THE APPLICATION OF REMOTE SENSING FOR DETECTION OF PLANT REFLECTANCE RESPONSE TO HERBICIDE STRESS IN CORN CROPPING SYSTEMS

A Thesis

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ABSTRACT

Everman, Wesley J. M.S., Purdue University, December, 2002. The Application of Remote Sensing for Detection of Plant Reflectance Response to Herbicide Stress in Corn Cropping Systems. Major Professor: Thomas T. Bauman.

Increased use of site specific management in agriculture and weed science has led to increased research efforts to map weed populations and the dynamics of those populations that impact the spectral reflectance properties of crops. It may be possible to find reflectance response patterns of individual species that would open the future to a broad expanse of possibilities in the field of remote sensing and site-specific weed management. To increase the ease of research being conducted in this area, the impacts of herbicides on corn reflectance response patterns are being researched. The identification of herbicides that do not impact the spectral response pattern of corn could be used for weed control over a large experiment area, with weeds of interest being established in untreated areas. This would reduce hand-weeding costs required to study reflectance response patterns of weed/crop population dynamics. PRE corn herbicides evaluated were alachlor, atrazine, flufenacet + metribuzin, isoxaflutole, metolachlor, and pendimethalin. POST corn herbicides included atrazine + crop oil, bromoxynil, dicamba + diflufenzopyr, dicamba, nicosulfuron, and primisulfuron-methyl. Treatments were selected for their range of symptomology as well as their common usage across the Midwestern corn belt. Multispectral and hyperspectral data were collected over the test area. Ground-based reflectance data were also collected with a field spectrometer mounted 7-m above the crop canopy. Spectral properties of the various treatment regimes were analyzed using SAS procedures and MultiSpec image analysis.

CHAPTER 1

LITERATURE REVIEW

INTRODUCTION

Growing concerns in agriculture regarding public awareness to pesticides and pest control costs have led to increased efforts to find methods that maximize pest control and minimize costs and effects on the environment. Health and environmental concerns, low commodity prices, and weed control costs have motivated researchers to seek ways to reduce herbicide inputs and costs (Browner et al., 1993; Fernandez-Cornejo and Jans, 1999). Herbicides, compared to cultivation, help reduce the labor and time needed for effective weed management, which can lead to increased economic return for the farmer. Reduced time and labor requirements for weed control can free resources needed to expand farming operations (Ashton and Monaco, 1991).

Negative aspects of herbicide use include the health risks associated with these chemicals. Data accumulated from laboratory animal and human case studies indicate many pesticides are immunomodulatory and may be health risks (Blakely et al., 1999). For example, 2,4-D acid can cause severe damage on the lymphatic organs, thymus and spleen of rats (Kaioumova et al., 2001). The triazine herbicides can cause reproductive complications in rats and pigs (Kniewald et al., 1998). Atrazine can affect the reproductive ability of male rats and ovarian function and endocrine profile of female rats (Cooper et. al., 1996). Gojmerac et al. (1999) reported delayed oestrus of gilts treated with atrazine serum. There are significant effects in human health studies as well. First-trimester miscarriages of spouses of pesticide applicators in the Red River Valley occur most frequently in the spring during the time when herbicides are applied (Garry et al., 2002). The use of sulfonylurea and imidazolinone herbicides has been statistically associated with those miscarriages.

Herbicidal impacts on the environment, particularly our surface and groundwater supplies, are another major concern. Battaglin et al. (2000) detected acetochlor, alachlor, atrazine, cyanazine, and metolachlor in 90% or more of 129 stream samples in the Midwest. At least one of the 16 sulfonylurea, sulfonamide, or imidazolinone herbicides was detected above the method reporting limit of 0.01 µg/L in 83% of 130 stream samples (Battaglin et al., 2000). Kolpin et al. (2000) found that when herbicide degradates were included in tests, the frequency of detection approached 90%. Rothstein et al. (1996) analyzed eight tile lines draining a research field and correlated increased flow rates with increase atrazine concentration in a stream. Baseline concentrations of atrazine leaving the field ranged between 0 and 0.4 µg/L, however, immediately following a 0.8 inch rainfall, 6 days after application of 1.4 kg/ha atrazine, the concentration reached 34.5 µg/L. Due to these health and environmental concerns more stringent herbicide regulations could lead to a reduction in the number and amount of herbicides available in the future.

A growing concern in the agricultural sector is the regulation of atrazine, a very effective and affordable herbicide used in corn (Zea mays L.). Without atrazine, weed control costs in corn could increase an estimated $37 per hectare (Pike et al., 1996). The cost of losing all the triazine herbicides for corn would be about $45 per hectare annually. Nationally, this would amount to approximately $680 million per year for the loss of atrazine and approximately $900 million per year for the loss of all triazines. These figures do not take into account the cost of additional soil erosion where tillage will be used as an alternative to atrazine.

Consideration must also be given to the application of the herbicides. Conventional weed control programs generally rely on the assumption of homogenous distribution of weed species within a given field. This usually results in the over application of herbicides since much of the field is weed free (Hughes, 1989; Thornton et al., 1990; Wiles et al., 1992). An area of growing interest is in application procedures that limit herbicide use to only weed infested areas. The use of remote sensing in locating weed infestations creates the opportunity for producers to treat only the infested areas of fields. This could reduce the volume of herbicides used in the environment as well as reduce herbicide costs. Lillesand and Kiefer (2000) define remote sensing as the science and art of obtaining information about an object, area, or phenomenon through the analysis of data acquired by a device that is not in contact with the object, area, or phenomenon. Although in the broad sense this may encompass many technologies, researchers in the field of weed science have directed their attention toward the sensing of light reflectance/absorbance differences. Light reflectance of plants is typically measured by a sensor that quantifies the amount of energy being reflected by the plant. Sensors are classified into two broad categories based on their sensing ability, multispectral and hyperspectral scanners.

Multispectral scanners operate on the principle of selective sensing of 3-7 spectral bands over a great range of the electromagnetic spectrum (Lillesand and Kiefer, 2000). The specificity of multispectral scanners range from 300 to approximately 2400 nm, including the ultraviolet (UV), visible, near-infrared (IR), mid-infrared, and thermal infrared spectral regions (Lillesand and Kiefer, 2000).

Hyperspectral sensors acquire data in many (>30), very narrow, contiguous spectral bands throughout the visible, near-IR, mid-IR, and thermal IR portions of the spectrum. The data collected from 200 or more reflectance bands enables the construction of an almost continuous reflectance spectrum for every pixel in the image. Hyperspectral systems can discriminate among earth surface features that have diagnostic absorption and reflection characteristics over narrow wavelength intervals that are "lost" within the relatively coarse bandwidths of the various bands of conventional multispectral scanners (Lillesand and Kiefer, 2000).

The introduction of hyperspectral sensors, and thus the collection of much more detailed spectral data, provides greater opportunities for extracting useful information from the data. However, these more detailed data require more sophisticated data analysis procedures if their full potentials are to be achieved

(Landgrebe, 1999A). Multispectral data are represented quantitatively and visualized in three principle ways, image, spectral, and feature space. Image space represents the data in image form, spectral space represents the data as a function of wavelength, and feature space illustrates how the response in the different wavelengths relate to each other, i.e. response in a wavelength plotted against that for the other wavelength.

The use of remote sensing for weed control has increased efforts to understand weed population dynamics and factors that impact their spectral reflectance properties. It may be possible to find reflectance response patterns of individual weed species that would open the future to site-specific weed management. Classification of weeds in crop and rangeland areas has been accomplished (Menges et al., 1985; Everitt et al., 1995; Lass et al., 1996; Lass and Callihan, 1997; Williams and Hunt, 2002; and Vrindts et al., 2002). Menges et al. (1985) found that discrete weed community areas could be determined by computer based image analyses with accuracies of 82% for Palmer amaranth and 81% for johnsongrass in a replicated monoculture plot study. Vrindts et al. (2002) correctly classified 90% of their remotely sensed data as crop or weed.

Medlin and Shaw (2000) found that simulated site-specific herbicide management in soybean production systems resulted in higher estimated net gains than broadcast herbicide management. This held true both for transgenic and non-transgenic cropping systems. Estimated net gains for site-specific herbicide management vs. broadcast herbicide management ranged from $13.32 to $29.66 per hectare in non-transgenic soybean, and from $22.15 to $29.45 per hectare in glyphosate-tolerant soybean.

Although the positive attributes of a site-specific application system seem endless, many hurdles must be overcome before the adoption of the technology. One issue that must be overcome is the day to day variability of remotely sensed data. Radiation reaching the surface of a material is subject to one or more of several processes, reflection (diffuse, specular), transmission (with refraction), or absorption compliant to the law of conservation of energy. This interaction of the radiation with the surface is dependent on both the properties of the radiation as well as the properties of the material (Suits, 1983). The radiance spectrum of the sun differs from day to day and place to place, partly due to the changes in the sun's surface, but in part due to changes of the earth's atmospheric composition absorbing part of the sun's radiation at particular wavelengths and the illumination angle. Due to this variation of incidence spectral radiation, as well as changes in the earth's surface characteristics, the radiance spectrum reflected from earth is highly variable. Therefore, to be able to compare spectral measurements of surfaces acquired on different days and in different illumination conditions, a currently nonexistent measure is required that is independent of illumination variation, or that is calibrated for changing illumination.

A practical problem also remains in how to measure reflectance, especially for remote sensing data. The measure of reflectance is the dimensionless ratio of radiation reflected from a surface, to the radiation hitting that surface. Different radiometric quantities can be ratioed to produce many reflectance indices with a multitude of names (e.g. fluorescence). Generally the reflectance of a surface can be measured in three different ways: the bi-hemispherical reflectance which is measured with an integrating sphere mostly in a laboratory, the hemispherical-conical reflectance which is measured with a flat Lambertian reference panel and most commonly utilized in remote sensing research conducted in the field, and the bi-directional distribution function which is a theoretical concept and can not be measured in practice (Kimes and Kirchner, 1982).

A third hurdle that must be overcome prior to widespread use of remote sensing for weed management is the resolution needed to accurately identify weeds in crops. The four types of resolution are spatial, spectral, radiometric, and temporal. These resolution characteristics help to describe the functionality of both remote sensing sensors and remotely sensed data. Spatial resolution is the minimum size of terrain features that can be distinguished from the background in an image (ERDAS, 1999). It is also defined by the area that a pixel represents in a digital image file (e.g. 4-m by 4-m). Large scale in remote sensing refers to imagery in which each pixel represents a small area on the ground. Small scale refers to imagery in which each pixel represents a large area on the ground.

Spectral resolution refers to the number and width of specific wavelength intervals in the electromagnetic spectrum to which a sensor or sensor band can record (ERDAS, 1999). Wide intervals in the electromagnetic spectrum are referred to as coarse spectral resolution, and narrow intervals are referred to as fine spectral resolution. Radiometric resolution refers to the dynamic range or number of possible data values in each band. This is referred to by the number of bits into which the recorded energy is divided. For 8-bit data, the total intensity of the energy, from zero to the maximum amount the sensor measures, is broken down into 256 brightness values. The data file values range from zero, for no energy return, to 255, for maximum return, for each pixel.

Temporal resolution is a measure of how often a given sensor system obtains imagery of a particular area, or how often an area can be revisited (ERDAS, 1999). The temporal resolution of satellites is on a fixed schedule, which allows for more repetitive views. This revisit capability makes it possible to use several passes, perhaps covering two or three seasons or multiple years, for interpretation.

If wide-scale use of remote sensing for weed control is to occur, the impact of biotic and abiotic stresses on weed and crop reflectance must be understood. For example, it is unknown whether commonly used herbicides will impact the reflectance characteristics of tolerant weeds and crops. Plant stress reflectance sensitivities are generally greatest in the orange and red spectra, except for peaks in the violet and green spectra that accompany herbicide damage (Carter, 1993). General plant stresses can be detected by an increase in reflectance in the 695-725 nm wavelength range. This area is often overlooked for spectral change detection due to the steep slope of the reflectance curves in the far-red spectrum often producing an illusion that stress-induced differences are negligible near 700 nm (Carter and Knapp, 2001). In addition, Carter (1993) reported the maximum reflectance peak at 409 nm responds differently for herbicide stress in persimmon than other stressors. Persimmon showed reflectance sensitivities and differences in wavelength ranges of 405-409, 519-573, 688-735, 1,384-1,401, and 1,875-1,905 nm with a maximum near 409 nm when treated with diuron (Carter, 1993).

One of the largest problems facing the remote sensing field, especially hyperspectral analysis, is that the number of training samples is usually not as numerous as desired. The number of training samples needed to adequately define the classes quantitatively, regardless of what discriminant function is used, grows very rapidly with the number of spectral bands to be used. This suggests that for a fixed number of training samples there is an optimal measurement complexity. Too many spectral bands or too many brightness levels per spectral band are undesirable from the standpoint of expected classification accuracy (Landgrebe, 1999B). This is known as the Hughes effect.

However, there are ways to reduce or limit this effect. It has been found that when the accuracy is below optimality due to limited training because of the Hughes effect described above, a less complex classifier algorithm may provide increased classification accuracy.

The classification rule that results from using the class conditional maximum likelihood estimates for the mean and covariance in the discriminant function, as if they were the true mean and covariance, achieves optimal classification accuracy only asymptotically as the number of training samples increases toward infinity. This classification scheme is not optimal when the training sample is finite. When the training set is small, the sample estimated covariance is most likely different from the true covariance. In fact, for p features, when the number of training samples is less than p+1, the sample covariance is always singular (Landgrebe, 1999B).

In high dimensional cases, it has been found that feature extraction methods are especially useful to transform the problem to a lower dimensional space with the loss of little or no information (Kuo and Landgrebe, 2002).

Recent advances in personal computer storage and processing capabilities have allowed more researchers to analyze complex images and data sets. This increase in computer power has also led to the development of more accurate data analysis techniques and algorithms.

The possibilities for the use of remote sensing as a "weed detection tool" has increased research efforts to (1) manage monocultures or desired mixed populations of certain species, and (2) determine the impact of production practices on the spectral reflectance properties of the crop canopy. Therefore, if a herbicide can be identified that does not impact the spectral response pattern of a crop it could be used for weed control over a large experiment area. Weed patches of interest, with known populations and locations, could be established in untreated areas. Hand-weeding that is regularly needed to maintain species compositions would be effectively reduced. Combined with research done to identify the reflectance response patterns of individual weed species, the stage would be set for an experiment that would test classification accuracy of weed compositions in a field setting. This research could allow the integration of remote sensing with site-specific application technologies for an integrated weed control system.

The use of this technology could be expanded to commercial applicators and producers as well. If differences can be consistently be found in how individual herbicides affect the reflectance of corn, previous herbicide treatments could be determined and subsequent applications could be planned accordingly.

There is also potential for the use of herbicide identification using remote sensing to identify areas of misapplication or to find herbicide drift. Specific rate tests will need to be conducted to determine the spectral response of corn due to herbicide applications below labeled rates.

Therefore the objective of this research is to assist future research conducted in this area by investigating what impacts pre-emergence herbicides alachlor, atrazine, flufenacet + metribuzin, isoxaflutole, metolachlor, and pendimethalin at labeled rates have on corn canopy reflectance. The effects of post emergence herbicides 2,4-D, atrazine, bromoxynil, dicamba + diflufenzopyr, nicosulfuron, and primisulfuron-methyl at labeled rates will also be investigated.

These herbicides have been selected due to their common use in the Midwestern Corn Belt, as well as their wide range of symptomology. No effect is expected on corn canopy reflectance due to the pre herbicides alachlor, atrazine, and metolachlor because they are metabolized quickly into inactive compounds, however some level of injury, buggy whipping or interveinal chlorosis, can occur when using these herbicides if weather or stress conditions slow growth and the herbicide is accumulated. Spectral differences in corn treated with flufenacet + metribuzin are anticipated damage to corn plants by inhibiting root and shoot growth and inhibiting photosynthesis. Isoxaflutole causes bleaching and can cause whitening of corn leaves when environmental conditions are right, potentially causing spectral reflectance changes. Pendimethalin can possibly cause a spectral change by inhibiting root development in corn and by causing reddish or purple leaf margins on the plant.

