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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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leased from the target (Al-Kahatib and Peterson 1999; Auch and Arnold 1978; Cranmer and Linscott 1990; Miller 1993; Nordby and Skuterud 1975).

Soybean is typically planted later in the growing season than corn. Burndown applications on these fields, as well as early POST applications of glyphosate to soybean, may drift off-target and affect adjacent fields of corn or susceptible, conventional soybean (Al-Khatib and Peterson 1999). Early in the growing season (April–May) is a particularly windy time of the year in Mississippi, thereby increasing the likelihood of a drift occurrence when herbicides are applied. Glyphosate and paraquat injury may decrease growth, reduce yield, or kill the susceptible crop entirely if the drift dosage exceeds the target tolerance level. Environmental conditions such as high winds or a temperature inversion favor herbicide drift and may result in injury up to a mile or more away. Determining the type and degree of injury is important to a producer. To use remote sensing to identify herbicide injury on crops, the manner in which herbicides affect crops must be considered.

Glyphosate is a foliar-applied, nonselective herbicide used for burndown and POST applications in glyphosate-resistant transgenic crops (James and Krattiger 1996). Inhibition of growth occurs almost immediately, followed by chlorosis at the newest growing points and necrosis throughout the entire plant within 1 to 2 wk. Glyphosate inhibits 5-enolpyruvylshikimate-3-phosphate (EPSP) synthase in the shikimate pathway (Amrhein et al. 1980). Without EPSP, the plant is unable to produce the aromatic amino acids phenylalanine, tryptophan, and tyrosine needed for growth. Paraquat is also a nonselective, foliar-applied herbicide (Calderbank 1968). Paraquat accepts electrons from photosystem I of photosynthesis and in the process reduces molecular oxygen, resulting in superoxide radicals (Calderbank 1968). Hydroxyl radicals are generated that readily oxidize lipid membranes. In full sunlight, exposed vegetation becomes chlorotic within hours and necrotic within 1 to 3 d (Fuerst and Vaughn 1990).

A challenge in detecting herbicide injury caused by drift rates is that crops often do not exhibit extensive injury symptoms; however, yield may still suffer. Rowland (2000) determined that low rates of glyphosate could reduce the yield of corn, and that stand height was one of the best parameters for estimating the degree of damage. If a crop is injured to the degree that height is limited and yield is decreased, perhaps a remotely sensed image could be used to detect these injury symptoms seemingly invisible to the naked eye.

Using remotely sensed data to determine the extent and location of herbicide injury would allow a producer an opportunity to seek out the guilty party, whose herbicide drifted. In 1998, drift accounted for 21% of the insurance claims in Iowa, and by 1999, over 80% of the complaints investigated by the Iowa Department of Agriculture and Land Stewardship dealt with drift (Pringnitz 1999). Drift became quite a problem in the Mississippi Delta in 2000 and 2001, with 145 cases of drift reported to the Bureau of Plant Industries in 2001 (T. McDaniel, personal communication). Because the frequency of drift events was increasing, herbicide labels were recently rewritten to ban the aerial application of glyphosate from March 15 through April 30 (T. McDaniel, personal communication). Determining the herbicide that drifted onto his or her crop is the first step before seeking out the guilty applicator. Second, the status of the crop must be determined. A producer needs to know what percentage of his or her acreage has been affected and to what degree. With this information, he or she could make an informed crop management and mitigation decision.

Remote sensing has been used in a variety of applications such as detecting weed infestations (Medlin et al. 2000), nutrient deficiencies (Bausch and Duke 1996; Kokaly 2001), disease (Nutter 1989; Nutter and Guan 2002), and hail damage (Heller 1978; Peters et al. 2000; Schiller 2001). Remote sensing imagery coupled with geospatial technologies could potentially be used to identify drift-affected portions of a field and also to determine the amount of herbicide that drifted onto the plant, resulting in injury. A producer could use this information to make informed decisions on a site-specific basis about terminating the crop and replanting or leaving the injured crop in the field, hoping that it will overcome the injury. Thus, the objectives of this research were to determine whether hyperspectral remote sensing data be used to identify crops onto which herbicide had drifted and, if so, at what rates.

MATERIALS AND METHODS

A drift experiment was conducted twice during the summer of 2001 outdoors at the R. Rodney Foil Plant Science Research Center at Mississippi State, MS. These experiments focused on nonselective herbicides prone to drift off-site and affect nontarget crops. These experiments were conducted in a randomized complete block design with a 2 by 5 by 2 factorial arrangement of treatments, with herbicide, rate, and species as factors. Soybean (cultivar 'Hutcheson') and corn (cultivar 'Pioneer

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).

