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Remote Sensing to Detect Herbicide Drift on Crops[1]

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Abstract: Glyphosate and paraquat herbicide drift injury to crops may substantially reduce growth or yield. Determining the type and degree of injury is of importance to a producer. This research was conducted to determine whether remote sensing could be used to identify and quantify herbicide injury to crops. Soybean and corn plants were grown in 3.8-L pots to the five- to seven-leaf stage, at which time, applications of nonselective herbicides were made. Visual injury estimates were made, and hyperspectral reflectance data were recorded 1, 4, and 7 d after application (DAA). Several analysis techniques including multiple indices, signature amplitude (SA) with spectral bands as features, and wavelet analysis were used to distinguish between herbicide-treated and nontreated plants. Classification accuracy using SA analysis of paraquat injury on soybean was better than 75% for both 1/2- and 1/8× rates at 1, 4, and 7 DAA. Classification accuracy of paraquat injury on corn was better than 72% for the 1/2× rate at 1, 4, and 7 DAA. These data suggest that hyperspectral reflectance may be used to distinguish between healthy plants and injured plants to which herbicides have been applied; however, the classification accuracies remained at 75% or higher only when the higher rates of herbicide were applied. Applications of a 1/2× rate of glyphosate produced 55 to 81% soybean injury and 20 to 50% corn injury 4 and 7 DAA, respectively. However, using SA analysis, the moderately injured plants were indistinguishable from the uninjured controls, as represented by the low classification accuracies at the 1/8-, 1/32-, and 1/64× rates. The most promising technique for identifying drift injury was wavelet analysis, which successfully distinguished between corn plants treated with either the 1/8- or the 1/2× rates of paraquat compared with the nontreated corn plants better than 92% 1, 4, and 7 DAA. These analysis techniques, once tested and validated on field scale data, may help determine the extent and the degree of herbicide drift for making appropriate and, more importantly, timely management decisions.
Nomenclature: Corn, *Zea mays* L.; soybean, *Glycine max* (L.) Merr.
Additional index words: Glyphosate, hyperspectral imagery, indices, paraquat, ROC curve, wavelet analysis.
Abbreviations: DAA, days after application; DINO, differential index of normalized observations; DWT, discrete wavelet transform; EPSP, 5-enolpyruvylshikimate-3-phosphate; LDA, linear discriminant analysis; NDVI, normalized difference vegetation index; NIR, near-infrared; POST, postemergence; ROC, receiver operator characteristics; SA, signature amplitudes.

INTRODUCTION

Herbicide spray drift is not a new problem; however, with the increase in herbicide-resistant crops, burndown herbicide applications on conservation and no-tillage hectarage, and postemergence (POST) herbicide applications, the occurrence of drift incidents has increased (Drapala 2001). Spray drift, as defined by the Environmental Protection Agency, is "The physical movement of a pesticide through air at the time of application or soon thereafter, to any site other than that intended for application (often referred to as off-target)" (Anonymous 1999). This definition of drift does not include damages caused by volatilization, erosion, or windblown soil particles to which herbicides are attached. Drift is influenced by a variety of variables such as environmental conditions (wind, temperature, and humidity), herbicide formulation, pressure, nozzle type, droplet size, cultivar, growth stage, and distance that the herbicide is re-

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3167') were the conventional, nontransgenic crops selected for the drift experiment. All the plants in both experiments were grown in 3.8-L pots containing a topsoil from a Bosket fine-loamy, mixed, active, thermic Mollic Hapludalfs from the Delta Research and Extension Center, Stoneville, MS. Seeds were sown in excess, and plants were thinned to one plant per pot after emergence. 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 two herbicides used were glyphosate and paraquat. Herbicides were applied to plants at the five- to seven-leaf stage with a CO_2-pressurized backpack sprayer in 140 L/ha at 160 kPa for the 0.5× rate. A 0.5× rate of the typical burndown rates of glyphosate, 1.12 kg ae/ha, and paraquat, 0.45 kg cation/ha, was applied at 1.61 km/h (Ahrens 1994). The paraquat treatment included a 0.25% (v/v) nonionic surfactant.[4] Concentration of the herbicide solution was then held constant, whereas application speed and subsequent spray volumes were adjusted to deliver herbicides at 0.125-, 0.063-, and 0.031× rates in 35, 8.75, and 4.375 L/ha, respectively. The reason for selecting this particular methodology for herbicide application was to avoid the potential underestimation of herbicide efficacy by applying dilute concentration of herbicide in a large carrier volume. Previous research dealing with simulated drift has suggested that in addition to the amount of herbicide delivered, the droplet size and the concentration of the herbicide solution should ideally be held in the same proportion as it would have been applied to the original target field (Banks and Schroeder 2000). Spray volume and concentration have been studied for both paraquat (McKinlay et al. 1974) and glyphosate (Cranmer and Linscott 1990; Ellis et al. 2001). In the field, a single, concentrated droplet of herbicide will be more effective at reducing plant growth than several drops of a more dilute herbicide containing the same amount of herbicide. In an effort to limit the underestimation of drift injury, application speed, as opposed to herbicide concentration, was adjusted.