Atrazine, nicosulfuron, and primisulfuron-methyl were selected as post emergence treatments because they generally do not injure the corn plants, and should not alter the spectral response corn. Atrazine can cause yellow leaf tips or interveinal chlorosis if weather conditions are right or oil is used in hot weather. Nicosulfuron can cause yellow flash on the leaf whorl, chorosis, buggy-whipping, or purpling of the stem and leaves if corn is under stress or the herbicide is applied at the wrong growth stage. Bromoxynil was selected due to its tendency to cause oblong, oval shaped lesions on the leaves of corn plants. This can be a result of weather conditions changing from cool to hot weather before application, thinning the leaf cuticle. A spectral difference should be easily detected if the spectral response of the leaves is changed due to the lesions. 2,4-D is an auxin growth regulator and can stress and affect the growth of corn plants by onion-leafing the new leaves or bending the stem. These actions would change the reflectance properties on the plant and should be detectable using remote sensing methods. Dicamba + diflufenzopyr is a growth regulator and should create similar spectral changes as the 2,4-D treatment. These symptoms can sometimes be attributed to late application, soil type, or shallow corn planting.

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CHAPTER 2

THE EFFECT OF PREEMERGENCE HERBICIDES ON THE SPECTRAL RESPONSE CHARACTERISTICS OF CORN CANOPY REFLECTANCE

INTRODUCTION

Growing concerns in agriculture regarding public awareness to pesticides and pest control cost has led to increased efforts to find methods that maximize pest control and minimize costs and effects on the environment. Health and environmental concerns, low commodity prices, and weed control costs are the basis for researchers seeking ways to reduce herbicide inputs and costs (Browner et al., 1993; Fernandez-Cornejo and Jans, 1999).

Herbicides, compared to cultivation, help reduce the labor and time needed for effective weed management, which can lead to increased economic return for the farmer. Reduced time and labor requirements for weed control can free resources needed to expand farming operations (Ashton and Monaco, 1991).

A growing concern in the agricultural sector is the regulation of atrazine, a very effective and affordable herbicide used in corn. Without atrazine, weed control costs in corn could increase an estimated \$37 per hectare (Pike et al., 1996). The cost of losing all the triazine herbicides for corn would be near \$45 per hectare annually. Nationally, this would amount to approximately \$680 million per year for the loss of atrazine and approximately \$900 million per year for the loss of all triazines. These figures do not take into account the cost of additional soil erosion where tillage will be used as an alternative to atrazine. Therefore, other ways of reducing weed control costs should be explored.

Conventional weed control programs generally rely on the assumption of homogenous distribution of weed species within a given field. This usually results in the over application of herbicides since much of the field is weed free (Hughes, 1989; Thornton et al., 1990; Wiles et al., 1992). An area of growing interest is in application procedures that limit herbicide use to only those weed infested areas. The use of remote sensing in locating weed infestations creates the opportunity for producers to treat only the infested areas of fields. This could reduce the volume of herbicides used in the environment as well as reduce herbicide costs. Lillesand and Kiefer (2000) define remote sensing as the science and art of obtaining information about an object, area, or phenomenon through the analysis of data acquired by a device that is not in contact with the object, area, or phenomenon. Although in the broad sense this may encompass many technologies, researchers in the field of weed science have directed their attention toward the sensing of light reflectance/absorbance differences. Light reflectance of plants is typically measured by a sensor that quantifies the amount of energy being reflected by the plant. Sensors are classified into two broad categories based on their sensing ability, multispectral and hyperspectral scanners.

The use of remote sensing for weed control has increased efforts to understand weed population dynamics and factors that impact their spectral reflectance properties. It may be possible to find reflectance response patterns of individual weed species that would open the future to site-specific weed management. Classification of weeds in crop and rangeland areas has been accomplished (Menges et al., 1985; Everitt et al., 1995; Lass et al., 1996; Lass and Callihan, 1997; Williams and Hunt, 2002; and Vrindts et al., 2002). Menges et al. (1985) found that discrete weed community areas could be determined by computer based image analyses with accuracies of 82% for Palmer amaranth and 81% for johnsongrass in a replicated monoculture plot study. Vrindts et al. (2002) correctly classified 90% of their remotely sensed data as crop or weed.

Medlin and Shaw (2000) found that simulated site-specific herbicide management in soybean production systems resulted in higher estimated net gains than broadcast herbicide management. This held true both for transgenic and non-transgenic cropping systems. Estimated net gains for site-specific herbicide management vs. broadcast herbicide management ranged from $13.32 to $29.66 per hectare in non-transgenic soybean, and from $22.15 to $29.45 per hectare in glyphosate-tolerant soybean.

If wide-scale use of remote sensing for weed control is to occur, the impact of biotic and abiotic stresses on weed and crop reflectance must be understood. For example, it is unknown whether commonly used pre-emergence herbicides will impact the reflectance characteristics of tolerant weeds and crops. Plant stress reflectance sensitivities are generally greatest in the orange and red spectra, except for peaks in the violet and green spectra that accompany herbicide damage (Carter, 1993). General plant stresses can be detected by an increase in reflectance in the 695-725 nm wavelength range. This area is often overlooked for spectral change detection due to the steep slope of the reflectance curves in the far-red spectrum often producing an illusion that stress-induced differences are negligible near 700 nm (Carter and Knapp, 2001). In addition, Carter (1993) reported the maximum reflectance peak at 409 nm responds differently for herbicide stress in persimmon than other stressors. Persimmon, when treated with diuron, showed reflectance sensitivities and differences in wavelength ranges of 405-409, 519-573, 688-735, 1,384-1,401, and 1,875-1,905 nm with a maximum near 409 nm (Carter, 1993).

The possibilities for the use of remote sensing as a "weed detection tool" has increased research efforts to (1) manage monocultures or desired mixed populations of certain species, and (2) determine the impact of production practices on the spectral reflectance properties of the crop canopy. Therefore, if a herbicide can be identified that does not impact the spectral response pattern of a crop it could be used for weed control over a large experiment area. Weed patches of interest, with known populations and locations, could be established in untreated areas. Hand-weeding that is regularly needed to maintain species compositions would be reduced. Combined with research done to identify the reflectance response patterns of individual weed species, the stage would be set for an experiment that would test classification accuracy of weed compositions in a field setting. This research could allow the integration of remote sensing with site-specific application technologies for an integrated weed control system.

Therefore, the objective of this research is to assist future research conducted in this area by investigating what impacts PRE applied herbicides have on corn canopy reflectance. The herbicides alachlor, atrazine, flufenacet + metribuzin, isoxaflutole, metolachlor, and pendimethalin were selected for use due to their common use in the Midwestern Corn Belt, as well as their wide range of symptomology. No effect is expected on corn canopy reflectance due to the alachlor, atrazine, and metolachlor because they are metabolized quickly into inactive compounds, however some level of injury, buggy whipping or interveinal chlorosis, can occur when using these herbicides if weather or stress conditions slow growth and the herbicide is accumulated. Spectral differences in corn treated with flufenacet + metribuzin are anticipated damage to corn plants by inhibiting root and shoot growth and inhibiting photosynthesis. Isoxaflutole causes bleaching and can cause whitening of corn leaves when environmental conditions are right, potentially causing spectral reflectance changes. Pendimethalin can possibly cause a spectral change by inhibiting root development in corn and by causing reddish or purple leaf margins on the plant.

MATERIALS AND METHODS

Two field experiments were established at the Agronomy Center for Research and Education near West Lafayette, Indiana to determine the effect of preemergence herbicides on canopy reflectance of corn. Six herbicide treatments were evaluated and compared to an herbicide-free hand-weeded plot (i.e. untreated control) and a bare ground plot for calibration purposes. All treatments were maintained weed-free by hand weeding throughout the growing season. The experimental design was a randomized complete block with four replications. Individual plot dimensions were approximately 6 by 6 meter. The experiments were planted on May 24, 2002 (referred to as early experiment) and June 17, 2002 (referred to as late experiment). Preemergence herbicides were applied on the early experiment on May 27, 2002, and on the late experiment on June 18, 2002. No post emergence herbicides were used.

Preemergence corn herbicide treatments evaluated were 3.6 kg a.i./ha acetochlor, 2.2 kg a.i./ha atrazine, 880 g a.i./ha flufenacet + 220 g a.i./ha metribuzin, 120 g a.i./ha isoxaflutole, 2.1 kg a.i./ha metolachlor, and 2.0 kg a.i./ha pendimethalin. These herbicides were selected to represent the majority of chemicals used in the corn production systems throughout the Midwestern Corn Belt. These herbicides also allowed for a broad range of active ingredients and modes of action to be used on the plants with the potential to create a broad range of plant reflectance response patterns.

A boom truck-mounted field GER 2600 field spectrometer, also known as a spectroradiometer, was used to collect ground-based hyperspectral data approximately 5 weeks after planting (June 28, 2002) for the early experiment and approximately 4 weeks after planting (July 15, 2002) for the late experiment on clear days with less than 5% cloud cover. This spectrometer collects 640 bands of data in 1.5 nm increments. Using both silicon and lead sulfide sensors, a spectral range from 350 nm to 2500 nm was obtained. Of the 640 bands of data collected, approximately 500 bands outside of the major water absorption bands were useable.

A highly diffuse, highly reflective reflectance panel was used to measure the potential radiance from the area immediately prior to collecting the radiance from the crop canopy. This panel was a 60 by 60 cm Labsphere panel made with spectralon (Robinson and Biehl, 1979). The boom was extended over the crop canopy at a height of 7 meters, and with the GER 2600 field of view of 9 degrees, the GER collected data from a 1.1 m^2 area at the top of the canopy. The reflected radiance was measured from the canopy to determine the spectral reflectance. The truck and boom were positioned so that shadows were eliminated over the plot area.

Therefore, five measurements were collected for each plot, three measurements with the sensor centered over a row of corn and two collections taken with the sensor centered between rows (Figure 2.1).

Daughtry et. al. (1982) found more measurements are required at low altitudes to obtain a representative sample of the canopy reflectance because reflectance measurements tended to be erratic as the sensor was moved across the rows. Therefore, measurements taken at half row spacing (on and off row) were more efficient and representative of canopy reflectance than random sampling methods and averaging of measurements across the plot.

This method also creates a more representative canopy reflectance for the whole plot than if all samples were taken over the crop and none were taken between rows. This is particularly true since during the early development of the crop, there is not complete canopy closure and the soil can have a large impact on the reflectance values.

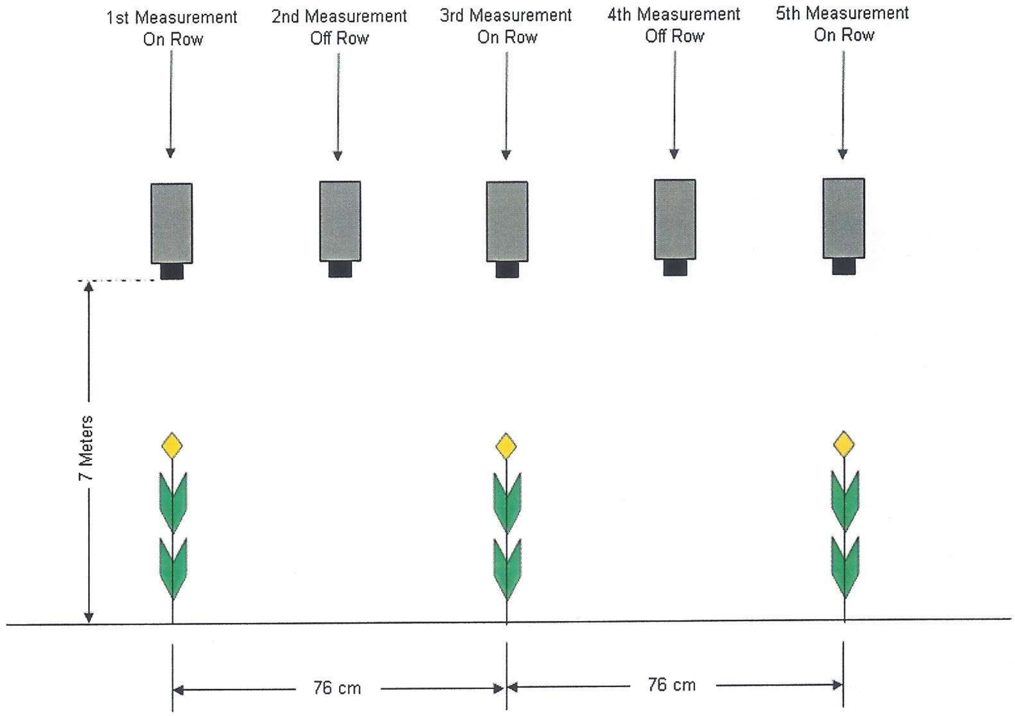

Figure 2.1. Placement of sensor for measurements in each plot showing on and off row placement.

The measurements were converted to reflectance using a scene to reference comparison with linear interpolation between two reference observations using the formula:

$$R_s(\theta,\lambda) = [V_s(\theta,\lambda) - d_s(\lambda)] / V_r^1(\theta,\lambda) * R_r(\theta,\lambda)$$

Where: $V_r^1(\theta,\lambda) = V_{r1}(\theta,\lambda) - d_{r1}(\lambda) + [\{V_{r2}(\theta,\lambda) - d_{r2}(\lambda)\} - \{V_{r1}(\theta,\lambda) - d_{r1}(\lambda)\}]$
$* \, t_s - t_{r1} / t_{r2} - t_{r1}$

Where:

$V_s(\theta,\lambda)$ = GER 2600 response over corn canopy for solar illumination angle (θ) and wavelength (λ).

$V_{r1}(\theta,\lambda)$ = GER 2600 response over spectralon reflectance panel collected before corn canopy observation.

$V_{r2}(\theta,\lambda)$ = GER 2600 response over spectralon reflectance panel collected after corn canopy observation.

$R_s(\theta,\lambda)$ = Reflectance of corn canopy for solar illumination angle (θ) and wavelength (λ).

$R_r(\theta,\lambda)$ = Reflectance of spectralon panel for illumination angle (θ) and wavelength (λ).

d_s, d_{r1}, d_{r2} = Dark levels of GER 2600, all = 0.

t_s, t_{r1}, t_{r2} = Time for data collection for corn canopy, reference before and reference after, respectively.

Radiance data images were also collected from aerial flights obtained by Agri-Vision[1] at an approximate altitude of 2,400 meters. The images were composed of three bands of reflectance with the spectral ranges for the bands were 510 – 590 nm 635 – 705 nm, and 736.5 – 863.5 nm for band 1, 2, and 3 respectively. The numerical reflectance data were extracted for analysis from the aerial images using MultiSpec[2]. When aerial and ground-based data were compared, only the wavelengths common to both the aerial and ground-based data sets were used for analyses.

Data Analysis – Hyperspectral/Ground-based Data

<u>Discriminant Analysis using SAS[3]</u>

The 500 band hyperspectral data set was analyzed using PROC STEPDISC and PROC DISCRIM (Medlin et al., 2000). PROC STEPDISC was used first to determine if the reflectance properties of plots treated with herbicide were different than the reflectance properties of the untreated check, then second to select the reflectance bands important for differentiating between a pair-wise comparison of each herbicide treatment and the untreated check. PROC DISCRIM was then used to develop a model (from the bands selected with PROC STEPDISC) for classifying the plots as herbicide treated or untreated, and to determine the classification accuracy of the model. Discriminate analysis

[1] Agri-Vision, Columbus, Indiana 47201.
[2] MultiSpec, West Lafayette, IN 47907.
[3] SAS Institute Inc., SAS Campus Drive, Cary, NC 27513.

techniques (SAS, 1992) were used to identify and model the reflectance of up to twelve spectral bands from the ground-based data most useful for differentiating between individual herbicide treatments and untreated plots. The models were used to compare the impact of each herbicide treatment on the crop's spectral reflectance, relative to the untreated check. Both the resubstitution and the cross-validation (leave-one-out) methods of checking classification accuracies were calculated. Cross-validation summaries of classification results were used to report classification accuracies of the ground-based and aerial analyses.

Analysis Using MultiSpec

As a second means of analyzing the hyperspectral data collected with the GER spectrometer, these data were converted into .bip (band interleaved by pixel) image files using Matlab[4]. The image files were then analyzed using remote sensing techniques to determine classification effectiveness and treatment separability using MultiSpec (Figure 2.2).

Each of the five observations per plot was represented as a pixel, positioned on-off-on-off-on the rows of corn. Cluster maps, created using the isodata clustering algorithm (within eigenvector volume, six to eight clusters, and 98% convergence) within MultiSpec, were compared to treatment maps and plot plans to determine if any initial correlation or separation between plots was evident. These correlations or differences were then used to help in training and test sample determination for a supervised classification.

Several factors were controlled in the MultiSpec classification analysis. First, the number of bands was reduced to either (1) the bands included in the range of the multispectral aerial image bands, a reduction in the number of bands from 640 to 189 bands, or (2) the bands selected by the SAS STEPDISC procedure (Table 2.1).

