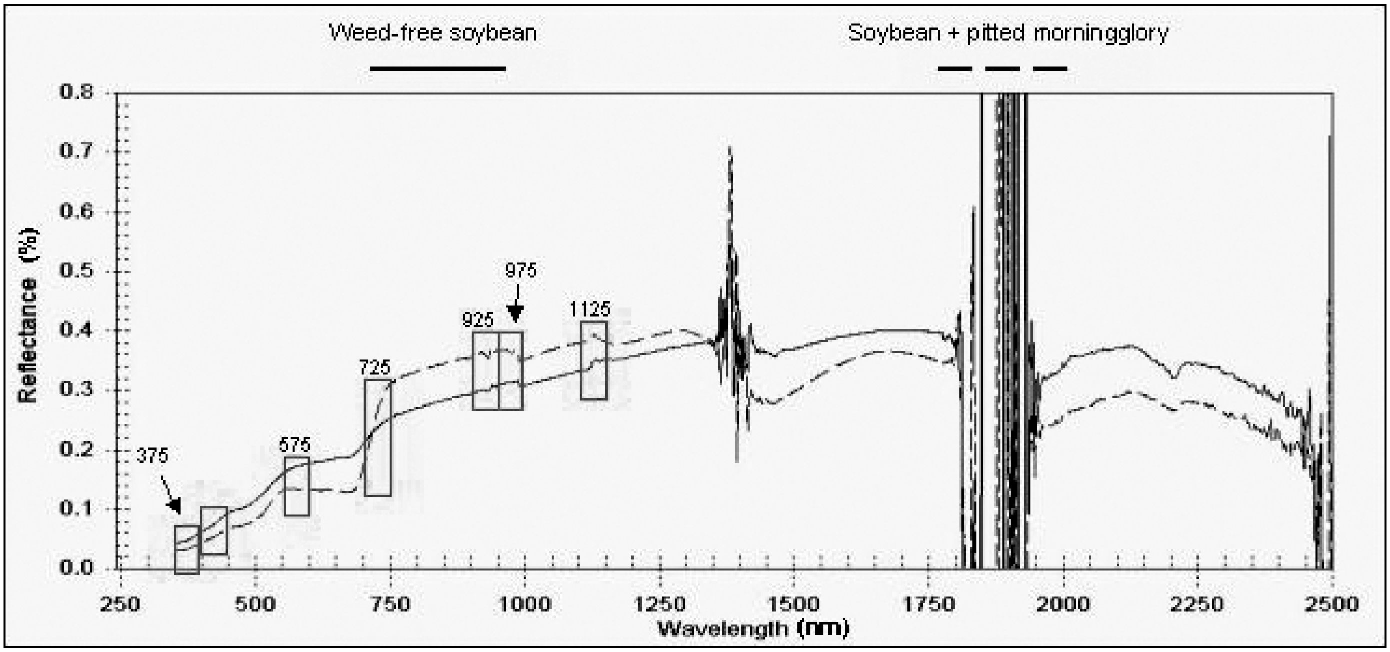

FIGURE 1. Seven 50-nm bands used to discriminate weed-free soybean and soybean intermixed with pitted morningglory at Starkville and Stoneville. Reflectance measurements for weed-free soybean and soybean intermixed with pitted morningglory were averaged across tillage, residue, pitted morningglory growth stages, and experiments.

Effect of Tillage and Cover Crop Residue

Tillage and cover crop residue had less effect than pitted morningglory growth stage on discrimination capabilities when discriminant models were used within each experiment. When pooled across residue systems, overall correct discrimination accuracy for soybean intermixed with pitted morningglory and weed-free soybean in the till and no-till systems was 63 to 79% at Starkville and Stoneville when pitted morningglory was in the cotyledon to two-leaf growth stage, compared with 85 to 96% at the four- to six-leaf growth stage (Table 5). When pooled across tillage systems, discrimination accuracy increased for all cover crop residue systems as pitted morningglory plant size increased (Table 6).

When using discriminant models developed for the other experiment across tillage (pooled across residue) and residue (pooled across tillage) systems, soybean intermixed with pitted morningglory and weed-free soybean were classified accurately 46 to 61% in till and no-till systems (Table 5) and 43 to 64% in residue systems (Table 6) at the cotyledon to two-leaf growth stage. However, by the four- to six-leaf growth stage, discrimination accuracy was 82 to 92% in the till and no-till systems and 64 to 94% in the residue systems. Maintaining high levels of discriminant capabilities when information regarding the type of tillage and residue is available, and while pitted morningglory is still small enough to be controlled with herbicide, provides evidence of the potential of the 50-nm bands with respect to weed detection capabilities when information regarding the background soil–residue environment is available. Accurate discrimination of weed-free crop and crop intermixed with weeds when type of tillage–residue system is known also sheds light on the need for investigating the seven bands in an aerial- or satellite-based sensor. Reflectance data collected for these seven spectral bands may have more discriminatory power if information regarding the specific tillage–residue system is available.