Visual injury ratings were taken 4, 7, and 10 d after application (DAA). The basis for assigning injury ratings included chlorosis, necrosis, and stunting and was assigned on a scale of 0 to 100, with 100 representing total plant mortality and 0 representing no injury.

Hyperspectral data were generated from individual leaves at 1, 4, and 7 DAA. For both soybean and corn, the second and third unfurled leaves from the top of the plant were measured. Leaves were specifically chosen from similar age classes across species to control for differences caused by leaf age or maturity.

Hyperspectral reflectance data were collected with a handheld spectroradiometer.[5] An active light source (tungsten filament) was used to minimize 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. The reflectance of individual leaves, or leaflets in the case of 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 that the sensor was positioned directly above the leaf. A black circular aperture restricted the area the sensor could measure to a diameter of approximately 3 cm. This window was placed on the upper leaf surface, directly in the center of the corn leaves, and in the bottom center of the middle leaf of the soybean leaflet. A black background positioned directly beneath the leaf was used to eliminate background effects.

These hyperspectral reflectance measurements were collected in the spectral range of 350 to 2,500 nm. This 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 1,050 and 2,500 nm. Hyperspectral responses potentially suggesting herbicide injury were analyzed, and pertinent features were extracted using indices and signature amplitudes (SA).

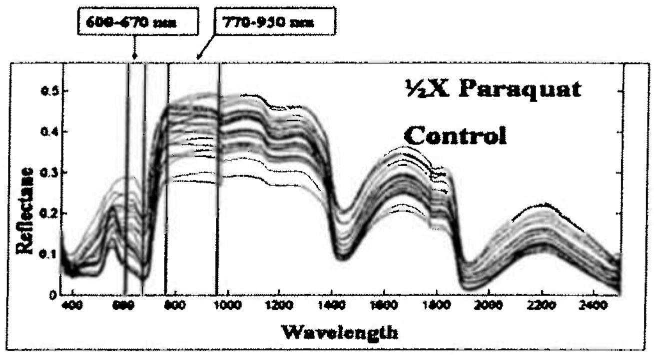
Multiple indices were used as features in traditional statistical classification procedures. This was conducted with a stepwise discriminant analysis procedure[6] using crossvalidation (leave-one-out testing) in all instances. Rouse et al. (1973) and Tucker (1979) were pioneers in using portions of the 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 high NDVI value. Conversely, as plant health declines, so too does the ability

[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.

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



*Regions, five linearly spaced spectral bands were chosen between 600-670 and also between 770-950 nm. These 10 spectral bands were used as features for classification.

Figure 2. Two regions were chosen that exhibited the greatest differences in spectral response between corn plants that were treated with a 1/2–time rate of paraquat and control corn plants.

the second analysis technique. A fixed set of features is potentially useful for extending the analysis technique to other sensor systems.

The final feature extraction technique used wavelets, a multiresolutional analysis tool, having recently gained popularity among a diverse cross section of engineering applications (Burrus et al. 1998). This technique was particularly suited for this application because there were large-scale differences between the two data sets that potentially would be captured in the wavelet transform domain. The Haar mother wavelet was used to compute wavelet coefficients (Haar 1910). The discrete wavelet transform (DWT) coefficients were computed for a 10-level wavelet decomposition using the Haar function as the mother wavelet. The DWT decomposes a signal into a number of detailed coefficients and approximation coefficients, depending on the desired level of decomposition (Graps 1995). Multiple mother wavelets and wavelet bases are available for use in decompositions and may be selected accordingly depending on the application (Burrus et al. 1998; Koger 2001; Leon 2001). The Haar wavelet was a good choice for image processing because of its simplicity and fast computational algorithm.