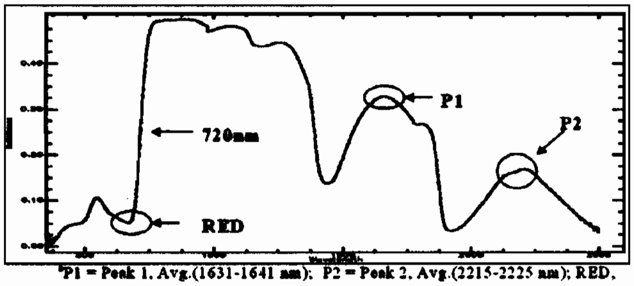
Multiple indices were used as features in traditional statistical classification procedures. This was conducted with a stepwise discriminant analysis procedure[6] using crossvalidation (leave-one-out testing) in all instances. Rouse et al. (1973) and Tucker (1979) were pioneers in using portions of the 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.



*P1 = Peak 1, Avg.(1631-1641 nm); P2 = Peak 2, Avg.(2215-2225 nm); RED, Avg.(670-680 nm); 720 = 720 nm.

Figure 1. Differential indices of normalized observation indices were constructed from multiple regions of the electromagnetic spectrum including the range between 1,400 and 2,500 nm.

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 2).

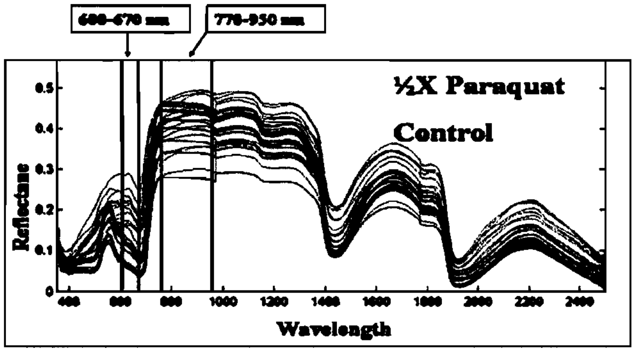
Additional indices such as soil-adjusted vegetation index have been created that address issues such as minimizing soil background interference (Huete 1988). With this concept of tailoring an index to address a particular need, additional differential index of normalized observations (DINO) indices (Table 3; Figure 1) 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 and Knapp (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 shortwave infrared (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 influence the moisture status 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.

Reflectance data were analyzed within each day, experimental run, between experimental runs, 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 experiments. 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 characteristic (ROC) analysis was used to determine the efficacy of each band as a potential classification feature. ROC analysis used in this study assumes that the two classes' features have Gaussian distributions. The area under the ROC curve ranges from 0.5 to 1.0, with 0.5 representing features not useful in classification (exact overlap of the two classes' distribution curves) and 1.0 corresponding to ideal classification features (no overlap between distribution curves) (Hanley and McNiel 1982). The area under the ROC curve was used as a design parameter for choosing a subset of spectral bands to use as classification features. The reflectance values for the top five bands (largest area under the ROC curve) of the original data set of 2,151 bands were used as features. The extracted feature for each spectral response is a one by five 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 one by five feature vector is eventually reduced to a one by one feature vector. Finally, the one by one 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 crossvalidation analysis.

In addition to using reflectance values of the five best bands as features, two alternative feature extraction techniques were also used. The motivation for the third analysis technique stemmed from visual inspection of the hyperspectral reflectance data. Differences in reflectance between the plants to which herbicide had been applied and the control plants were particularly evident in two regions of the electromagnetic spectrum between 600 to 670 nm and 770 to 950 nm (Figure 2). Five linearly spaced spectral bands within each of these two regions 600 to 670 nm (600, 618, 635, 653, and 670 nm) and 770 to 950 nm (770, 815, 860, 905, and 950 nm) resulted in 10 features for classification. LDA was also used with



ᵃRegions, 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	
Rateᵇ	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 2. 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, thermatic mapper.

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

73% correct for paraquat on soybean 4 DAA in the first experimental run (data not shown). Although classification accuracies were relatively good in this one scenario, when averaged across herbicides, species, time, and experimental runs, they were only slightly higher (29%) than by random (20%) in a five-class system. In the instance that indices were successful (73% classification accuracy) in classifying rates of paraquat on soybean 4 DAA in the first experimental run, the highest rate, 1/2×, and controls generated 100 and 83% classification accuracies, respectively. Misclassification of the 1/64× rate of soybean as controls, and also misclassification of the 1/32× as 1/8×, resulted in reduced overall accuracies.