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[4] The MathWorks, Inc., 3 Apple Hill Drive, Natick, MA 01760-2098

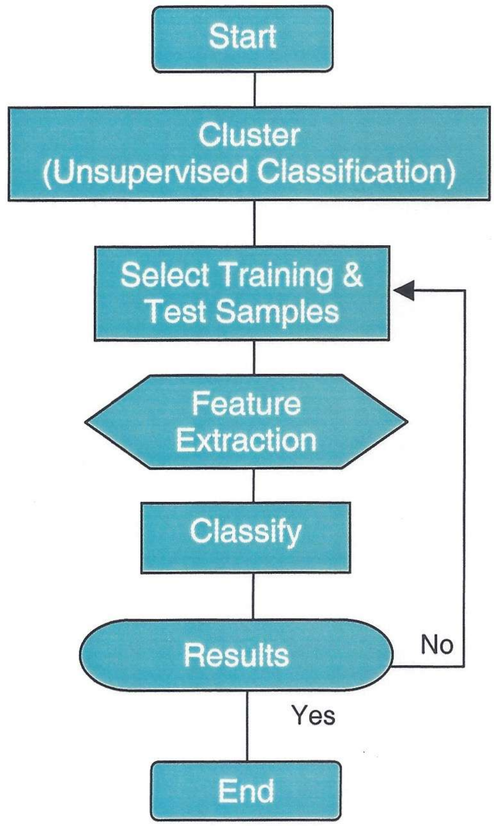

Figure 2.2. Diagram of the classification process used to analyze images in MultiSpec.

The high dimensionality of the data warranted band reduction to avoid the Hughes phenomenon. The Hughes phenomenon is a decrease in the accuracy of statistics estimation as dimensionality increases, which leads to a decline in the accuracy of classification (Figure 2.3). Although increasing the number of spectral bands or dimensionality potentially provides more information about class separability, this positive effect is diluted by poor parameter estimation. As a result, the classification accuracy first grows and then declines as the number of spectral bands increases (Kuo and Landgrebe, 2001).

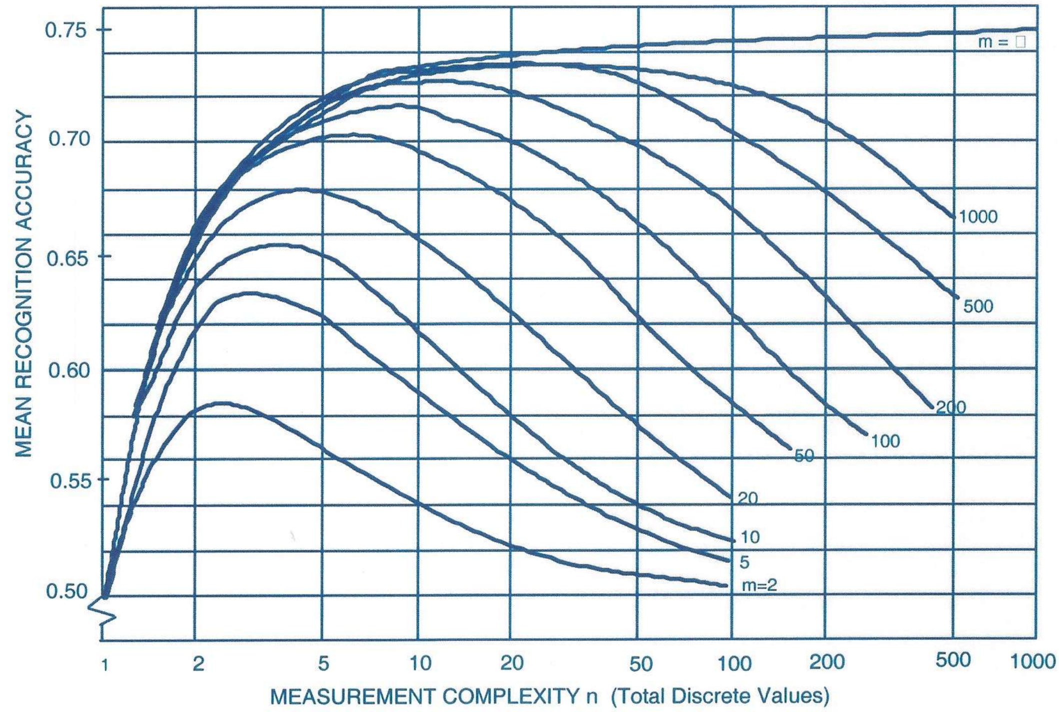

Figure 2.3. Concept of the Hughes Effect with wavelengths on the x-axis, mean recognition accuracy on the y-axis, and number of training samples next to the representative curve. (Landgrebe, 1999)

A leave–one-out covariance (LOOC) matrix was used for all classifications. LOOC is a method used to estimate the sample covariance for those cases when the number of training samples for a class is equal to the number of channels being used or fewer. This estimator examines the sample covariance and the common covariance estimates, as well as their diagonal forms, to determine which would be most appropriate.

The value of the mixing parameter is selected by removing one sample, estimating the mean and covariance from the remaining samples, then computing the likelihood of the sample which was left out, given the mean and covariance estimates. Each sample is removed in turn, and the average log likelihood is computed. Several mixtures are examined by changing the value of the mixing parameter then the value that maximizes the average log likelihood is selected.

Though an estimated covariance matrix is ordinarily singular and therefore not usable when the number of samples used to estimate it is less than or equal to the number of features, the LOOC returns a usable covariance matrix estimate when the number of samples available is at least three or more (Landgrebe and Biehl, 2001).

Training and test class selection was done two ways to evaluate the affect samples had on classification accuracy. For the first classification, the left three pixels of the five observations per plot were used to train the classifier. The right three pixels of the plot were used as the test samples to test the accuracy of the classifier. The center pixel was used in both the training and test samples to include more vegetation to influence the classification. The classification accuracies of the left and right training classifications were averaged together to give accuracy for the whole plot (Table 2.2).

Data Analysis – Multispectral/Aerial Data

Discriminant Analysis using SAS

The multispectral data set with three bands of aerial reflectance data were analyzed using PROC STEPDISC and PROC DISCRIM (Medlin et al., 2000). Twenty-five reflectance values representing the pixels totally contained within the plot, to avoid edge effect, were averaged together by band to get a composite pixel value for each plot. PROC STEPDISC was used first to determine if the reflectance properties contained in the bands of reflectance could be used to differentiate between plots treated with herbicide and the untreated check, then second to select the reflectance bands important for this differentiation process. PROC DISCRIM was then used to develop a model (from the bands selected with PROC STEPDISC) for classifying the plots as herbicide treated or untreated, and to determine the classification accuracy of each model.

The STEPDISC procedure performs a stepwise discriminant analysis to select a subset of the quantitative variables for use in discriminating among the classes using forward selection, backward elimination, or stepwise selection

(SAS, 1992). Stepwise selection begins with no variables in the model. At each step, the model is examined. If the variable(s) in the model that contributes least to the discriminatory power of the model fails to meet the criterion to stay, it is removed. Otherwise, the variable not in the model that contributes most to the discriminatory power is entered into the model. When all variables in the model meet the criterion to stay and none of the other variables meet the criterion to enter, the stepwise selection process stops (SAS, 1992).

Analysis Using MultiSpec

Aerial images were also analyzed in MultiSpec. The images did not have to go through the band selection required for the GER data since the data consisting of only three bands. Training and test sample selection differed as well. For the aerial data, 25 pixels in the center of each plot were selected to reduce the edge effect from neighboring treatments. Only data from one replication were used to train the classifier, while data from the other three replications were used for test samples.

Classification was done using quadratic maximum likelihood, Fisher linear likelihood, and Spectral Angle Mapper (SAM) classification algorithms in MultiSpec, listed in decreasing order of classifier complexity. The quadratic maximum likelihood classifier uses a discriminant function, which includes the means and covariance estimates for each class. A pixel is assigned to the class whose distribution function gives the highest likelihood for that pixel belonging to it. Fisher linear likelihood uses the same principal as maximum likelihood, however it uses the common covariance matrix from all the classes instead of the class covariance matrix from each class. Spectral Angle Mapper (SAM) is a correlation classifier used to compare the shape of a sample's spectral response to the mean for each training class using a correlation coefficient and ignoring the absolute difference or offset between the spectral response curves. All the methods of classification were examined for the algorithm with the highest reference and Kappa Statistic accuracy ratings.

For each classification, two accuracies were given, reference and reliability. The reference accuracy represented how often the treatment was correctly classified in a pair-wise comparison with the untreated check. The reliability accuracy percentage indicates how accurate the classifier is at identifying the treatment. Reference classification accuracy near 50% indicates a treatment is virtually indistinguishable from the untreated check (i.e. 50% of the time the treated plots were classified as untreated) and reliability accuracy near 50% indicates the untreated check is nearly indistinguishable from the treatment (i.e. the same number of treated and untreated plots were classified as treated). For comparison purposes, the reference accuracy will be used when discussing classification results. The Kappa Statistic is an accuracy based upon analysis of the classification matrix's major diagonals, which indicates actual agreement between reference & classified data, and the row and column totals, which indicates chance agreement, i.e. it is a measure of how much better the classification was compared to a random classifier. Kappa Statistic accuracies were characterized by Landis & Kock (1977) into three groups based on percentages. Greater than 80% indicates strong agreement, 40 – 80% means moderate agreement, and less than 40% implies poor agreement.

RESULTS

Analysis of Hyperspectral/Ground-based Data

In Early experiment, plots treated with metolachlor could not be separated from the untreated plots using STEPDISC methods (Table 2.1). This indicated any change in the reflectance properties of corn treated with metolachlor were undetectable using these statistical procedures. The reflectance properties of corn treated with atrazine, isoxaflutole, pendimethalin, alachlor, or flufenacet + metribuzin were altered enough to allow those plots to be separable from the untreated check using discriminant analysis procedures in SAS. Atrazine, pendimethalin, alachlor, and flufenacet + metribuzin treated plots were classified as such with 100% accuracy in pair-wise comparisons with the untreated check in the early experiment (Table 2.2). Plots treated with isoxaflutole were correctly classified 75% of the time.

Using the Fisher linear discriminant classification method in MultiSpec, changes in the spectral responses of alachlor, atrazine, isoxaflutole, metolachlor, and pendimethalin treated plots were detectable and separable with 75% to 96% accuracy (Table 2.2).

Classification accuracies were generally lower for the quadratic maximum likelihood classifier or the correlation (Spectral Angle Mapper) classifier than for the SAS discriminant or Fisher linear discriminant classifications. In general, quadratic maximum likelihood classifications did not reproduce similar results to the SAS discriminant analysis. In addition, all the Kappa Statistics for the quadratic maximum likelihood classifier were below 40%, which makes the usefulness of the accuracies suspect for treatment separability.

Flufenacet + metribuzin treated plots were highly separable (100%) using discriminant analysis techniques in SAS, and only marginally separable (42%, 17%, or 42%) using Fisher's linear discriminant analysis, quadratic maximum likelihood classification, or correlation classification techniques, respectively. Flufenacet + metribuzin has quadratic maximum likelihood and correlation classification reference accuracies of 17% and 42%, therefore, it is virtually indistinguishable from the untreated check, using these analytical methods.

The treatment most difficult to distinguish from the untreated check was metolachlor. The metolachlor treatment was inseparable with discriminant analysis techniques in SAS and had classification accuracies of 92%, 92% (23% Kappa), and 58% with Fisher's linear discriminant analysis, quadratic maximum likelihood classification, and correlation classification techniques, respectively. Therefore, with the low Kappa Statistic for the quadratic maximum likelihood classification, three out of four analysis procedures rendered metolachlor virtually indistinguishable from the untreated check.

In the late experiment, when the data were analyzed with PROC STEPDISC, none of the treatments were found to be separable from the untreated (Table 2.2). However, when the data were analyzed using MultiSpec, results similar to early experiment in 2002 were obtained. Fisher linear discriminant classification had the highest overall classification accuracy (Table 2.2). Isoxaflutole treated plots were inseparable using SAS discriminant analysis techniques, and had low Fisher's, quadratic maximum likelihood, and correlation classification accuracies, 58%, 42%, and 56% respectively. Therefore, no classifiers were able to separate isoxaflutole from the untreated. The low reliability accuracies or Kappa Statistics (below 40%) for quadratic maximum likelihood and correlation classification indicate that those classifiers had difficulty distinguishing between treated and untreated plots. Once again, metolachlor treated plots were not separable from the untreated using discriminant analysis methods in SAS. Results from the MultiSpec analysis were 92%, 75%, and 67% reference accuracies for Fisher's, quadratic maximum likelihood, and correlation classifications, respectively, however, low reliability accuracies for Fisher linear discriminant (58%) and correlation (53%) classifications indicate approximately 50% of the pixels classified as metolachlor were in fact untreated. Additionally, the low Kappa Statistics indicate the untreated checks could not be classified separately from metolachlor, therefore, we can conclude that the reflectance of the corn canopy was virtually unchanged from the preemergence metolachlor application.

For the two experiments, the results using the quadratic maximum likelihood classifier did not show similarities to the SAS STEPDISC procedure (Table 2.2). Low Kappa Statistics across all treatments of both experiments indicate a low ability to distinguish between treated and untreated when using the quadratic classifier. Fisher linear discriminant classification had high Kappa Statistics across most treatments in both experiments, indicating classifications that are robust (Table 2.2). For the early experiment in 2002, Fisher linear discriminant classification of metolachlor had a Kappa Statistic of 83% lending credibility to the classification. This result is considerably different from the late experiment in 2002 where metolachlor treated plots were similar in reflectance to the untreated check across all analytical procedures.

Accuracies for the correlation classification were low compared to results using the Fisher classification. Low reference accuracy combined with low reliability and Kappa Statistics make the correlation classification more like the SAS STEPDISC results. The reference accuracies indicate there was difficulty discriminating treated plots from untreated plots and reliability accuracies indicate difficulty in discriminating the untreated plots from the treated plots (Table 2.2).

Using SAS for Band Selection and MultiSpec for Data Analysis

To determine the accuracy of the band selection method in SAS, the bands selected by STEPDISC in the early experiment in 2002 were used to classify the image created from that data in MultiSpec (Table 2.3). Metolachlor was not separable using discriminant analysis techniques in SAS, so it was left out of the MultiSpec classification. Using only those reflectance bands selected by STEPDISC, classification accuracies with Fisher linear discriminant classification were similar to the SAS techniques, however the treatments also had low Kappa Statistics (Table 2.3), which indicates low agreement in the classification. This is more like the SAS analysis of the late experiment in 2002, where none of the treatments was separable from the untreated.

To determine if bands from one experiment can be used to classify data from another experiment, hyperspectral ground-based wavelengths selected by the SAS models for the early experiment were used to classify the hyperspectral ground-based data from the late experiment using MultiSpec.

Reference accuracies using Fisher linear discriminant, quadratic maximum likelihood, and correlation classifications were low, from 46% to 75%, for all pair-wise comparisons. Likewise, reliability accuracies using the MultiSpec classifiers for all pair-wise comparisons ranged from a low of 45% to a high of 77% (Table 2.3) indicating very little separation from the untreated plots. These accuracies, combined with Kappa Statistics all below 50%, indicate there is minimal separability between the treatments and the untreated checks when using bands selected for the early experiment to classify data from the late experiment. This is also supportive of the results of the SAS discriminant analysis for the late experiment that no treatments are separable. It is possible that the treatments were separable in the early experiment, but were not in the late experiment due to environmental factors.

Analysis of Aerial Collected Data

Multispectral reflectance data were analyzed using SAS PROC STEPDISC and PROC DISCRIM to focus on only those bands useful in class discrimination. Plots treated with flufenacet + metribuzin were correctly identified 75% of the time in the early experiment (Table 2.4). Atrazine, metolachlor, isoxaflutole, pendimethalin, and alachlor treatments could not be separated from the untreated plots using SAS techniques in either experiment (Table 2.4).

All treatments were classified using a linear discriminant function in SAS to cross-validate the stepwise discrimination for the early experiment (Table 2.5). Isoxaflutole (75%) and the bare soil (100%) were the only treatments correctly classified when all treatments were analyzed together (Table 2.5). However, in pair-wise classifications isoxaflutole was not separable from the untreated. It is also notable that flufenacet + metribuzin was not separable when all classes were used for SAS analysis, but was separable in a pair-wise classification with the untreated.

Fisher linear discriminant and correlation classifications of aerial data collected from the early experiment produced no Kappa Statistics over 50%, indicating alachlor, atrazine, flufenacet + metribuzin, metolachlor, and pendimethalin treatments were practically identical to the untreated plots with this analysis (Table 2.4). Isoxaflutole had Kappa Statistics of 48, 54, and 45% and reference classification accuracies of 61, 84, and 48% for Fisher, quadratic maximum likelihood, and correlation classifiers, respectively. Therefore, isoxaflutole was separable using three of the four classification methods (78% reliability accuracy for correlation classification). This shows some similarity to the cross-validation of the aerial data in SAS for all classes (Table 2.4).