Discriminant Capabilities within Each Tillage–Residue System

Pitted morningglory growth stage had more influence on discrimination capabilities than type of tillage–residue sys-

TABLE 4. Overall discrimination accuracy for soybean intermixed with pitted morningglory and weed-free soybean when pooled across tillage and residue systems for each pitted morningglory growth stage using the discriminant model developed within each experiment and for the other experiment.[a]

Pitted morningglory growth stage	Correct discrimination using the discriminant model developed within experiment		Correct discrimination for Starkville data using the discriminant model developed for Stoneville	Correct discrimination for Stoneville data using the discriminant model developed for Starkville
	Starkville	Stoneville		
no. of leaves	%			
Cotyledon–2	71	73	55	57
2–4	80	75	55	65
4–6	95	86	73	62

[a] All discriminant analyses were performed using the seven 50-nm bands as discrimination variables pooled across tillage and residue systems.

TABLE 5. Overall discrimination accuracy for soybean intermixed with pitted morningglory and weed-free soybean in till and no-till systems for each pitted morningglory growth stage using the discriminant model developed within each experiment and for the other experiment.[a]

Pitted morningglory growth stage	Correct discrimination using the discriminant model developed within location		Correct discrimination for Starkville data using the discriminant model developed for Stoneville	Correct discrimination for Stoneville data using the discriminant model developed for Starkville
	Starkville	Stoneville		
no. of leaves	%			
Till				
Cotyledon–2	76	79	55	61
2–4	74	81	78	80
4–6	96	85	85	92
No-till				
Cotyledon–2	63	78	55	46
2–4	72	83	78	77
4–6	90	91	82	83

[a] All discriminant analyses were performed within till and no-till systems using the seven 50-nm bands as discrimination variables pooled across residue systems.

tem. Discrimination accuracy for soybean intermixed with pitted morningglory and weed-free soybean was 56 to 84% at Starkville and 75 to 86% at Stoneville (Table 7) for all tillage–residue combination systems when pitted morningglory was in the cotyledon to two-leaf growth stage. Discrimination accuracy was 87 to 97% by the four- to six-leaf stage. Better discrimination of pitted morningglory beyond the cotyledon to two-leaf growth stage may be attributed to less soil–residue background reflectance. Ground cover estimate for vegetation (soybean plus pitted morningglory) in soybean intermixed with pitted morningglory plots at the four- to six-leaf pitted morningglory growth stage was 74% at Starkville and 86% at Stoneville (Table 2), whereas, vegetation ground cover estimates of pitted morningglory at the cotyledon to two-leaf growth stage were 53 and 57% at Starkville and Stoneville, respectively.

Discrimination accuracy in the different tillage and residue systems when using discriminant models developed for each tillage–residue combination system at one experiment to test the other experiment increased as pitted morningglory plant size increased for all tillage and residue systems except the till–rye residue system, where discrimination accuracy was lower at the two- to four-leaf growth stage than in the other tillage–residue systems. This low level of accuracy is attributed to differences in rye residue biomass on the soil surface between the two experiments. This difference in biomass may have caused differences in background reflectance in the till–rye residue plots in the two experiments. Discrimination accuracy by the four- to six-leaf pitted morningglory growth stage was 84 to 90% and increased only slightly compared with the two- to four-leaf stage in the no-till–no cover crop and hairy vetch residue systems and the till–no cover crop residue systems (Table 7).

The seven 50-nm bands investigated in this study proved to be versatile for detecting pitted morningglory in a variety of tillage and residue systems at growth stages controllable with most labeled postemergence herbicides. Knowing the specific tillage–residue system improved discriminant capabilities because discrimination accuracy was higher within each tillage–residue system than by pooling across all tillage–residue systems. Discrimination capabilities were influenced more by weed growth stage than tillage and presence or absence of cover crop residue. This may be advantageous with respect to weed detection capabilities because little can be done about the amount of biomass residue on the soil surface or the type of tillage and cover crop residue system after crop and weed emergence. However, limited scouting can be used to identify the weed size that will potentially result in the best weed detection capabilities by remote sensing.