To circumvent the difficulties presented by misclassification of the moderate and low rates (1/8, 1/32, and 1/64×), and still generate useful information, the five rates were grouped into two categories: plants to which a 1/32× or greater rate of herbicide was applied (1/2, 1/8, and 1/32×) and plants to which a 1/64× or no herbicide was applied (1/64× and control). Continuing to analyze data within species, herbicide, and experimental run, classification accuracies, using multiple indices as features in step-wise discriminant analysis with cross-validation testing, remained relatively poor when the number of categories was reduced from a five-class to a two-class system (data not shown).

Table 3. 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	$(10P2)^2/720$
DINO9	$((P2)^2 - 720)/((P2)^2 + 720)$
DINO10	$((5P2)^2 - 720)/((5P2)^2 + 720)$
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.

There was no interaction with respect to experimental run and the visual injury data; therefore, data from both experimental runs were pooled (Table 1). Pooling experimental runs is beneficial because it increases the sample size and adds to the robustness and predictive capabilities of models generated from a larger data set. Data were again analyzed with multiple indices, and each rate was compared individually with the controls (Table 4). Substantial injury was caused by the two highest rates (1/2 and 1/8×) of glyphosate, resulting in 50 to 81% injury on soybean and 42 to 67% injury on corn (Table 1). Although visual injury symptoms greater than 40% were present, at neither 4 nor 7 DAA were indices able to distinguish between either of these two rates and the control any better than 77%. The injury symptoms were present, but this analysis technique was not able to distinguish between injured plants and unaffected (control) plants. Glyphosate injury may be more difficult to detect because of its mode of action. Glyphosate inhibits the production of essential aromatic amino acids, resulting in injury symptoms that are visible in the treated plants several DAA. There were no, or only minor, injury symptoms associated with the contact of glyphosate on the leaf, so at low application rates, there may be no visible injury symptoms beyond stunting or a slight height reduction (Rowland 2000). These features, although they would have been more likely to affect the newer leaves that were measured (second and third unfurled leaf from the top of the plant), were difficult to detect spectrally. Conversely, paraquat injury was successfully detected in both soybean and corn, particularly at the 1/2- and 1/8× rates. Whereas glyphosate injury symptoms were visible after several days, paraquat acted within a matter of hours. The 1/2× rate of paraquat on both soybean and corn was distinguished better than 91% from controls at both 1 and 4 DAA (Table 4). By 7 DAA, the plants exposed to the 1/2× rate of paraquat

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.

Table 6. SA analysis using the five best bands[a] as features was used to distinguish between corn controls and corn 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	50 ± 24	50 ± 33	50 ± 19	75 ± 21	83 ± 18	79 ± 14
0.125	42 ± 23	50 ± 33	44 ± 19	42 ± 23	67 ± 22	54 ± 17
0.031	30 ± 24	17 ± 25	25 ± 18	58 ± 23	67 ± 22	63 ± 16
0.016	67 ± 22	50 ± 33	61 ± 19	42 ± 23	58 ± 23	50 ± 17
4 DAA						
0.500	50 ± 22	33 ± 32	45 ± 18	75 ± 21	75 ± 21	75 ± 15
0.125	39 ± 22	17 ± 25	32 ± 17	75 ± 21	75 ± 21	75 ± 15
0.031	40 ± 25	17 ± 25	31 ± 19	67 ± 22	67 ± 22	67 ± 16
0.016	50 ± 24	50 ± 33	50 ± 19	42 ± 23	58 ± 23	50 ± 17
7 DAA						
0.500	58 ± 23	67 ± 32	61 ± 19	67 ± 32	75 ± 21	72 ± 17
0.125	58 ± 23	33 ± 32	50 ± 19	33 ± 32	58 ± 23	50 ± 19
0.031	30 ± 24	17 ± 25	25 ± 18	57 ± 27	75 ± 21	67 ± 17
0.016	67 ± 22	50 ± 33	61 ± 19	25 ± 21	58 ± 23	42 ± 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: corn 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: corn plants treated with various rates of paraquat compared with nontreated controls.