SAS discriminant analysis techniques failed to show treatments to be separable from the untreated for the late experiment (Table 2.4). Similarities between the SAS discriminant analysis and the MultiSpec classifications were apparent (Table 2.4). For the Fisher linear discriminant, quadratic maximum likelihood, and correlation classifications, all treatments had a Kappa Statistic below 45%, and Fisher linear discriminant classification had reference classification accuracies near or below 50% for alachlor, atrazine, isoxaflutole, metolachlor, and pendimethalin. Therefore, all treatments were inseparable from the untreated MultiSpec classifiers were used.

DISCUSSION

Analysis of the hyperspectral ground-based data can be used for separating treated corn from untreated corn. SAS techniques and Fisher linear discriminant classifications seem the most capable of finding differences in spectral properties. The quadratic maximum likelihood classifier may be too complex with the statistics becoming confounded with the high dimensional data with limited training samples. Aerial data was not useful for separating treated corn from untreated corn. This is most likely due to the flights coming later in the growing season than the hyperspectral ground-based data collection. Most of the herbicide would have been metabolized by the corn plants by then, and any symptoms present would have disappeared.

Alachlor, atrazine, and metolachlor treatments were not expected to affect the spectral properties of corn, however, alachlor and atrazine had an effect. In general, the reflectance properties of metolachlor were unchanged compared to the reflectance properties of the untreated check. Excluding Fisher linear discriminant classification, this was the case with every analytical procedure used, whether hyperspectral or multispectral data were used in the analysis, and for both the early experiment and the late experiment. These results are similar to what was expected based on metabolism by the corn plant and mode of action.

Alachlor was expected to have a similar effect on the reflectance of the corn as metolachlor, however, alachlor was separable using Fisher linear discriminant and SAS techniques to analyze the early experiment data, but was virtually identical to the untreated using SAS techniques, quadratic maximum likelihood, and correlation classifiers for the late experiment.

Atrazine treated plots were separable using the hyperspectral ground based data, but not separable when the aerial image data was used. The effect of atrazine on reflectance may be on leaf level and not on an overall canopy level, unless environmental conditions are right as a symptom of atrazine can be stunted growth patches in a field.

Surprisingly, isoxaflutole was only separable from the untreated when SAS techniques and Fisher linear discriminant classification were used to analyze the hyperspectral data. None of the other classification methods could separate isoxaflutole treated plots from the untreated plots. The warm weather combined with average rainfall allowed for normal growing conditions for both experiments and did not result in any bleached corn, which would have influenced the spectral properties of corn.

Flufenacet + metribuzin impacted the reflectance properties of the plots with one method of classification in both trials and in the hyperspectral and multispectral data sets. This spread of separability across experiments and data types indicates factors have an influence on spectral change in a corn plan when flufenacet + metribuzin are absorbed. These may be variable due to environmental factors, amount of herbicide absorbed, or metabolism of the herbicide.

Pendimethalin treated plots in the early experiment were separable from the untreated plots for all classification methods except quadratic maximum likelihood classification. Pendimethalin plots were also separable in the late experiment using Fisher linear discriminant classification. The plots were not separable, however, when the aerial data was used. The plant would have recovered from any effects on the root system by this time in the season.

The results show that hyperspectral data may prove to be a useful tool in the future if wavebands specific to herbicide treatments can be found. This could be used for insurance purposes, herbicide use surveys, or for herbicide misuse cases. Spectral libraries could be developed for use by commercial applicators and crop consultants to use for recommendations based on previous applications. Commercial applicators and insurance companies could use spectral tendencies to determine misapplications or drift concerns, eliminating the need for costly chemical analysis of plant tissues, and relieve confusion over symptomologies common to several herbicide families.

Ground-based hyperspectral data was much more sensitive to minor changes brought about by these herbicide applications than multispectral data collected from the aerial platform. Therefore, multispectral aerial data may be useful in future research where minor changes brought about by herbicide applications would not confound the data of interest.

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Table 2.1. Wavelengths used by the SAS PROC DISCRIM procedure to separate treatments in pair-wise comparisons with the untreated check in the PRE early experiment. Models could not be formed to differentiate metolachlor from the untreated check.

Treatment	Bands used in SAS DISCRIM procedure (micrometers)
Alachlor	0.76, 0.893, 0.997
Atrazine	0.472, 0.585, 0.66, 0.76, 1.069, 2.015
Flufen.+metr.	0.76, 0.763
Isoxaflutole	1.332, 1.345
Metolachlor	ND [a]
Pendimethalin	0.397, 0.519, 0.576, 0.701, 1.168

Table 2.2. Classification accuracy of pair-wise comparisons of preemergence herbicide treatments used in corn based on reflectance properties using various analysis techniques with bands included in multispectral image bands on ground collected reflectance data.

			Herbicide					
Exp.	Analysis	Procedure	Alachlor	Atrazine	Flufen.+Metr.	Isoxaflutole	Metolachlor	Pendimethalin
Early	DA[a]	PROC DISCRIM %	100	100	100	75	ND[e]	100
	FLD[b]	Reference Accuracy %	96	88	42	75	92	100
		Kappa Statistic %	79	82	24	75	83	96
	QML[c]	Reference Accuracy %	50	100	17	21	92	29
		Kappa Statistic %	28	26	13	11	23	26
	CC[d]	Reference Accuracy %	79	54	42	79	58	83
		Kappa Statistic %	50	24	24	50	28	50
Late	DA	PROC DISCRIM %	ND	ND	ND	ND	ND	ND
	FLD	Reference Accuracy %	67	83	92	58	92	92
		Kappa Statistic %	54	54	71	67	46	63
	QML	Reference Accuracy %	42	58	83	42	75	33
		Kappa Statistic %	17	44	33	11	71	8
	CC	Reference Accuracy %	50	50	58	56	67	67
		Kappa Statistic %	17	0	8	21	18	17

[a] Discriminant analysis using the PROC STEPDISC and PROC DISCRIM procedures in SAS.
[b] Fisher linear discriminant classification using MultiSpec.
[c] Quadratic maximum likelihood classification using MultiSpec.
[d] Correlation classification (Spectral Angle Mapper) using MultiSpec.
[e] Treatment could not be differentiated from the untreated check using the discriminant analysis procedures in SAS.

Table 2.3. Classification accuracy of pair-wise comparisons of preemergence herbicide treatments used in corn based on reflectance properties using various analysis techniques with bands used in SAS analysis from the early experiment ground collected reflectance data. Metolachlor is left out of the table because models could not be formed in SAS to separate it from the untreated check.

			Herbicide				
Exp.	Analysis	Procedure	Alachlor	Atrazine	Flufen.+Metr.	Isoxaflutole	Pendimethalin
Early	DA [a]	PROC DISCRIM %	100	100	100	75	100
	FLD [b]	Reference Accuracy %	71	71	75	71	63
		Kappa Statistic %	40	46	40	38	35
	QML [c]	Reference Accuracy %	71	83	75	75	63
		Kappa Statistic %	40	66	32	28	66
	CC [d]	Reference Accuracy %	58	58	42	75	71
		Kappa Statistic %	19	15	0	54	44
Late	DA	PROC DISCRIM %	ND	ND	ND	ND	ND
	FLD	Reference Accuracy %	46	58	50	71	50
		Kappa Statistic %	4	9	10	48	10
	QML	Reference Accuracy %	54	63	54	58	54
		Kappa Statistic %	-4	26	-4	45	31
	CC	Reference Accuracy %	67	54	54	75	67
		Kappa Statistic %	33	-7	15	25	33

[a] Discriminant analysis using the PROC STEPDISC and PROC DISCRIM procedures in SAS.
[b] Fisher linear discriminant classification using MultiSpec.
[c] Quadratic maximum likelihood classification using MultiSpec.
[d] Correlation classification (Spectral Angle Mapper) using MultiSpec.
[e] Treatment could not be differentiated from the untreated check using the discriminant analysis procedures in SAS.

Table 2.4. Classification accuracy of pair-wise comparisons of preemergence herbicide treatments used in corn based on reflectance properties using various image analysis techniques and SAS analysis on aerial image data.

			Herbicide					
Exp.	Analysis Procedure		Alachlor	Atrazine	Flufen.+Metr.	Isoxaflutole	Metolachlor	Pendimethalin
Early	DA [a]	PROC DISCRIM %	ND [e]	ND	75	ND	ND	ND
	FLD [b]	Reference Accuracy %	16	48	77	61	73	75
		Kappa Statistic %	9	-1	26	48	3	27
	QML [c]	Reference Accuracy %	68	73	72	84	48	91
		Kappa Statistic %	41	20	26	54	3	38
	CC [d]	Reference Accuracy %	24	36	56	48	63	20
		Kappa Statistic %	-24	-17	25	45	-9	-24
Late	DA	PROC DISCRIM %	ND	ND	ND	ND	ND	ND
	FLD	Reference Accuracy %	52	45	67	28	47	24
		Kappa Statistic %	7	-24	36	19	18	19
	QML	Reference Accuracy %	68	59	33	76	53	56
		Kappa Statistic %	18	6	42	10	27	44
	CC	Reference Accuracy %	65	51	73	28	55	8
		Kappa Statistic %	3	-20	31	27	22	8

[a] Discriminant analysis using the PROC STEPDISC and PROC DISCRIM procedures in SAS.
[b] Fisher linear discriminant classification using MultiSpec.
[c] Quadratic maximum likelihood classification using MultiSpec.
[d] Correlation classification (Spectral Angle Mapper) using MultiSpec.
[e] Treatment could not be differentiated from the untreated check using the discriminant analysis procedures in SAS.

Table 2.5. Cross-validation summary showing classification accuracies using the linear discriminant function in SAS comparing all treatments in the early experiment test. Data points consisted of 100 values for each treatment.

	Number of Observations and Percent Classified into Herbicide Treatment								
Herbicide	Atrazine	Metolachlor	Isoxaflutole	Pendimethalin	Alachlor	Flufen.+metr.	Untreated	Bare Soil	Total
Atrazine	0	1	0	0	1	2	0	0	4
%	0	25	0	0	25	50	0	0	100
Metolachlor	2	0	0	0	0	0	2	0	4
%	50	0	0	0	0	0	50	0	100
Isoxaflutole	0	0	3	0	0	1	0	0	4
%	0	0	75	0	0	25	0	0	100
Pendimethalin	0	0	2	0	0	1	1	0	4
%	0	0	50	0	0	25	25	0	100
Alachlor	0	1	2	1	0	0	0	0	4
%	0	25	50	25	0	0	0	0	100
Flufen.+metr	1	1	1	0	0	0	1	0	4
%	25	25	25	0	0	0	25	0	100
Untreated	0	2	0	0	1	1	0	0	4
%	0	52	0	0	25	25	0	0	100
Bare Soil	0	0	0	0	0	0	0	4	4
%	0	0	0	0	0	0	0	100	100
Total	3	5	8	1	2	5	4	4	32
%	9	16	25	3	6	16	13	13	100
Priors	0.125	0.125	0.125	0.125	0.125	0.125	0.125	0.125	

CHAPTER 3

THE EFFECT OF POSTEMERGENCE HERBICIDES ON THE SPECTRAL RESPONSE CHARACTERISTICS OF CORN CANOPY REFLECTANCE

INTRODUCTION

Growing concerns in agriculture regarding public awareness to pesticides and pest control costs have increased the need to maximize pest control and minimize environmental effects. Health and environmental concerns, low commodity prices, and weed control costs are the basis for researchers seeking ways to reduce herbicide inputs and costs (Browner et al., 1993; Fernandez-Cornejo and Jans, 1999).

Herbicides, compared to cultivation, help reduce the labor and time needed for effective weed management, which can lead to increased economic return for the farmer. Reduced time and labor requirements for weed control can free resources needed to expand farming operations (Ashton and Monaco, 1991).

A growing concern in the agricultural sector is the regulation of atrazine, a very effective and affordable herbicide used in corn. Without atrazine, corn weed control costs could increase an estimated $37 per hectare (Pike et al., 1996). The cost of losing all the triazine herbicides for corn would be about $45 per hectare annually. Nationally, this would amount to approximately $680 million per year for the loss of atrazine and approximately $900 million per year for the loss of all triazines. These figures do not take into account the cost of additional soil erosion where tillage will be used as an alternative to atrazine. Therefore, other ways of reducing weed control costs should be explored.

Conventional weed control programs generally rely on the assumption of homogenous distribution of weed species within a given field. This usually results in the over application of herbicides since much of the field is weed free (Hughes, 1989; Thornton et al., 1990; Wiles et al., 1992). An area of growing interest is in application procedures that limit herbicide use to only those weed infested areas. The use of remote sensing in locating weed infestations creates the opportunity for producers to treat only the infested areas of fields. This could reduce the volume of herbicides used in the environment as well as reduce herbicide costs. Lillesand and Kiefer (2000) define remote sensing as the science and art of obtaining information about an object, area, or phenomenon through the analysis of data acquired by a device that is not in contact with the object, area, or phenomenon. Although in the broad sense this may encompass many technologies, researchers in the field of weed science have directed their attention toward the sensing of light reflectance/absorbance differences. Light reflectance of plants is typically measured by a sensor that quantifies the amount of energy being reflected by the plant. Sensors are classified into two broad categories based on their sensing ability, multispectral and hyperspectral scanners.

The use of remote sensing for weed control has increased efforts to understand weed population dynamics and factors that impact their spectral reflectance properties. It may be possible to find reflectance response patterns of individual weed species that would open the future to site-specific weed management. Classification of weeds in crop and rangeland areas has been accomplished (Menges et al., 1985; Everitt et al., 1995; Lass et al., 1996; Lass and Callihan, 1997; Vrindts et al., 2002; and Williams and Hunt, 2002). Menges et al. (1985) found that discrete weed community areas could be classified by computer based image analyses with accuracies of 82% for Palmer amaranth and 81% for johnsongrass in a replicated monoculture plot study. Vrindts et al. (2002) correctly classified 90% of their remotely sensed data as crop or weed.

Medlin and Shaw (2000) found that simulated site-specific herbicide management in soybean production systems resulted in higher estimated net gains than broadcast herbicide management. This held true for transgenic and non-transgenic cropping systems. Estimated net gains for site-specific herbicide management vs. broadcast herbicide management ranged from $13.32 to $29.66

per hectare in non-transgenic soybean, and from $22.15 to $29.45 per hectare in glyphosate-tolerant soybean.

If wide-scale use of remote sensing for weed control is to occur, the impact of biotic and abiotic stresses on weed and crop reflectance must be understood. For example, it is unknown whether commonly used preemergence herbicides will impact the reflectance characteristics of tolerant weeds and crops. Plant stress reflectance sensitivities are generally greatest in the orange and red spectra, except for peaks in the violet and green spectra that accompany herbicide damage (Carter, 1993). General plant stresses can be detected by an increase in reflectance in the 695-725 nm wavelength range. This area is often overlooked for spectral change detection due to the steep slope of the reflectance curves in the far-red spectrum often producing an illusion that stress-induced differences are negligible near 700 nm (Carter and Knapp, 2001). In addition, Carter (1993) reported the maximum reflectance peak at 409 nm responds differently for herbicide stress in persimmon than other stressors. When used on persimmon, Diuron herbicide created reflectance sensitivities and differences in wavelength ranges of 405-409, 519-573, 688-735, 1,384-1,401, and 1,875-1,905 nm with a maximum difference near 409 nm (Carter, 1993).

The possibilities to use remote sensing as a "weed detection tool" has increased research efforts to (1) manage plant monocultures or desired mixed populations of certain species, and (2) determine the impact of production practices on the spectral reflectance properties of the crop canopy. Therefore, if a herbicide can be identified that does not impact the spectral response pattern of a crop it could be used for weed control over a large experiment area. Weed patches of interest, with known populations and locations, could be established in untreated areas. Hand-weeding that is regularly needed to maintain species compositions would be effectively reduced. Combined with research done to identify the reflectance response patterns of individual weed species, the stage would be set for an experiment that would test classification accuracy of weed compositions in a field setting. This research could allow the integration of remote sensing with site-specific application technologies for an integrated weed control system.

Therefore, the objective of this research is to assist future research conducted in this area by investigating what impacts POST applied herbicides have on corn canopy reflectance. The herbicide treatments 2,4-D, atrazine, bromoxynil, dicamba + diflufenzopyr, nicosulfuron, and primisulfuron-methyl were selected since they are commonly used in corn systems in the Midwest, as well as for their range of symptoms and modes of action.