The DWT coefficients obtained from the Haar decomposition were then subjected to ROC analysis, and five coefficients with the largest area under the ROC curve were chosen. LDA was then applied to form the optimum scalar feature. This scalar was then input into a maximum-likelihood classifier. Crossvalidation was used for the system training and testing.

Indices were also examined for their utility in distinguishing between glyphosate or paraquat drift. Injury was recorded (Table 1), and a data set was compiled containing all hyperspectral responses taken across rates (except for the controls), herbicides, and species. Multiple indices were used as features in traditional statistical classification procedures (Tables 2 and 3). These procedures were conducted with stepwise discriminant analysis procedure using crossvalidation (leave-one-out testing) in all instances. Classification accuracies were generated with respect to day.

RESULTS AND DISCUSSION

Injury from the lowest rate of glyphosate, 1/64 times, ranged from 1 to 12%, regardless of DAA or species (Table 1), and would most likely not affect yield (Rowland 2000). Paraquat injury at the 1/64× rate was higher, 56% on corn and 47% on soybean at 7 DAA, but began to decline to 37 and 10%, respectively, by 10 DAA as the plants grew out of the injury (Table 1).

Reflectance data were initially analyzed with multiple indices within experimental runs and days. Classification accuracies were generated for each of the four rates plus the control with respect to herbicide, species, time, and experimental run. These classification accuracies were quite variable, ranging from 8% correct for glyphosate on soybean 4 DAA in the second experimental run to

Table 1. Visual percent injury ratings of paraquat and glyphosate injury on corn and soybean at 4, 7, and 10 DAA.[a]

	Soybean 4 DAA		Corn 4 DAA		Soybean 7 DAA		Corn 7 DAA		Soybean 10 DAA		Corn 10 DAA	
Rate[b]	Glyphosate	Paraquat	Glyphosate	Paraquat	Glyphosate	Paraquat	Glyphosate	Paraquat	Glyphosate	Paraquat	Glyphosate	Paraquat
	%											
0.500	55	99	20	94	81	99	50	89	78	98	60	90
0.125	47	93	11	89	67	93	42	71	68	89	55	77
0.031	28	71	4	76	50	68	28	59	41	50	36	68
0.016	10	52	1	62	8	47	12	56	6	22	10	37
0.000	0	0	0	0	0	0	0	0	0	0	0	0
LSD	12		9		22		13		18		19	

[a] Abbreviation: DAA, days after application.

[b] Expressed as a fraction of the full (labeled) rate, which were glyphosate, 1.12 kg ae/ha, and paraquat, 0.45 kg ai/ha, applied at 1/2-, 1/8-, 1/32-, and 1/64× rates of typical burndown applications.

Table 4. Multiple indices generated from hyperspectral data were used to distinguish between controls and plants to which herbicide was applied in various amounts.[a]

	1 DAA				4 DAA				7 DAA			
	Glyphosate		Paraquat		Glyphosate		Paraquat		Glyphosate		Paraquat	
Rate[b]	Soybean	Corn	Soybean	Corn	Soybean	Corn	Soybean	Corn	Soybean	Corn	Soybean	Corn
	%											
0.500	71	86	91	96	58	77	100	100	58	42	—	54
0.125	75	41	65	83	62	71	100	62	63	66	75	37
0.031	54	70	73	83	36	53	58	71	54	50	54	62
0.016	42	59	70	75	48	42	60	46	42	37	50	42

[a] Abbreviation: DAA, days after application.

[b] Expressed as a fraction of the full (labeled) rate, which were glyphosate, 1.12 kg ae/ha, and paraquat, 0.45 kg ai/ha, applied at 1/2-, 1/8-, 1/32-, and 1/64× rates of typical burndown applications.

had either died (soybean) or had new, uninjured growth emerging (corn). These new corn leaves, spectrally indistinguishable from the new leaves on the control plants, accounted for the lower classification accuracy, 54%, at 7 DAA (Table 4).

SA analysis using the five best bands as features and comparing each rate separately with the controls produced classification accuracy trends similar to those produced by the multiple indices analysis technique (Tables 5 and 6). Glyphosate-injured plants were virtually indistinguishable from the control plants, regardless of rate, species, or time. Glyphosate injury at the 1/2× rate was present at 4 and 7 DAA on soybean at 55 and 81% and on corn 20 and 50%, respectively (Table 4.1). Classification accuracy of paraquat injury on soybean was better than 75% for both 1/2- and 1/8× rates at 1, 4, and 7 DAA (Table 5). Classification accuracy of paraquat injury on corn was better than 72% for the 1/2× rate at 1, 4, and 7 DAA (Table 6). These data suggest that hyperspectral reflectance may be used to distinguish between healthy plants and injured plants to which herbicides have been applied; however, the classification accuracies remained at 75% or higher only when the higher rates of herbicide were applied and visual injury ratings were 90% or greater. Substantial injury was generated by applications of 1/32- and 1/64× rates of paraquat, ranging from 47 to 71% on soybean and 56 to 76% on corn (Table 1) at 4 and 7 DAA, respectively. In addition,