Table 7. SA analysis using 10 bands as features chosen from two spectral regions[a] exhibiting the greatest difference between the treated corn plants and the controls.[b]

Rate[c]	Paraquat	Control	Overall[d]
	%		
1 DAA			
0.500	92 ± 13	100 ± 0	96 ± 7
0.125	100 ± 0	100 ± 0	100 ± 0
0.031	92 ± 13	83 ± 18	88 ± 11
0.016	75 ± 21	100 ± 0	88 ± 11
4 DAA			
0.500	100 ± 0	100 ± 0	100 ± 0
0.125	75 ± 21	75 ± 21	75 ± 15
0.031	100 ± 0	100 ± 0	100 ± 0
0.016	58 ± 23	67 ± 22	63 ± 16
7 DAA			
0.500	67 ± 32	92 ± 13	83 ± 14
0.125	67 ± 32	75 ± 21	72 ± 17
0.031	67 ± 26	58 ± 23	62 ± 17
0.016	58 ± 23	42 ± 23	50 ± 17

[a] Five linearly spaced spectral bands were chosen between 600 and 670 and also between 770 and 950 nm. These 10 spectral bands were used as features for classification.

[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: corn plants treated with various rates of paraquat compared with nontreated controls.

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, with these analysis techniques, 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. With this in mind, additional analysis techniques were used.

A data set with which to try additional analysis techniques was chosen from the paraquat treatments because these treatments provided a broad range of injury, as well as the most promising results from the first two analysis techniques. Corn was chosen instead of soybean because there was significant soybean mortality at the higher paraquat application rates. The third analysis technique was similar to the top five bands technique, but as opposed to selecting the top five bands with ROC curve analysis, two regions were selected in which differences between the treated and the control spectral responses were most evident (Figure 2). Within each of these two regions, five linearly spaced spectral bands were chosen for a total of 10 features. These features were used to generate classification accuracies (Table 7). Classification accuracies, regardless of rate, were 88% or higher 1 DAA (Table 7). Excluding the 1/64× rate at 4 DAA, classification accuracies were 100, 75, and 100% for the 1/2-, 1/8-, and 1/32× rates, respectively (Table

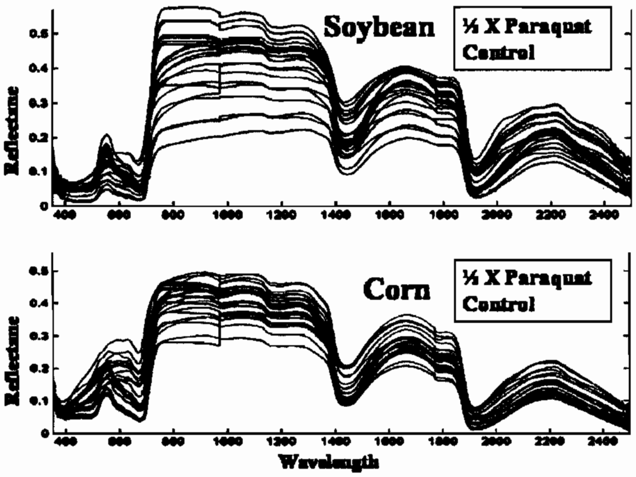


Figure 3. Hyperspectral responses of soybean and corn at 1 d after application of paraquat.

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.

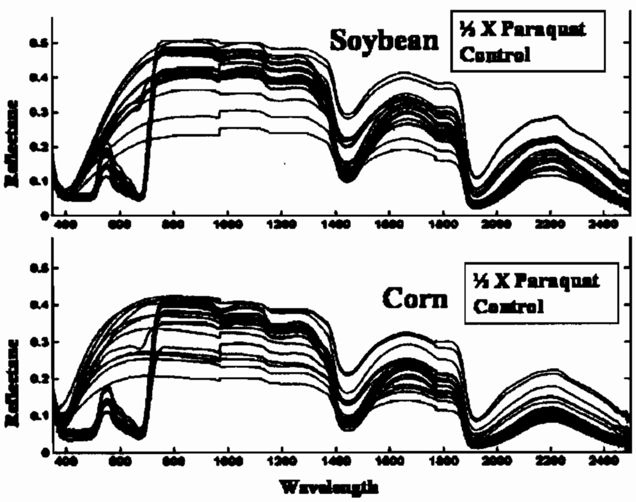
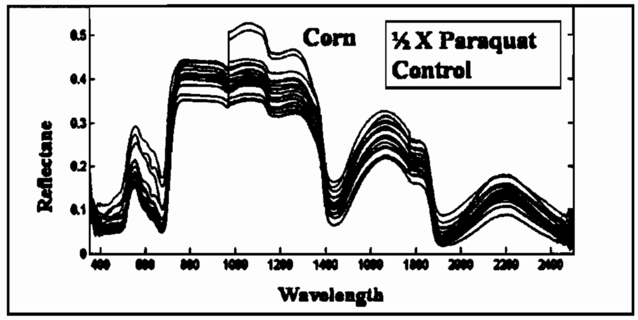


Figure 4. Hyperspectral responses of soybean and corn at 4 d after application of paraquat.