Atrazine, nicosulfuron, and primisulfuron-methyl were selected as postemergence treatments because they generally do not cause visible injury to the corn plants, and are not expected to alter the spectral response corn. Atrazine can cause yellow leaf tips or interveinal chlorosis under certain weather conditions or when applied with crop oil under hot conditions. Nicosulfuron can cause yellow flash near the whorl, chorosis, buggy whipping, or purpling of the stem and leaves if corn is under stress or if the herbicide is applied at the wrong growth stage.

Bromoxynil, 2,4-D, and dicamba + diflufenzopyr were selected due to their propensity to cause visible injury or stress to corn after application. Bromoxynil was selected due to its tendency to cause oblong, oval shaped lesions on the leaves of corn plants. This can be a result of weather conditions changing from cool to hot weather before application and thinning of the leaf cuticle. A spectral difference should be easily detected if the spectral response of the leaves is changed due to the lesions. Due to its growth regulator function in plants, 2,4-D can stress corn plants by onion-leafing the new leaves or bending the stem. These actions would change the reflectance properties of plants and should be detectable using remote sensing methods. Dicamba + diflufenzopyr is a growth regulator and should create similar spectral changes as the 2,4-D treatment. These symptoms can sometimes be attributed to late application, soil type, or shallow planted corn.

MATERIALS AND METHODS

Field experiments were established in 2001 and 2002 to determine the effect of postemergence herbicides on canopy reflectance of corn. Six herbicide treatments were used, as well as a herbicide-free, hand-weeded plot for a control and a bare ground plot for calibration purposes. All treatments were maintained weed-free by hand weeding throughout the growing season. The experiments were conducted at the Agronomy Center for Research and Education near West Lafayette, Indiana. Experimental design was a randomized complete block with four replications. Individual plot dimensions were 6 by 6 meter. The 2001 test was planted on May 2, 2001 (POST 2001) with postemergence herbicides applied on June 7, 2001. The 2002 test was planted on May 24, 2002 (POST 2002) with postemergence herbicides applied on June 16, 2002. All herbicides were applied at labeled rates, and no preemergence herbicides were used.

Postemergence corn herbicide treatments evaluated were 1.7 kg a.i./ha atrazine + .95 L/ha COC, 560 g a.i./ha bromoxynil + 1% v/v COC, 798 g a.i./ha. 2,4-D, 212 g a.i./ha dicamba + 83 g a.i./ha diflufenzopyr + 0.25% v/v NIS, 70 g a.i./ha nicosulfuron + 1% v/v COC, and 40 g a.i./ha primisulfuron-methyl + 0.25% v/v NIS. The herbicides were selected to represent a large percentage of the chemicals used in the Midwest and those that have varying modes of action that can result in various corn injury symptoms. This range of symptomology has the potential to create a broad range of plant reflectance response patterns.

A boom truck-mounted field GER 2600 field spectrometer, also known as a spectroradiometer, was used to collect ground based spectral data. This spectrometer collects 640 bands of data in 1.5 nm increments. Using both silicon and lead sulfide sensors, a spectral range from 350 nm to 2500 nm was obtained. Of the 640 wavelengths of data collected, approximately 500 wavelengths outside of the major water absorption bands were useable.

A highly diffuse, highly reflective reflectance panel was used to measure the radiance between plot measurements. This panel was a 60 by 60 cm Labsphere panel made with spectralon (Robinson and Biehl, 1979). The boom was extended over the plot area at a height of 7 meters above the canopy. The GER 2600 had a field of view of 9 degrees, allowing it to collect data from a 1.1 m^2 area on the ground. The reflectance radiance was then measured from the canopy to determine the spectral reflectance. The truck and boom were positioned so that shadows were not created over the plot area.

Five samples were taken for each plot with three "on-row" samples collected with the sensor centered over a crop row and two "off-row" samples collected with the sensor centered between the crop rows (Figure 3.1). This method allowed for a sampling pattern that created more representative canopy reflectance for the plot when the five samples were averaged than if all samples were taken over the crop row and none were taken between the crop rows.

Daughtry et. al. (1982) found more measurements are required at low altitudes to obtain a representative sample of the canopy reflectance because reflectance measurements tended to be erratic as the sensor was moved across the rows. Therefore, measurements taken at half row spacing (on and off row) were more efficient and representative of canopy reflectance than random sampling methods and averaging of measurements across the plot.

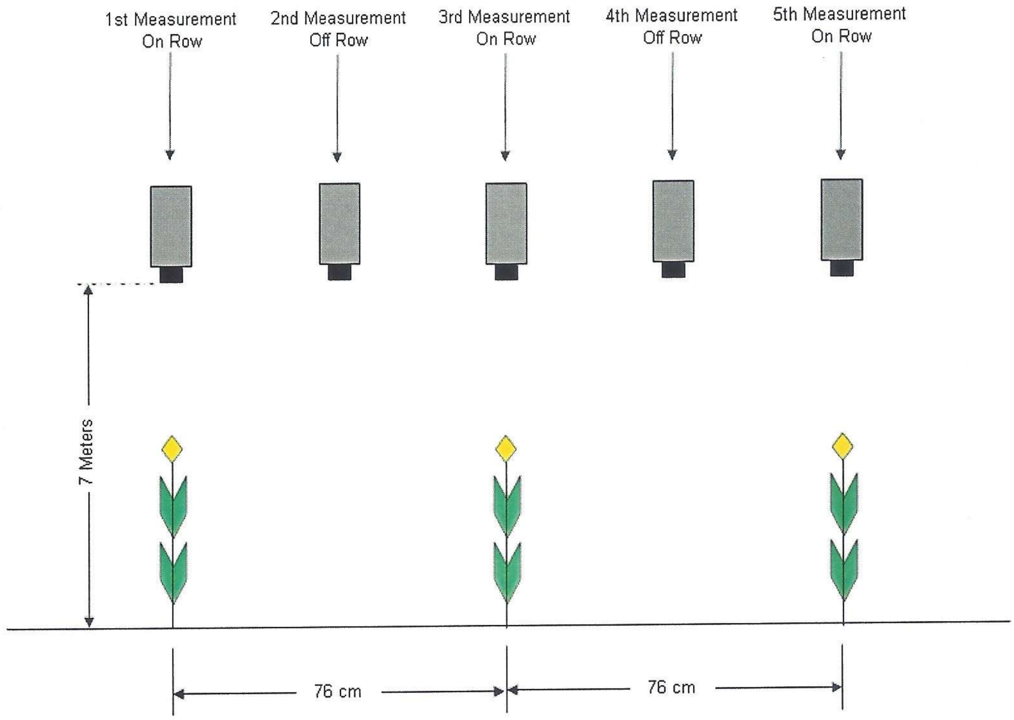


Figure 3.1. Placement of sensor for measurements in each plot showing on-row and off-row placement.

The spectrometer data were collected once for each test, approximately 6 weeks after planting for the POST 2001 trial on June 16, 2001 and approximately 5 weeks after planting for the POST 2002 trial on June 28, 2002. Data collection occurred on a clear day with less than 5% cloud cover near solar noon.

The measurements were converted to reflectance using a scene to reference comparison with linear interpolation between two reference observations using the formula:

$$R_s(\theta,\lambda) = [V_s(\theta,\lambda) - d_s(\lambda)] / V_r^1(\theta,\lambda) * R_r(\theta,\lambda)$$

Where:

$$V_r^1(\theta,\lambda) = V_{r1}(\theta,\lambda) - d_{r1}(\lambda) + [\{V_{r2}(\theta,\lambda) - d_{r2}(\lambda)\} - \{V_{r1}(\theta,\lambda) - d_{r1}(\lambda)\}]$$
$$* \ t_s - t_{r1} / t_{r2} - t_{r1}$$

Where:

$V_s(\theta,\lambda)$ = GER 2600 response over corn canopy for solar illumination angle (θ) and wavelength (λ).

V_{r1} (θ,λ) = GER 2600 response over spectralon reflectance panel collected before corn canopy observation.

V_{r2} (θ,λ) = GER 2600 response over spectralon reflectance panel collected after corn canopy observation.

R_s (θ,λ) = Reflectance of corn canopy for solar illumination angle (θ) and wavelength (λ).

R_r (θ,λ) = Reflectance of spectralon panel for illumination angle (θ) and wavelength (λ).

d_s, d_{r1}, d_{r2} = Dark levels of GER 2600, all = 0.

t_s, t_{r1}, t_{r2} = Time for data collection for corn canopy, reference before and reference after, respectively.

Aerial data, obtained from Agri-Vision[1], were collected over each experiment to supplement the ground-based data at an approximate altitude of 2,400 m on July 2, 2001 and July 2, 2002. The images were composed of three spectral bands with the spectral ranges centered at 550 nm, 655 nm, and 800 nm for band 1, 2, and 3, respectively. The numerical reflectance data were extracted for analysis from the aerial images using MultiSpec[2]. When aerial and ground-based data were compared, only the wavelengths common to both the aerial and ground-based data sets were used for analysis.

Data Analysis – Hyperspectral/Ground-based Data

Discriminant Analysis using SAS[3]

The hyperspectral reflectance data collected with the GER field spectrometer were analyzed using PROC STEPDISC and PROC DISCRIM (Medlin et al., 2000). PROC STEPDISC was used (1) to determine if the reflectance properties of the corn treated with herbicide were different than the reflectance properties of the untreated check and (2) to select the reflectance

[1] Agri-Vision, Columbus, IN 47201.
[2] MultiSpec, West Lafayette, IN 47907.
[3] SAS Institute Inc., SAS Campus Drive, Cary, NC 27513.

bands important for differentiating between each herbicide treatment and the untreated check. PROC DISCRIM was then used to develop a model from those selected bands for classifying the plots as herbicide treated or untreated, and to determine the classification accuracy of the model.

The STEPDISC procedure performs a stepwise discriminant analysis to select a subset of the quantitative variables for use in discriminating among the classes using forward selection, backward elimination, or stepwise selection (SAS, 1992). Stepwise selection begins with no variables in the model. In the first step, the band that adds the most discriminator power to the model is included. At each step, the model is examined. If the variable in the model that contributes least to the discriminatory power of the model fails to meet the criterion to stay, then that variable is removed (Tables 3.1, 3.2, 3.3, & 3.4). Otherwise, the variable not in the model that contributes most to the discriminatory power of the model is entered. Up to twelve bands of reflectance were allowed to enter any given model. When twelve or fewer variables in the model met the criterion to stay and none of the other variables met the criterion to enter, the stepwise selection process was stopped (SAS, 1992). The models were then used to compare the impact of each herbicide treatment on the crops spectral reflectance, relative to the untreated check. If, in the first step, none of the bands contributed to the discriminatory power of the model, the process was stopped and the treatment and the untreated check were assumed to be similar in their reflectance characteristics.

Analysis Using MultiSpec

The hyperspectral data collected with the GER spectrometer were converted into .bip (band interleaved by pixel) image files using Matlab[4]. They were then analyzed using remote sensing techniques to determine classification effectiveness and treatment separability using MultiSpec (refer to Figure 2.2 in chapter 2). Each of the five observations per plot is represented as a pixel,

[4] The MathWorks, Inc., Natick, MA 01760-2098

positioned on-row or off-row depending on its orientation according to data collection. Cluster maps, created using the isodata clustering algorithm (within eigenvector volume, six to eight clusters, and 98% convergence) within MultiSpec, were compared to treatment maps and plot plans to determine if any initial correlation or separation between plots were evident. These correlations or differences were then used to help in training and test sample determination for a supervised classification.

When running classifications, several factors can be controlled. First, the number of bands used was either the bands included in the aerial bands or bands selected by the SAS STEPDISC procedure. Second, feature extraction was included on some of the classifications. Discriminant Analysis Feature Extraction (DAFE) was the primary method used. Decision Boundary Feature Extraction (DBFE) was also investigated briefly, then determined to be less effective than DAFE. Feature extraction was used to reduce the dimensionality of the image data. The high dimensionality of the data warranted band reduction and feature extraction to avoid the Hughes effect (Figure 3.2). The Hughes phenomenon is a decrease in the accuracy of statistics estimation as dimensionality increases, which leads to a decline in the accuracy of classification. Although increasing the number of spectral bands or dimensionality potentially provides more information about class separability, this positive effect is diluted by poor parameter estimation. As a result, the classification accuracy first grows and then declines as the number of spectral bands increases (Kuo and Landgrebe, 2001).

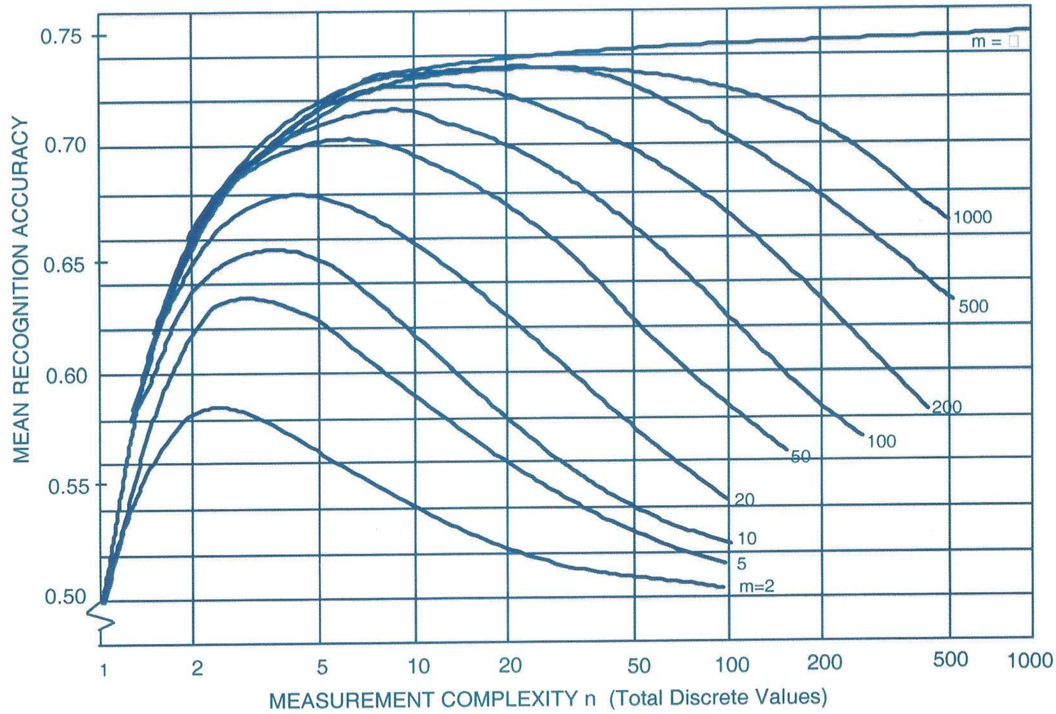


Figure 3.2. Concept of the Hughes Effect with wavelengths on the x-axis, mean recognition accuracy on the y-axis, and number of training samples next to the representative curve. (Landgrebe, 1999)

Finally, a leave one out covariance (LOOC) matrix was used for all classifications. LOOC is a method used to estimate a value for the sample covariance for those cases when the number of training samples for a class is equal to the number of channels being used or fewer. This estimator examines the sample covariance and the common covariance estimates, as well as their diagonal forms, to determine which would be most appropriate. The value of the mixing parameter is selected by removing one sample, estimating the mean and covariance from the remaining samples, then computing the likelihood of the sample which was left out, given the mean and covariance estimates. Each sample is removed in turn, and the average log likelihood is computed. Several mixtures are examined by changing the value of, and the value that maximizes the average log likelihood is selected. Though an estimated covariance matrix is ordinarily singular and therefore not usable when the number of samples used to estimate it is less than or equal to the number of features, the LOOC returns a usable covariance matrix estimate when the number of samples available is at least three or more (Landgrebe and Biehl, 2001).

Training and test class selection was done two ways to see what affect the samples had on classification accuracy. For the first classification, the left three pixels were used to train the classifier. The right three pixels were used as the test samples to test the accuracy of the classifier. The center pixel was used in both the training and test samples to include more vegetation to influence the classification. Then the test and training samples were switched and the classifications were averaged together to obtain representative classifications for each treatment (Table 3.5). The second classification was done using three replications to train the classifier and one replication to test the classifier (Table 3.6). This provided 15 training pixels and five test pixels. This was repeated until each replication was used as the test data set. The classifications showed no similarity to the SAS analysis when reps 1, 2, or 4 were used to test the classifier. However, when rep 3 was used to test the classifier and reps 1, 2, and 4 were used as training classes, results were similar to the SAS analysis.