Table 5. SA analysis using the five best bands[a] as features was used to distinguish between soybean controls and soybean to which various rates of glyphosate or paraquat had been applied.[b]

Rate[c]	Glyphosate	Control	Overall[d]	Paraquat	Control	Overall[e]
	%					
1 DAA						
0.500	58 ± 23	50 ± 24	54 ± 17	92 ± 13	100 ± 0	96 ± 7
0.125	50 ± 24	58 ± 23	54 ± 17	67 ± 22	83 ± 18	75 ± 15
0.031	58 ± 23	58 ± 23	58 ± 17	42 ± 23	58 ± 23	50 ± 17
0.016	58 ± 23	25 ± 21	42 ± 17	58 ± 23	50 ± 24	54 ± 17
4 DAA						
0.500	25 ± 21	0	13 ± 11	83 ± 18	83 ± 18	83 ± 12
0.125	83 ± 18	50 ± 24	67 ± 16	67 ± 22	83 ± 18	75 ± 15
0.031	67 ± 22	25 ± 21	46 ± 17	75 ± 21	83 ± 18	79 ± 14
0.016	67 ± 22	33 ± 22	50 ± 17	58 ± 23	42 ± 23	50 ± 17
7 DAA						
0.500	50 ± 22	67 ± 22	61 ± 19	—	—	—
0.125	50 ± 22	67 ± 22	59 ± 17	100 ± 15	75 ± 21	79 ± 18
0.031	67 ± 22	67 ± 22	67 ± 16	50 ± 24	58 ± 23	54 ± 17
0.016	42 ± 21	25 ± 21	33 ± 16	42 ± 23	67 ± 22	54 ± 17

[a] The five best spectral bands for discriminating between treatments were determined by receiver operator characteristic analysis.

[b] Abbreviations: SA, signature amplitude; DAA, days after application.

[c] Expressed as a fraction of the full (labeled) rate, which were glyphosate, 1.12 kg ae/ha, and paraquat, 0.45 kg ai/ha, applied at 1/2-, 1/8-, 1/32-, and 1/64× rates of typical burndown applications.

[d] Classification accuracy represents how accurately SA analysis correctly classified plants in a two-class system: soybean plants treated with various rates of glyphosate compared with nontreated controls.

[e] Classification accuracy represents how accurately SA analysis correctly classified plants in a two-class system: soybean plants treated with various rates of paraquat compared with nontreated controls.

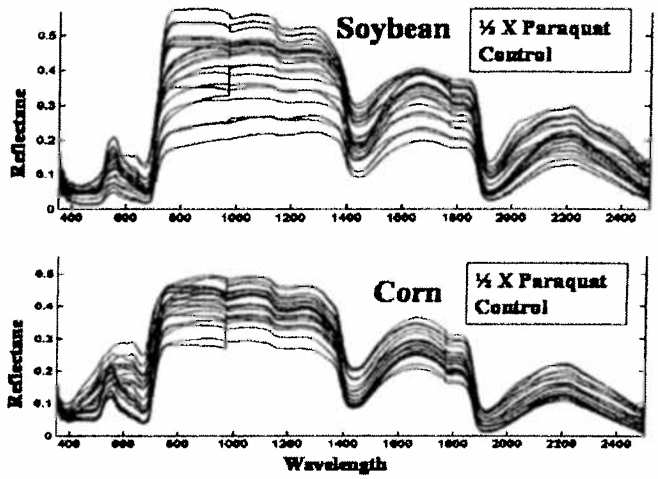


Figure 3. Hyperspectral responses of soybean and corn at 1 d after application of paraquat.

7). By 7 DAA, classification accuracy of the 1/2× rate remained relatively high at 83% compared with indices 54% (Table 4) and SA top five bands (Table 6). Benefits associated with this technique include increased likelihood of distinguishing between treated plants and control plants, even as drift rates decrease. However, this type of analysis requires a more robust data set to develop the procedure and train the system. Data must be collected of the vegetation's baseline spectral response before herbicide application. These data would then need to be compared with affected vegetation, and the regions exhibiting the greatest difference between treated and untreated spectral responses would be designated and spectral bands could then be extracted and used as features in a classification. Figures 3–5 are examples of the type of information needed to make an informed decision with respect to herbicide influence on vegetation spectral response with respect to time.