[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.

Table 9. Indices[a] were used to build discriminant models that distinguished between glyphosate and paraquat injury on soybean and corn at 1, 4, and 7 DAA.[b]

1 DAA				4 DAA				7 DAA			
Soybean (78%)[c]		Corn (93%)[d]		Soybean (90%)		Corn (89%)		Soybean (60%)		Corn (65%)	
Index	CCC[e]	Index	CCC	Index	CCC	Index	CCC	Index	CCC	Index	CCC
DINO12	0.37	RVI	0.53	RVI	0.67	RVI	0.61	DINO2	0.06	NDVIg	0.06
DINO6	0.41	NDVIg	0.59	DINO12	0.71	DINO12	0.63	DINO5	0.17	DINO12	0.10
		NDVI	0.62	NDVIg	0.74	MSI	0.66	DINO7	0.21	MSI	0.22
				DINO4	0.78	DINO4	0.67			DINO11	0.26
						DINO2	0.69				
						DINO3	0.73				

[a] Indices (Tables 2 and 3) created from hyperspectral data were used as classifiers.

[b] Abbreviations: DAA, days after application; DINO, differential index of normalized observations; RVI, ratio vegetation index; NDVIg, normalized difference vegetation index (green), MSI, moisture stress index; CCC, canonical correlation coefficient.

[c] Soybean to which either glyphosate or paraquat was applied at 1/2-, 1/8-, 1/32-, or 1/64-× rates.

[d] Corn to which either glyphosate or paraquat was applied at 1/2-, 1/8-, 1/32-, or 1/64-× rates.

[e] CCC measures the amount of variability accounted for by each index as it is added to a discriminant model distinguishing between paraquat and soybean injury on crops.

techniques, wavelet analysis distinguished the paraquat from the control treatments 94% at both the 1/2- and 1/8× rates 7 DAA. By 7 DAA, the leaves that were being measured were new growth that had not been directly injured (at least with respect to contact injury) by paraquat. These plants remained stressed, 71% or higher injury at 7 DAA (Table 1), but wavelet analysis showed promise for detecting both the contact burn caused by paraquat at 1 and 4 DAA, as well as the stress that would be evident in the new growth at 7 DAA of a plant whose leaves had recently been substantially injured with paraquat. This is the scenario that would most likely be seen in a field-scale drift event. Of course, considering the timing of the imagery acquisition with respect to the date that the drift event occurred would be beneficial in determining the extent and degree of the injury throughout the field. Some leaves would exhibit the necrotic symptomology, whereas newer regrowth, depending on how soon after the drift event the imagery was gathered, would lack the necrotic lesions but could potentially reflect light differently compared with a plant that had never been exposed to paraquat.

Indices were also examined for their utility in distinguishing between glyphosate or paraquat drift. Classification accuracies were generated with respect to day (Table 9). Classification accuracies ranged from 60% for soybean at 7 DAA to 93% for corn at 1 DAA. Considering how low the classification accuracies were for the glyphosate treatments compared with the controls (approximately 50% that was effectively equivalent to chance in a two-class system) (Table 4), the differences being measured are most likely an injured reflectance (paraquat) compared with a much less injured reflectance (glyphosate). In fact, at 7 DAA, as the glyphosate injury increased to 81 and 50% on beans and corn, respectively, the paraquat injury began to decline as the plants grew new leaves. This resulted in plants with similar degrees of injury, albeit caused by different herbicides, which were difficult (60 to 65% classification accuracies) to classify spectrally (Table 9). Of the indices that were useful in distinguishing between herbicides, ratio vegetation index, a ratio comprising the red and NIR regions of the spectrum, and DINO12, an NDVI-like index comprising a region around 2,200 nm, were two of the indices that contributed the most to explaining the variability in these classification models. This information is useful to isolate the regions of the electromagnetic spectrum that contribute the most to discriminating between treatments should it ever be necessary to apply additional data analysis techniques such as 10 linear bands.

The analysis techniques described in this study are now available for field validation and testing. Geospatial technologies used to map a field in which a drift event has occurred can be combined with remote sensing spectral algorithms and techniques for management decisions such as assessing the extent and perhaps the degree of damage by creating management zones so that the grower could make timely and informed decisions with respect to terminating the crop and replanting, filing suit against an irresponsible pesticide applicator, or letting the crop continue to grow, hoping that it will recover before harvest.

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