Using a limited number of 50-nm bands rather than all individual (1.0 and 1.4 nm) bands allows for a reduction in the spectral data by eliminating those bands that are not useful as discriminant variables. Another potential benefit of using broad 50-nm bands rather than narrow, individual (1.0 or 1.4 nm) bands to discriminate weeds from crop is that fewer spectral bands are needed, thus sensor costs could be reduced. Also, broad bands (10 to 70 nm in width) collected from the visible and near-infrared portions of the spectrum have proven to be more successful than narrow bands for making inferences toward crop growth factors (Thenkabail et al. 2000). Therefore, sensors collecting spectral data in fewer bands, but across similar regions of the spectrum, may be cheaper and as useful for detecting weeds as sensors that collect data from many narrow spectral bands.

Overall, the ability to detect pitted morningglory intermixed with crop vs. weed-free crop studied here is comparable with work conducted by Medlin et al. (2000), who used aerial multispectral data to classify infestations of pitted morningglory with at least 85% accuracy. However, populations had to reach 10 plants m^{-2} before these accuracy levels were reached, and the soil was conventionally tilled before planting, so the soil background reflectance was consistent, whereas background reflectance varied across the different tillage and residue systems in this study. Detection of small weeds is also very promising because this is the time frame in which weed control is most crucial for minimizing the impact on crop yield (Barrentine 1974; Bloomberg et al. 1982). Further research is needed on these selected bands for detecting different weeds and weed complexes and other agricultural parameters such as soil characterization and detection of insect and water stress. In addition, research is needed to address what factor(s), such as differences in veg-

TABLE 6. Overall discrimination accuracy for soybean intermixed with pitted morningglory and weed-free soybean in each cover crop residue system for each pitted morningglory growth stage using the discriminant model developed within each experiment and for the other experiment.[a]

Pitted morningglory growth stage	Correct discrimination using the discriminant model developed within location		Correct discrimination for Starkville data using the discriminant model developed for Stoneville	Correct discrimination for Stoneville data using the discriminant model developed for Starkville
	Starkville	Stoneville		
no. of leaves	%			
No cover crop residue				
Cotyledon–2	68	74	46	54
2–4	87	81	72	74
4–6	98	87	85	87
Rye residue				
Cotyledon–2	75	64[b]	43[b]	53[b]
2–4	83	71[b]	51[b]	62[b]
4–6	94	78[b]	64[b]	84[b]
Hairy vetch residue				
Cotyledon–2	72	74	51	64
2–4	83	83	77	88
4–6	97	85	86	94

[a] All discriminant analyses were performed within each cover crop residue system using the seven 50-nm bands as discrimination variables pooled across tillage systems.
[b] Till plots only, pitted morningglory did not emerge in no-till plots at Stoneville.

TABLE 7. Overall discrimination accuracy for soybean intermixed with pitted morningglory and weed-free soybean in each tillage by cover crop residue system for each pitted morningglory growth stage using the discriminant model developed within each experiment and for the other experiment.[a]

Pitted morningglory growth stage	Correct discrimination using the discriminant model developed within location		Correct discrimination for Starkville data using the discriminant model developed for Stoneville	Correct discrimination for Stoneville data using the discriminant model developed for Starkville
	Starkville	Stoneville		
no. of leaves	%			
No-till–no cover crop residue				
Cotyledon–2	74	76	57	48
2–4	82	84	85	91
4–6	97	90	84	90
Till–no cover crop residue				
Cotyledon–2	77	82	48	36
2–4	83	85	74	93
4–6	91	93	87	84
No-till–rye residue				
Cotyledon–2	56	—[b]	—[b]	—[b]
2–4	80	—[b]	—[b]	—[b]
4–6	92	—[b]	—[b]	—[b]
Till–rye residue				
Cotyledon–2	83	75	57	70
2–4	87	85	64	56
4–6	90	87	85	80
No-till–hairy vetch residue				
Cotyledon–2	84	86	56	61
2–4	89	88	88	90
4–6	96	87	90	89
Till–hairy vetch residue				
Cotyledon–2	81	79	52	41
2–4	88	85	90	90
4–6	96	88	85	90

[a] All discriminant analyses were performed within each tillage–cover crop residue system using the seven 50-nm bands as discrimination variables.
[b] Pitted morningglory did not emerge in no-till plots at Stoneville.

etation ground cover between different plots or differences in reflectance patterns between pitted morningglory and soybean, affect the ability to discriminate weed-infested crop from weed-free crop.

Sources of Materials

[1] Pitted morningglory seed, Azlin Seed Service, P.O. Box 914, Leland, MS 38756.

[2] Spectroradiometer, FieldSpec Pro. Analytical Spectral Devices Inc., 5335 Sterling Drive, Boulder, CO 80301-2344.

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

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