Data Analysis – Multispectral/Aerial Data

Aerial images were also analyzed in MultiSpec. Band selection was not required for the aerial images since the data were composed of only three bands. Training and test sample selection differed as well. For the aerial data, 25 pixels in the center of each plot were selected to reduce the edge effect from neighboring treatments. Only data from one replication was used to train the classifier, while the other three replications were used as test samples.

Classification was done using Quadratic maximum likelihood, Fisher linear likelihood, and Correlation classification algorithms in MultiSpec. All the methods of classification were examined, to determine the algorithm with the highest reference and Kappa Statistic accuracies.

The quadratic maximum likelihood classifier uses a discriminant function, which includes the means and covariance estimates for each class. A pixel is assigned to the class whose distribution function gives the highest likelihood for that pixel. Fisher linear likelihood uses the same principal as maximum likelihood, however it uses the common covariance matrix from all the classes instead of the class covariance matrix from each class. Spectral Angle Mapper (SAM) is a correlation classifier used to compare the shape of a sample's spectral response to the mean for each training class using a correlation coefficient and ignoring the absolute difference or offset between the spectral response curves.

For each classification, two accuracies are given, reference and reliability. The reference accuracy represents how often the treatment is correctly classified in the pairwise comparison with the untreated check. The reliability accuracy percentage indicates how accurate the classifier is at identifying the treatment and how inaccurate the classifier is at identifying the untreated check. For comparison purposes, the reference accuracy will be used when discussing classification results. The Kappa Statistic is an accuracy based upon analysis of the classification matrix's major diagonals, which indicates actual agreement between reference & classified data, and the row and column totals, which indicates chance agreement. Kappa Statistic accuracies are categorized by Landis and Kock (1977) into three groups based on percentages. Greater than 80% is strong agreement, 40 – 80% is moderate agreement, and less than 40% is poor agreement.

RESULTS

Analysis of Hyperspectral/Ground-collected Data

In the POST 2001 trial, corn treated with atrazine or primisulfuron could not be separated from the untreated plots using STEPDISC methods. This indicates the reflectance characteristics of the corn canopies treated with these herbicides were not affected (Table 3.5). Bromoxynil, 2,4-D, dicamba + diflufenzopyr, and nicosulfuron were separable from untreated corn using the STEPDISC analysis procedures. The classification accuracies were 100% for these treatments (Table 3.5).

Fisher linear discriminant classification accuracies for the 2001 trial did not return the same findings as the SAS analysis. Treatments that were separable in SAS were at least 96% separable with the Fisher linear discriminant classification, however, with the Fisher linear classification analysis, atrazine and primisulfuron-methyl treated plots were correctly classified 83 and 92% of the time (Table 3.5). The Kappa Statistics for all treatments were greater than 80% indicating a high level of agreement of the classifications.

Dicamba + diflufenzopyr, 2,4-D, and nicosulfuron were separable from the untreated with at least 92% accuracy for three of the four classification techniques, indicating these treatments influenced the reflectance properties of corn (Table 3.5). Reliability classification accuracies for Fisher linear discriminant, quadratic maximum likelihood, and correlation classifications were near or above 90% for all treatments, indicating the untreated treatment was highly separable from the herbicide treatments (Table 3.5).

Results from the POST 2002 trial were different from the POST 2001 results (Table 3.5). There were similarities in the discriminant analysis techniques for the POST 2002 experiment which were able to differentiate between the untreated check and the 2,4-D or dicamba + diflufenzopyr treated plots with 100% and 75% accuracy, respectively, compared to 100% for both treatments in 2001. However, atrazine, bromoxynil, nicosulfuron, or primisulfuron treated plots were not separable from the untreated using these same discriminant procedures. This is considerably different from the 2001 results where bromoxynil and nicosulfuron were not only distinguishable from the untreated check, but were correctly classified 100% of the time in the pair-wise comparisons.

Fisher linear classification resulted in moderate reference accuracies for all classes (67 to 79%) (Table 3.5). 2,4-D and dicamba + diflufenzopyr had higher Kappa Statistics (61% and 65%, respectively) indicating these data are most likely more repeatable than some of the other treatments whose Kappa Statistics are low (<40%).

Across Replication Model Evaluations

To evaluate the robustness of the models, three reps (1, 2, and 4) of the POST 2001 data were used as a training data set and one replication (3) was used as a test data set. Discriminant analysis, Fisher linear discriminant classification, quadratic maximum likelihood, and correlation classifications of these data were very similar (Table 3.6). Pair-wise comparisons of the 2,4-D, dicamba + diflufenzopyr, or nicosulfuron treated plots with untreated check plots resulted in high separation (near 100%). Bromoxynil treated plots were correctly classified 100% with discriminant analysis and Fisher linear classifier but only marginally classified using quadratic maximum likelihood or correlation classifiers. The classification of atrazine or primisulfuron treated plots was generally less than 50% and usually 0% regardless of the classification procedure used. Discriminant analysis procedures were not able to differentiate between the untreated check and primisulfuron treated plots. The atrazine treatment was inseparable with discriminant analysis techniques and had classification accuracies of 0% with Fisher's linear discriminant, quadratic maximum likelihood, and correlation classification techniques. This suggests that these herbicides do not dramatically impact the reflectance properties of corn and thus are not distinguishable from untreated corn.

The results from using replications 1, 2, and 4 of the POST 2002 trial for the training data set and replication 3 as the test data set were very similar to the results from 2001 (Table 3.6). In the 2002 data, discriminant analysis techniques were unable to distinguish between the atrazine or bromoxynil treated plots and the untreated check just as in 2001. In addition to these treatments, discriminant analysis could not develop models for the bromoxynil or nicosulfuron treated plots. However, using the Fisher linear discriminant classifier resulted in no more than 60% classification accuracy of the pair-wise comparisons regardless of herbicide treatment. This is drastically different from the 100% classification accuracies from the similar 2001 analysis.

Primisulfuron treated plots were not separable using discriminant analysis techniques in SAS, and were not separable (40%, 0%, & 20%) using Fisher's linear discriminant, quadratic maximum likelihood, or correlation classification techniques, respectively (Table 3.6).

Using SAS for Band Selection and MultiSpec for Analysis

Fisher linear discriminant, quadratic maximum likelihood, and correlation classification techniques, using bands selected by SAS PROC STEPDISC, resulted in at least 92% classification accuracy for bromoxynil, 2,4-D, dicamba + diflufenzopyr or nicosulfuron treated plots (Table 3.7) in 2001. These results reflect the results from discriminant analysis and support the ability of PROC STEPDISC to determine bands used for treatment separability. Atrazine and primisulfuron were not separable from the untreated check, when the bands for analysis were determined by PROC STEPDISC, regardless of statistical procedure used (Table 3.7).

A similar analysis was conducted for the POST 2002 data using the bands selected from the 2001 data set by the PROC STEPDISC procedure. Classification accuracies of bromoxynil, 2,4-D, dicamba + diflufenzopyr, and nicosulfuron were generally much lower than results from the POST 2001 experiment. However, atrazine, and primisulfuron were still indistinguishable from the untreated check, regardless of analytical procedure used.

Classification accuracy of the POST 2002 trial using SAS for band determination from the POST 2001 trial and MultiSpec for the actual analysis were very positive (Table 3.7). However, when SAS was used to determine the band selection from the POST 2002 trial and MultiSpec was for the analysis of the 2001 and 2002 data sets, atrazine, bromoxynil, nicosulfuron, and primisulfuron treated plots were not distinguishable from the untreated check (Table 3.8). Fisher linear discriminant and quadratic maximum likelihood classifier accuracies for classifications of 2001 data resulted in 100% classification accuracy of 2,4-D treated plots. However, the 2,4-D plots classified by MultiSpec in the 2002 data set resulted in less than 60% accuracy using the Fisher linear classification or the quadratic maximum likelihood classification techniques, and low Kappa statistics (<40%).

The conclusion can be drawn from the cross-classification using 2001 bands on the 2002 data and vice versa that the treatments were more separable in 2001. Reference and reliability accuracies for the POST 2001 treatments, when using the wavelengths selected from POST 2001 data using SAS techniques, are all greater than 90% with Kappa Statistics greater than 90% (Table 3.7). When the same wavelengths were used for POST 2002 classification, reference accuracies and Kappa Statistics indicate low classification accuracies. The correlation classifier had the highest classification accuracies, with Kappa Statistics greater than 70%. Quadratic maximum likelihood and correlation classifiers had high reference accuracies for nicosulfuron, but low Kappa Statistics make the high accuracies questionable (Table 3.7). POST 2001 2,4-D treated plots were highly separable from the untreated using SAS selected bands with all classifiers, and high classification accuracy was obtained for 2,4-D in POST 2002 using the correlation classifier, although the Fisher linear discriminant and quadratic maximum likelihood classifiers do not support this high accuracy. Fisher linear discriminant classification accuracies for the POST 2001 2,4-D treated plots indicate 100% separability from the untreated check using SAS selected bands from both 2001 and 2002 (Table 3.7 & 3.8). Accuracies for the POST 2002 2,4-D treated plots are not as high using bands from either data set. The classification accuracies for the classifiers are similar using the different bands. For example, using POST 2001 SAS bands, reference accuracy of the Fisher linear discriminant classification of POST 2002 2,4-D was 54% with a 29% Kappa Statistic, and using the POST 2002 SAS bands the reference accuracy was 58% with a 31% Kappa Statistic (Table 3.7 & 3.8). Classification accuracies using the quadratic maximum likelihood and correlation classifiers produce similar results. These correlations, combined with the high classification accuracies for POST 2001 2,4-D plots, show that similar results are obtained using wavelengths from both years. The low accuracies for the POST 2002 2,4-D treated plots using both sets of SAS selected bands show higher separation in POST 2001 data.

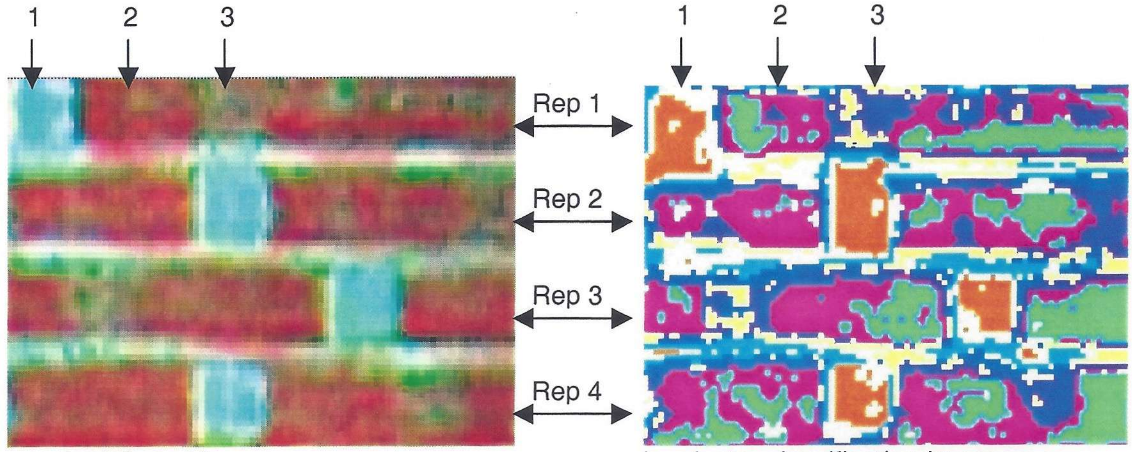
Analysis of Aerial collected data

In 2001, all herbicide treated corn plots could be separated from the untreated plots using SAS PROC STEPDISC, which indicated canopy reflectance of corn treated with these herbicides was altered (Table 3.9). Classification accuracies for each treatment were at least 75% or better in pair-wise comparisons with the untreated check. However, analysis of the POST 2002 data resulted in 75% classification accuracy of the 2,4-D treated plots and lack of differentiation of all other treatments in pair-wise comparisons with the untreated check.

Classification of all treatments by a single model using SAS discriminant analysis techniques was done to determine where misclassifications were occurring (Table 3.10). The untreated check was misclassified as atrazine and primisulfuron, and the atrazine and primisulfuron plots were misclassified as untreated. This supports the results of the SAS discriminant classification for the ground data, in that the reflectance properties of the untreated check plots were similar to the atrazine or primisulfuron treated plots. As would be expected from the previous analysis, 2,4-D and dicamba + diflufenzopyr were correctly classified 75% of the time and never misclassified as the untreated check, indicating that they are separable from the untreated (Table 3.10).

Discriminant analysis was conducted again after removing the bare soil treatment from the data set (Table 3.11). By removing the bare soil treatment, the accuracies of the classification became similar to the pair-wise classifications of treatments. Dicamba + diflufenzopyr and 2,4-D were separable from the untreated with accuracies of 100% and 75% respectively (Table 3.11). Atrazine and nicosulfuron had 0% classification accuracies and untreated plots were classified as primisulfuron and atrazine for 50% and 25% of the samples respectively (Table 3.11).

The collected multispectral images were cropped to include only the test areas. The image was then initially processed by running an isodata clustering algorithm on the data in MultiSpec (within eigenvector volume, six to eight clusters, and 98% convergence). In the POST 2001 image, collected July 2, 2001, subtle shading and color differences are apparent (Figure 3.3a). Notice the bright blue areas, bare soil, dark red areas, healthy vegetation, and green / gray areas, 2,4-D plots in the image.

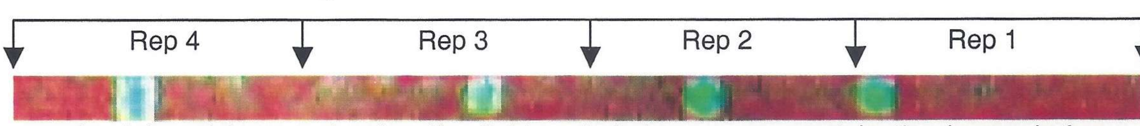


a. color infrared image

b. cluster classification image

Figure 3.3. POST 2001 aerial image collected July 2, 2001 before image classification (a) and after clustering (b) showing replications and distinguishable reflectance differences for bare soil (1), healthy corn (2), and 2,4-D treated corn (3) notice the plots of each distributed throughout the other replications.

After the isodata clustering was performed on the image, areas of separation were apparent (Figure 3.3b). Orange clusters represent bare soil, green areas coincide with healthy vegetation, and blue and yellow areas indicate stressed vegetation. The stressed areas are where the 2,4-D plots are located, and the healthy areas are where corn was untreated or treated with primisulfuron or atrazine. Color differences in the 2002 aerial data before clustering were apparent with noticeable differences among replications rather than treatments (Figure 3.4a). These differences became more apparent after clustering (Figure 3.4b). Bare soil areas are yellow, yellow and orange, or blue edged with green after isodata clustering.



a. color infrared image showing the light and dark areas present in the image before any classification.

b. cluster classification image showing that clusters are grouped according to replications instead of by treatments

Figure 3.4. POST 2002 aerial image collected July 2, 2002 showing color differences before image classification (a). and after clustering (b).

After clustering, training and test samples were selected for the image classification. Twenty-five pixels were selected to train the classifier, and seventy-five pixels were chosen to test the classification accuracy. Samples were selected in the center of the plots to avoid edge effect from neighboring plots (Figure 3.5).

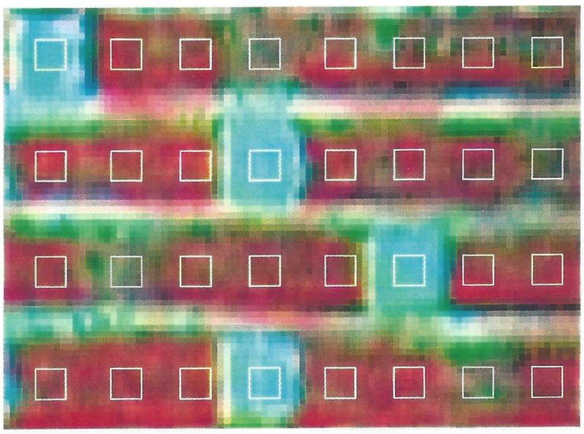


Figure 3.5a. POST 2001 aerial image collected July 2, 2001 with white boxes outlining selection areas for training and test samples.

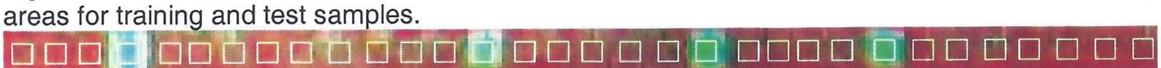


Figure 3.5b. POST 2002 aerial image collected July 2, 2002 with white boxes outlining selection areas for training and test samples.

Classification of the aerial images proceeded in two major steps. First, an analysis was performed to determine the separability of the treatments with all treatments incorporated into the analysis. Next, each treatment was classified versus the untreated, in pair-wise comparisons similar to the SAS and MultiSpec analyses conducted previously.