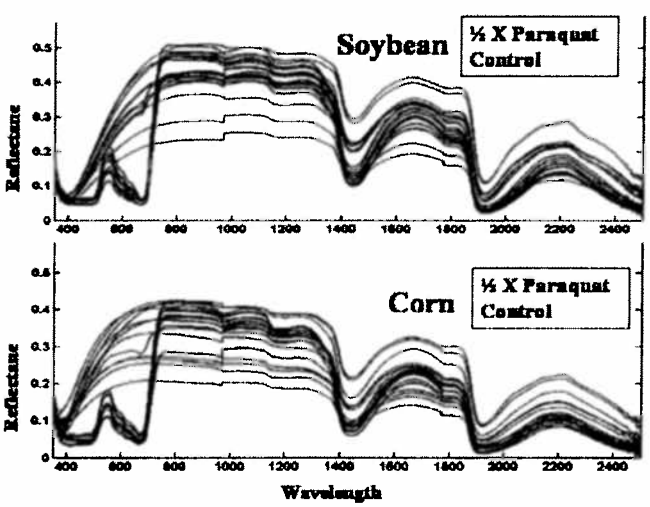
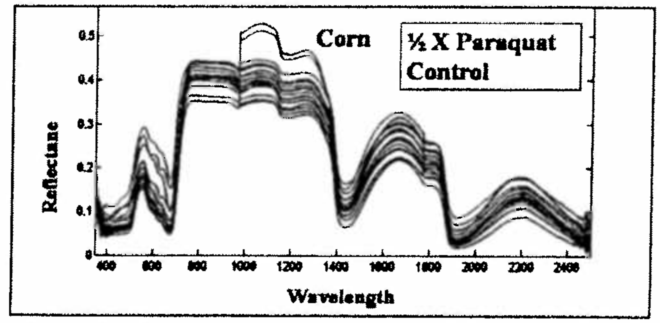


Figure 4. Hyperspectral responses of soybean and corn at 4 d after application of paraquat.



[a] Soybean receiving a 1/2X application of paraquat were dead at 7 days after application

Figure 5. Hyperspectral response of corn[a] at 7 d after application of paraquat.

The final analysis technique for detecting drift was wavelet analysis, and it was performed on the same paraquat–corn data set analyzed with the 10 linear bands. Classification accuracies 1 DAA were 88% or greater for all rates, with both 1/2- and 1/8× rates distinguishing 100% from the controls (Table 8). Classification accuracy remained high 4 DAA, with 1/2-, 1/8-, and 1/32× rates producing 100, 92, and 100% classification accuracies, respectively (Table 8). Unlike the other analysis

Table 8. Classification accuracies were determined using wavelet coefficients[a] as features to distinguish between corn controls and corn to which various rates of paraquat had been applied.[b]

Rate[c]	Paraquat	Control	Overall[d]
	%		
1 DAA			
0.500	100 ± 0	100 ± 0	100 ± 0
0.125	100 ± 0	100 ± 0	100 ± 0
0.031	92 ± 13	83 ± 18	88 ± 11
0.016	83 ± 18	92 ± 13	88 ± 11
4 DAA			
0.500	100 ± 0	100 ± 0	100 ± 0
0.125	92 ± 13	92 ± 13	92 ± 9
0.031	100 ± 0	100 ± 0	100 ± 0
0.016	75 ± 21	50 ± 24	63 ± 16
7 DAA			
0.500	100 ± 0	92 ± 13	94 ± 9
0.125	100 ± 0	92 ± 13	94 ± 9
0.031	56 ± 27	42 ± 23	48 ± 18
0.016	25 ± 21	67 ± 22	46 ± 17

[a] The five best wavelet coefficients were determined by receiver operator characteristics analysis.

[b] Abbreviation: DAA, days after application.

[c] Expressed as a fraction of the full (labeled) rate, which were glyphosate, 1.12 kg ae/ha, and paraquat, 0.45 kg ai/ha, applied at 1/2-, 1/8-, 1/32-, and 1/64× rates of typical burndown applications.

[d] Classification accuracy represents how accurately wavelet analysis correctly classified plants in a two-class system: corn plants treated with various rates of paraquat compared with nontreated controls.

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