Classification of all 2001 treatments was done with quadratic maximum likelihood, Fisher linear discriminant, and correlation classifiers (Tables 3.13, 3.14, & 3.15, respectively) for a comparison to the discriminant analysis done in SAS. All classifiers (quadratic maximum likelihood, Fisher linear discriminant, and correlation classifiers) were able to separate 2,4-D from all other treatments with at least 88% accuracy. Classification accuracies of all other treatments were less than 35%, regardless of classifier used. The untreated was not classified as 2,4-D when using any classifiers, or as dicamba + diflufenzopyr when using quadratic maximum likelihood and Fisher's classifiers. This matches the SAS aerial analysis and ground data classifications for 2,4-D. The low classification accuracy of the other treatments, as well as the untreated checks being classified as these various herbicide treatments, indicates the reflectance properties of the corn were not drastically changed due to atrazine, bromoxynil, nicosulfuron, or primisulfuron applications.

Pair-wise classifications using Fisher linear discriminant, quadratic maximum likelihood, and correlation classifications were done comparing each treatment to the untreated check (Table 3.9). Fisher classification accuracies for bromoxynil, 2,4-D, dicamba + diflufenzopyr, and nicosulfuron were greater than 90% (Table 3.9), which is very similar to the ground-based data results (Table 3.5). Of the POST 2002 data set, only 2,4-D was separable using PROC STEPDISC and was classified correctly 75% of the time using PROC DISCRIM (Table 3.9). In the analysis of the aerial data, classification of all treatments using PROC DISCRIM resulted with 2,4-D being the only treatment classified correctly. Untreated checks were misclassified as atrazine, bromoxynil, and primisulfuron, and similarly, bromoxynil and primisulfuron each had one observation that was classified as untreated (Table 3.12).

Classifications using all treatments of the POST 2002 image are shown (Tables 3.16, 3.17, & 3.18). The classifications show that none of the treatments can be accurately separated from the other treatments. Using the Fisher linear discriminant classifier, atrazine had a reference accuracy of than 60%, however, all other treatments in that classification had samples classified into that class, giving it low reliability accuracy (Table 3.17).

Pair-wise classification of aerial data in 2002 using Fisher linear discriminant classifier resulted in similar classifications as the ground-based data, separating bromoxynil, 2,4-D and dicamba + diflufenzopyr from the untreated check 81%, 87%, and 65% of the time (Table 3.9). Using SAS discriminant analysis techniques, Fisher linear discriminant, quadratic maximum likelihood, and correlation classifications, 2,4-D was highly separable from the untreated check with accuracies of 75% for SAS analysis and 87% for MultiSpec classifications (Table 3.9). The high classification accuracies combined with Kappa Statistics greater than 60% indicate SAS classification of the aerial data is similar to the image classification results.

DISCUSSION

2,4-D and dicamba + diflufenzopyr treated plots were separable from the untreated checks over both growing seasons using SAS discriminant analysis, Fisher linear discriminant, quadratic maximum likelihood, and correlation classifications using both the hyperspectral ground-based and multispectral aerial data. These differences were most likely due to stress induced by herbicide uptake. POST 2001 2,4-D and dicamba + diflufenzopyr treated corn plants had bent stalks after application and during hyperspectral ground-based data collection. The stalks straightened out, and the only visible symptom was slight stunting when the aerial data was collected. Cool wet weather in the spring of 2001 was a major factor in enhancing the effects of 2,4-D and dicamba + diflufenzopyr treated corn. Two effects of the weather, slowed metabolism and shorter plant height, contributed to injury due to the 2,4-D or dicamba + diflufenzopyr application. The cool weather slowed the corn's growth rate, shortening plant height. This is a potential factor due to the method of determining application restrictions for 2,4-D. According to application restrictions on the label, 2,4-D is not to be applied to corn taller than 10 cm. With the cool, wet weather, the corn did not grow normally, and was more physiologically mature than crop height indicated, creating potential for increased crop injury. The other effect of the cool weather came when the weather warmed after application. The corn plant was still absorbing the herbicide when it's metabolism rate was slowed due to the temperature, and when the weather warmed and a growth spurt occurred, the corn was not able to metabolize the 2,4-D or dicamba + diflufenzopyr present. 2002 did not have the abnormal weather conditions, therefore POST 2002 neither 2,4-D nor dicamba +

diflufenzopyr treated corn had bent stalks, and there was no visible stunting of corn in either treatment. The symptomology and injury differences were factors on the accuracy of classifications for POST 2001 and POST 2002. The visible injury in POST 2001 correlated with high spectral separability. Although there were not visible injury symptoms in POST 2002, 2,4-D and dicamba + diflufenzopyr treated plots were separable from untreated plots, though not as reliably as in POST 2001.

In situations where spectral reflectance change is not desired, neither 2,4-D nor dicamba + diflufenzopyr should be used. These herbicides have high potentials to change the spectral reflectance properties of corn. Through further characterization of bands to distinguish 2,4-D and improved classification procedures, areas treated with 2,4-D can be identified and potentially be used by researchers, commercial applicators, or insurance agents. Accurate and reliable identification of 2,4-D or other post applied herbicide application areas could become a useful tool in the future in production and legal matters.

Atrazine and primisulfuron-methyl treated corn were indistinguishable from untreated corn when discriminant analysis techniques and quadratic maximum likelihood classifiers were used on both POST 2001 and POST 2002 data (Table 3.5). Classification accuracies of atrazine and primisulfuron-methyl POST 2002 data using classifiers in MultiSpec show low Kappa Statistics and are virtually inseparable from untreated plots (Table 3.5). Likewise, SAS techniques were not able to separate atrazine or primisulfuron-methyl treated corn from the untreated corn in the 2002 aerial data (Table 3.9). The overall inability of the tested classification methods to separate atrazine and primisulfuron-methyl is due to the ability of the corn plant to quickly metabolize these herbicides into non-toxic compounds. Atrazine and primisulfuron-methyl treatments would be good candidates for postemergence applications where maintaining corn canopy reflectance properties are essential.

More work is needed to determine whether bromoxynil and nicosulfuron are consistently separable from the untreated since they were separable in 2001, but were inseparable in 2002. As with the 2,4-D and dicamba + diflufenzopyr treated plots, separability of treated plots from untreated plots is mostly due to the weather conditions. Again, the corn was stressed when the herbicides were applied, and the corn was not able to metabolize the herbicides efficiently. Crop height in relation to maturity could have been a factor as well for the nicosulfuron treated corn.

Another area of emphasis for future research may be on the plant level looking at what influences spectral change in plants after herbicide application, particularly those herbicide products that are not expected to injure the crop for which they are labeled. Sites used to sequester herbicides may impact the light reflectance properties of the leaf by concentrating the herbicides or their degradates. The herbicides may have their own reflectance properties, and may influence the spectral response not by altering the plant, but rather by being present in or on the plant.

Consideration should also be given for research to determine if herbicide effect on spectral response of corn canopies can be correlated to herbicide modes of action. 2,4-D and dicamba + diflufenzopyr indicate there may be some correlation, however, nicosulfuron was not always similar to primisulfuron-methyl. If similarities can be drawn with in modes of action, research time to produce a useful tool to commercial applicators, crop advisors, or insurance representatives will be greatly reduced. This is the case because not every herbicide will have to be investigated initially, only the general classes of herbicides. Discrepancies that arise through hands on use can be used by researchers to enhance spectral databases.

Determination of the effects of postemergence herbicides on the spectral properties of corn will be one more useful tool available to farmers in the precision agriculture toolbox.

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Table 3.1. Classification accuracies for the SAS PROC DISCRIM procedure for pair-wise comparisons of POST treatments and the untreated check in 2001 showing the wavebands used from the hyperspectral data. Models could not be formed to separate atrazine or primisulfuron-methyl treated plots from the untreated check.

Treatment	Cross-validation Summary Percent Classified Correctly	Bands used in DISCRIM procedure (micrometers)
Bromoxynil	100%	0.364, 0.516, 0.669, 0.765, 0.774
2,4-D	100%	0.669, 0.76
Dicam.+diflu.	100%	0.663, 0.763
Nicosulfuron	100%	0.569, 0.694

Table 3.2. Classification accuracies for the SAS PROC DISCRIM procedure for pair-wise comparisons of POST treatments and the untreated check in 2002 showing the wavebands used from the hyperspectral data. Models could not be formed to separate atrazine, bromoxynil, nicosulfuron, or primisulfuron-methyl treated plots from the untreated check.

Treatment	Cross-validation Summary Percent Classified Correctly	Bands used in DISCRIM procedure (micrometers)
2,4-D	100%	0.548, 0.756, 0.997, 1.332, 1.54, 2.037
Dicam.+diflu.	75%	0.76, 0.787

Table 3.3. Classification accuracies for the SAS PROC DISCRIM procedure using aerial data for pair-wise comparisons of POST treatments and the untreated check in 2001 showing the wavelengths used.

Treatment	Cross-validation Summary Percent Classified Correctly	Bands used in DISCRIM procedure (micrometers)
Atrazine	75%	655 nm
Bromoxynil	100%	655 nm
2,4-D	100%	655 & 800 nm
Dicam.+diflu.	100%	655 nm
Nicosulfuron	75%	550 nm
Primisulfuron-methyl	75%	550 & 800 nm

Table 3.4. Classification accuracies for the SAS PROC DISCRIM procedure using aerial data for pair-wise comparisons of POST treatments and the untreated check in 2002 showing the wavelengths used. Models could not be formed to separate atrazine, bromoxynil, dicamba + diflufenzopyr, nicosulfuron, or primisulfuron-methyl treated plots from the untreated check.

Treatment	Cross-validation Summary Percent Classified Correctly	Bands used in DISCRIM procedure (micrometers)
2,4-D	75%	550 & 655 nm

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Table 3.5. Classification accuracy of pair-wise comparisons, using the average accuracy of left and right test pixel classifications, of postemergence herbicide treatments in corn based on reflectance properties using various analysis techniques and bands included in multispectral image bands on ground collected reflectance data.

Year	Analysis Procedure		Herbicide					
			Atrazine	Bromoxynil	2,4-D	Dicam.+Diflu.	Nicosulfuron	Primisulfuron
2001	DA[a]	PROC DISCRIM %	ND[e]	100	100	100	100	ND
	FLD[b]	Reference Accuracy %	83	96	100	100	100	92
		Kappa Statistic %	84	98	98	100	100	89
	QML[c]	Reference Accuracy %	46	54	46	33	42	13
		Kappa Statistic %	54	43	43	29	51	4
	CC[d]	Reference Accuracy %	83	88	96	92	92	88
		Kappa Statistic %	84	96	98	96	91	83
2002	DA	PROC DISCRIM %	ND	ND	100	75	ND	ND
	FLD	Reference Accuracy %	67	79	67	88	75	75
		Kappa Statistic %	45	58	61	65	40	36
	QML	Reference Accuracy %	92	42	54	100	100	0
		Kappa Statistic %	11	22	-14	8	1	-11
	CC	Reference Accuracy %	71	75	67	83	67	79
		Kappa Statistic %	42	48	61	67	38	36

[a] Discriminant analysis using the PROC STEPDISC and PROC DISCRIM procedures in SAS.
[b] Fisher linear discriminant classification using MultiSpec.
[c] Quadratic maximum likelihood classification using MultiSpec.
[d] Correlation classification (Spectral Angle Mapper) using MultiSpec.
[e] Treatment could not be differentiated from the untreated check using the discriminant analysis procedures in SAS.

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Table 3.6. Classification accuracy of pair-wise comparisons, using rep 3 to test the classifier, of postemergence herbicide treatments in corn based on reflectance properties using various analysis techniques and bands included in multispectral image bands on ground collected data.

			Herbicide					
Year	Analysis	Procedure	Atrazine	Bromoxynil	2,4-D	Dicam.+Diflu.	Nicosulfuron	Primisulfuron
2001	DA [a]	PROC DISCRIM %	ND [e]	100	100	100	100	ND
	FLD [b]	Reference Accuracy %	0	100	100	100	100	40
		Kappa Statistic %	55	100	100	100	100	42
	QML [c]	Reference Accuracy %	0	20	100	100	80	0
		Kappa Statistic %	27	14	100	55	46	7
	CC [d]	Reference Accuracy %	0	40	100	100	100	20
		Kappa Statistic %	43	55	100	100	100	49
2002	DA	PROC DISCRIM %	ND	ND	100	75	ND	ND
	FLD	Reference Accuracy %	40	20	40	40	20	60
		Kappa Statistic %	32	45	60	65	-15	40
	QML	Reference Accuracy %	100	40	100	60	0	0
		Kappa Statistic %	0	37	-17	20	-26	-11
	CC	Reference Accuracy %	80	0	40	40	20	40
		Kappa Statistic %	65	35	70	35	-15	30

[a] Discriminant analysis using the PROC STEPDISC and PROC DISCRIM procedures in SAS.
[b] Fisher linear discriminant classification using MultiSpec.
[c] Quadratic maximum likelihood classification using MultiSpec.
[d] Correlation classification (Spectral Angle Mapper) using MultiSpec.
[e] Treatment could not be differentiated from the untreated check using the discriminant analysis procedures in SAS.

Table 3.7. Classification accuracy of pair-wise comparisons of postemergence herbicide treatments in corn based on reflectance properties using various analysis techniques and bands used in 2001 SAS analysis on ground collected reflectance data. Models could not be formed to separate atrazine and primisulfuron-methyl treatments from the untreated check using the PROC STEPDISC in SAS.

			Herbicide			
Year	Analysis Procedure		Bromoxynil	2,4-D	Dicam.+Diflu.	Nicosulfuron
2001	FLD[a]	Reference Accuracy %	100	100	100	100
		Kappa Statistic %	100	100	100	94
	QML[b]	Reference Accuracy %	92	96	100	100
		Kappa Statistic %	96	97	99	95
	CC[c]	Reference Accuracy %	92	96	100	100
		Kappa Statistic %	94	98	100	94
2002	FLD	Reference Accuracy %	63	54	75	54
		Kappa Statistic %	37	29	40	12
	QML	Reference Accuracy %	71	33	75	96
		Kappa Statistic %	56	21	25	12
	CC	Reference Accuracy %	79	96	79	88
		Kappa Statistic %	65	75	65	50

[a] Fisher linear discriminant classification using MultiSpec.
[b] Quadratic maximum likelihood classification using MultiSpec.
[c] Correlation classification (Spectral Angle Mapper) using MultiSpec.

Table 3.8. Classification accuracy of pair-wise comparisons of postemergence herbicide treatments in corn based on reflectance properties using various analysis techniques and bands used in 2002 SAS analysis on ground collected reflectance data.

			Herbicide	
Year	Analysis	Procedure	2,4-D	Dicamba + Diflufenzopyr
2001	FLD [a]	Reference Accuracy %	100	67
		Kappa Statistic %	69	50
	QML [b]	Reference Accuracy %	100	54
		Kappa Statistic %	100	38
	CC [c]	Reference Accuracy %	79	67
		Kappa Statistic %	63	21
2002	FLD	Reference Accuracy %	58	67
		Kappa Statistic %	31	29
	QML	Reference Accuracy %	46	83
		Kappa Statistic %	28	36
	CC	Reference Accuracy %	83	54
		Kappa Statistic %	36	15

[a] Fisher linear discriminant classification using MultiSpec.
[b] Quadratic maximum likelihood classification using MultiSpec.
[c] Correlation classification (Spectral Angle Mapper) using MultiSpec.
[d] Treatment could not be differentiated from the untreated check using the discriminant analysis procedures in SAS.

Table 3.9. Classification accuracy of pair-wise comparisons of postemergence herbicide treatments in corn based on reflectance properties using various analysis techniques and analysis on aerial multispectral reflectance data.

			Herbicide					
Year	Analysis	Procedure	Atrazine	Bromoxynil	2,4-D	Dicam.+Diflu.	Nicosulfuron	Primisulfuron
2001	DA [a]	PROC DISCRIM %	75	100	100	100	75	75
	FLD [b]	Reference Accuracy %	69	92	100	91	92	57
		Kappa Statistic %	41	66	97	72	67	39
	QML [c]	Reference Accuracy %	65	93	100	92	87	60
		Kappa Statistic %	46	81	98	82	68	50
	CC [d]	Reference Accuracy %	61	69	100	89	80	53
		Kappa Statistic %	30	43	97	60	47	-6
2002	DA	PROC DISCRIM %	ND [e]	ND	75	ND	ND	ND
	FLD	Reference Accuracy %	68	81	87	65	9	5
		Kappa Statistic %	10	33	68	29	2	7
	QML	Reference Accuracy %	8	8	87	52	4	4
		Kappa Statistic %	-9	17	72	38	3	11
	CC	Reference Accuracy %	16	61	87	60	27	40
		Kappa Statistic %	-8	41	68	53	18	10

[a] Discriminant analysis using the PROC STEPDISC and PROC DISCRIM procedures in SAS.
[b] Fisher linear discriminant classification using MultiSpec.
[c] Quadratic maximum likelihood classification using MultiSpec.
[d] Correlation classification (Spectral Angle Mapper) using MultiSpec.
[e] Treatment could not be differentiated from the untreated check using the discriminant analysis procedures in SAS.

Table 3.10. Cross-validation summary showing classification accuracies of aerial data using the linear discriminant function in SAS comparing all treatments in 2001. Data points consisted of 100 values for each treatment.

	Number of Observations and Percent Classified into Herbicide Treatment								
Herb Treatment	Nicosulfuron	Atrazine	Dicam.+diflu.	Primisulfuron	2,4-D	Bromoxynil	Untreated	Bare Soil	Total
Nicosulfuron	0	0	2	1	0	0	1	0	4
	0.00	0.00	50.00	25.00	0.00	0.00	25.00	0.00	100.0
Atrazine	0	1	1	0	0	1	1	0	4
	0.00	25.00	25.00	0.00	0.00	25.00	25.00	0.00	100.0
Dicam.+diflu.	0	0	3	0	0	1	0	0	4
	0.00	0.00	75.00	0.00	0.00	25.00	0.00	0.00	100.0
Primisulfuron	0	0	0	2	0	1	1	0	4
	0.00	0.00	0.00	50.00	0.00	25.00	25.00	0.00	100.0
2,4-D	0	0	1	0	3	0	0	0	4
	0.00	0.00	25.00	0.00	75.00	0.00	0.00	0.00	100.00
Bromoxynil	1	2	1	0	0	0	0	0	4
	25.00	50.00	25.00	0.00	0.00	0.00	0.00	0.00	100.0
Untreated	0	1	0	2	0	0	1	0	4
	0.00	25.00	0.00	50.00	0.00	0.00	25.00	0.00	100.0
Bare Soil	0	0	0	0	0	0	0	4	4
	0.00	0.00	0.00	0.00	0.00	0.00	0.00	100.0	100.0
Total	1	4	8	5	3	3	4	4	32
	3.13	12.50	25.00	15.63	9.38	9.38	12.50	12.50	100.0
Priors	0.125	0.125	0.125	0.125	0.125	0.125	0.125	0.125	

Table 3.11. Cross-validation summary showing classification accuracies using the linear discriminant function in SAS comparing all treatments in 2001 after removing Bare Soil from the classification. Data points consisted of 100 values for each treatment.

Number of Observations and Percent Classified into Herbicide Treatment when Bare Soil is Removed

Herb Treatment	Nicosulfuron	Atrazine	Dicam.+diflu.	Primisulfuron	2,4-D	Bromoxynil	Untreated	Total
Nicosulfuron	0 0.00	1 25.00	2 50.00	1 25.00	0 0.00	0 0.00	0 0.00	4 100.00
Atrazine	1 25.00	0 0.00	0 0.00	0 0.00	0 0.00	2 50.00	1 25.00	4 100.00
Dicam.+diflu.	0 0.00	0 0.00	4 100.00	1 0.00	0 0.00	0 0.00	0 0.00	4 100.00
Primisulfuron	1 25.00	0 0.00	0 0.00	1 25.00	0 0.00	0 0.00	2 50.00	4 100.00
2,4-D	0 0.00	0 0.00	1 25.00	0 0.00	3 75.00	0 0.00	0 0.00	4 100.00
Bromoxynil	0 0.00	2 50.00	1 25.00	0 0.00	0 0.00	1 25.00	1 0.00	4 100.00
Untreated	0 0.00	1 25.00	0 0.00	2 50.00	0 0.00	0 0.00	1 25.00	4 100.00
Total	2 7.14	4 14.29	8 28.57	4 14.29	3 10.71	3 10.71	4 14.29	28 100.00
Priors	0.14286	0.14286	0.14286	0.14286	0.14286	0.14286	0.14286	

Table 3.12. Cross-validation summary showing classification accuracies of the aerial data using the linear discriminant function in SAS classifying all treatments in 2002. Data points consisted of 100 values for each treatment.

	Number of Observations and Percent Classified into Herbicide Treatment								
Herb Treatment	Nicosulfuron	Atrazine	Dicam.+diflu.	Primisulfuron	2,4-D	Bromoxynil	Untreated	Bare Soil	Total
Nicosulfuron	0	1	1	1	1	0	0	0	4
	0.00	25.00	25.00	25.00	25.00	0.00	0.00	0.00	100.00
Atrazine	1	0	0	2	0	1	0	0	4
	25.00	0.00	0.00	50.00	0.00	25.00	0.00	0.00	100.00
Dicam.+diflu.	1	0	0	1	1	1	0	0	4
	25.00	0.00	0.00	25.00	25.00	25.00	0.00	0.00	100.00
Primisulfuron	1	2	0	0	0	0	1	0	4
	25.00	50.00	0.00	0.00	0.00	0.00	25.00	0.00	100.00
2,4-D	0	0	0	0	2	2	0	0	4
	0.00	0.00	0.00	0.00	50.00	50.00	0.00	0.00	100.00
Bromoxynil	1	0	1	0	1	0	1	0	4
	25.00	0.00	25.00	0.00	25.00	0.00	25.00	0.00	100.00
Untreated	0	1	0	1	0	2	0	0	4
	0.00	25.00	0.00	25.00	0.00	50.00	0.00	0.00	100.00
Bare Soil	0	0	0	0	0	0	0	4	4
	0.00	0.00	0.00	0.00	0.00	0.00	0.00	100.00	100.00
Total	4	4	2	5	5	6	2	4	32
	12.50	12.50	6.25	15.63	15.63	18.75	6.25	12.50	100.00
Priors	0.125	0.125	0.125	0.125	0.125	0.125	0.125	0.125	

Table 3.13. Classification of 2001 test pixels using the quadratic maximum likelihood classifier in MultiSpec.

Class	Reference Accuracy (%)	Number Samples	Number of Samples Classified into Class using Quadratic Maximum Likelihood Classification							
			Atrazine	Bromoxynil	Dicam.+diflu.	2,4-D	Nicosulfuron	Primisulfuron	Untreated	Bare Soil
Atrazine	16	75	12	30	2	2	13	15	1	0
Bromoxynil	34.7	75	20	26	5	0	18	6	0	0
Dicam.+diflu.	16	75	17	31	12	7	1	3	4	0
2,4-D	100	75	0	0	0	75	0	0	0	0
Nicosulfuron	24	75	19	15	3	11	18	9	0	0
Primisulfuron	24	75	11	19	1	2	10	18	14	0
Untreated	25.3	75	16	16	0	0	16	8	19	0
Bare Soil	100	75	0	0	0	0	0	0	0	75
TOTAL		600	95	137	23	97	76	59	38	75
Reliability Accuracy (%)			12.6	19	52.2	77.3	23.7	30.5	50	100

OVERALL CLASS PERFORMANCE (255 / 600) = 42.5%

Kappa Statistic (X100) = 34.3%. Kappa Variance = 0.000520

Table 3.14. Classification of POST 2001 test pixels using the Fisher linear discriminant classifier in MultiSpec.

Class Number	Reference Accuracy (%)	Number Samples	Number of Samples Classified in Class using Fisher Linear Discriminant Classification							
			Atrazine	Bromoxynil	Dicam.+diflu.	2,4-D	Nicosulfuron	Primisulfuron	Untreated	Bare Soil
Atrazine	1.3	75	1	25	11	0	21	17	0	0
Bromoxynil	20	75	13	15	9	0	36	2	0	0
Dicam.+diflu.	13.3	75	13	38	10	4	10	0	0	0
2,4-D	88	75	0	9	0	66	0	0	0	0
Nicosulfuron	24	75	16	18	12	8	18	3	0	0
Primisulfuron	20	75	2	20	4	0	17	15	17	0
Untreated	18.7	75	9	4	0	0	39	9	14	0
Bare Soil	100	75	0	0	0	0	0	0	0	75
TOTAL		600	54	129	46	78	141	46	31	75
Reliability Accuracy (%)			1.9	11.6	21.7	84.6	12.8	32.6	45.2	100

OVERALL CLASS PERFORMANCE (214 / 600) = 35.7%

Kappa Statistic (X100) = 26.5%. Kappa Variance = 0.000497

Table 3.15. Classification of POST 2001 test pixels using the correlation classifier in MultiSpec.

Class Number	Reference Accuracy (%)	Number Samples	Number of Samples in Class using correlation Classification: Atrazine	Bromoxynil	Dicam.+diflu.	2,4-D	Nicosulfuron	Primisulfuron	Untreated	Bare Soil
Atrazine	2.7	75	2	15	16	2	20	14	6	0
Bromoxynil	14.7	75	13	11	26	0	25	0	0	0
Dicam.+diflu.	25.3	75	12	32	19	7	5	0	0	0
2,4-D	100	75	0	0	0	75	0	0	0	0
Nicosulfuron	21.3	75	14	12	21	10	16	2	0	0
Primisulfuron	13.3	75	1	18	9	1	21	10	15	0
Untreated	6.7	75	4	9	15	0	26	16	5	0
Bare Soil	100	75	0	0	0	0	0	0	0	75
TOTAL		600	46	97	106	95	113	42	26	75
Reliability Accuracy (%)			4.3	11.3	17.9	78.9	14.2	23.8	19.2	100

OVERALL CLASS PERFORMANCE (213 / 600) = 35.5%

Kappa Statistic (X100) = 26.3%. Kappa Variance = 0.000481

Table 3.16. Classification of POST 2002 test pixels using the quadratic maximum likelihood classifier in MultiSpec.

			Number of Samples Classified into Class using Quadratic Maximum Likelihood Classification							
Class Number	Reference Accuracy (%)	Number Samples	Atrazine	Bromoxynil	Dicam.+diflu.	2,4-D	Nicosulfuron	Primisulfuron	Untreated	Bare Soil
Atrazine	0	75	0	7	25	6	1	0	36	0
Bromoxynil	5.3	75	9	4	31	16	2	3	10	0
Dicam.+diflu.	33.3	75	11	11	25	13	0	0	13	2
2,4-D	9.3	75	4	1	44	7	3	1	6	9
Nicosulfuron	0	75	1	0	47	1	0	0	24	2
Primisulfuron	4	75	4	11	25	3	0	3	29	0
Untreated	26.7	75	8	4	23	5	0	15	20	0
Bare Soil	100	75	0	0	0	0	0	0	0	75
TOTAL		600	37	38	220	51	6	22	138	88
Reliability Accuracy (%)			0	10.5	11.4	13.7	0	13.6	14.5	85.2

OVERALL CLASS PERFORMANCE (134 / 600) = 22.3%

Kappa Statistic (X100) = 11.2%. Kappa Variance = 0.000341

Table 3.17. Classification of POST 2002 test pixels using the Fisher linear discriminant classifier in MultiSpec.

Class Number	Reference Accuracy (%)	Number Samples	Number of Samples Classified in Class using Fisher Linear Classification							
			Atrazine	Bromoxynil	Dicam.+diflu.	2,4-D	Nicosulfuron	Primisulfuron	Untreated	Bare Soil
Atrazine	60	75	45	0	5	0	0	6	19	0
Bromoxynil	5.3	75	51	4	6	0	0	4	10	0
Dicam.+diflu.	8	75	48	0	6	0	0	3	18	0
2,4-D	6.7	75	47	0	8	5	3	0	6	6
Nicosulfuron	0	75	50	0	0	0	0	9	16	0
Primisulfuron	12	75	43	0	0	0	0	9	23	0
Untreated	12	75	47	1	3	1	0	14	9	0
Bare Soil	100	75	0	0	0	0	0	0	0	75
	TOTAL	600	331	5	28	6	3	45	101	81
Reliability Accuracy (%)			13.6	80	21.4	83.3	0	20	8.9	92.6

OVERALL CLASS PERFORMANCE (153 / 600) = 25.5%

Kappa Statistic (X100) = 14.9%. Kappa Variance = 0.000346

Table 3.18. Classification of POST 2002 test pixels using the Correlation classifier in MultiSpec.

Class Number	Reference Accuracy (%)	Number Samples	Number of Samples in Class using Correlation Classification							
			Atrazine	Bromoxynil	Dicam.+diflu.	2,4-D	Nicosulfuron	Primisulfuron	Untreated	Bare Soil
Atrazine	5.3	75	4	4	2	0	2	29	34	0
Bromoxynil	1.3	75	32	1	1	8	13	8	12	0
Dicam.+diflu.	6.7	75	20	2	5	22	2	23	1	0
2,4-D	9.3	75	3	1	1	7	57	2	4	0
Nicosulfuron	5.3	75	2	4	3	12	4	33	17	0
Primisulfuron	40	75	6	3	13	3	0	30	20	0
Untreated	38.7	75	8	4	1	3	3	27	29	0
Bare Soil	100	75	0	0	0	0	0	0	0	75
	TOTAL	600	75	19	26	55	81	152	117	75
Reliability Accuracy (%)			5.3	5.3	19.2	12.7	4.9	19.7	24.8	100

OVERALL CLASS PERFORMANCE (155 / 600) = 25.8%

Kappa Statistic (X100) = 15.2%. Kappa Variance = 0.000393

CHAPTER 4

THE EFFECT OF TRAINING PIXEL SELECTION ON THE CLASSIFICATION ACCURACY OF HYPERSPECTRAL DATA WITH A LIMITED NUMBER OF TRAINING SAMPLES

INTRODUCTION

The introduction of hyperspectral sensors, and thus the collection of much more detailed spectral data, provides greater opportunities for extracting useful information from reflectance data. However, these more detailed data require more sophisticated data analysis procedures if their full potentials are to be achieved (Landgrebe, 1999A). Multispectral data are represented quantitatively and visualized in three principle ways, image, spectral, and feature space. Image space represents the data in image form, spectral space represents the data as a function of wavelength, and feature space illustrates how the response in the different wavelengths relate to each other, i.e. response in a wavelength plotted against that for the other wavelength.

One of the largest problems facing the remote sensing field, especially hyperspectral analysis, is that the number of training samples is usually not as numerous as one would desire. The number of training samples needed to adequately define the classes quantitatively, regardless of what discriminant function implementation is used, grows very rapidly with the number of spectral bands to be used. This suggests that for a fixed number of training samples there is an optimal measurement complexity. Too many spectral bands or too many brightness levels per spectral band are undesirable from the standpoint of expected classification accuracy (Landgrebe, 1999B). This is known as the Hughes effect.

However, there are ways to limit this effect. It has been found that when, the accuracy is below optimality due to limited training because of the Hughes effect, a less complex classifier algorithm may provide increased classification accuracy.

The classification rule that results from using the class conditional quadratic maximum likelihood estimates for the mean and covariance in the discriminant function as if they were the true mean and covariance achieves optimal classification accuracy only asymptotically as the number of training samples increases toward infinity. This classification scheme is not optimal when the training sample is finite. When the training set is small, the sample estimate of the covariance can vary from the true covariance. In fact, for p features, when the number of training samples is less than p+1, the sample covariance is always singular (Landgrebe, 1999B).

Therefore, in high dimensional cases, it has been found that feature extraction methods are especially useful to transform the problem to a lower dimensional space without loss of information (Kuo and Landgrebe, 2002).

MATERIALS AND METHODS

A boom truck-mounted field GER 2600 field spectrometer, also known as a spectroradiometer, was used to collect ground-based hyperspectral data for the four tests on clear days with less than 5% cloud cover. This spectrometer collects 640 bands of data in 1.5 nm increments. Using both silicon and lead sulfide sensors, a spectral range from 350 nm to 2500 nm was obtained. Of the 640 bands of data collected, approximately 500 bands outside the major water absorption bands were useable.

Five reflectance samples were collected for each plot with three collections with the sensor centered over a row of corn and two collections taken with the sensor centered between the rows (Figure 4.1). This method created a more representative canopy reflectance for the plot than if all samples were taken over the crop and none were taken between rows. This is particularly true since during the early development of the crop, there is not complete canopy closure and the soil can have a large impact on the reflectance values.

Daughtry et. al. (1982) found more measurements are required at low altitudes to obtain a representative sample of the canopy reflectance because reflectance measurements tended to be erratic as the sensor was moved across the rows. Therefore, measurements taken at half row spacing (on-row and off-row) were more efficient and representative of canopy reflectance than random sampling methods and averaging of measurements across the plot (Figure 4.1).

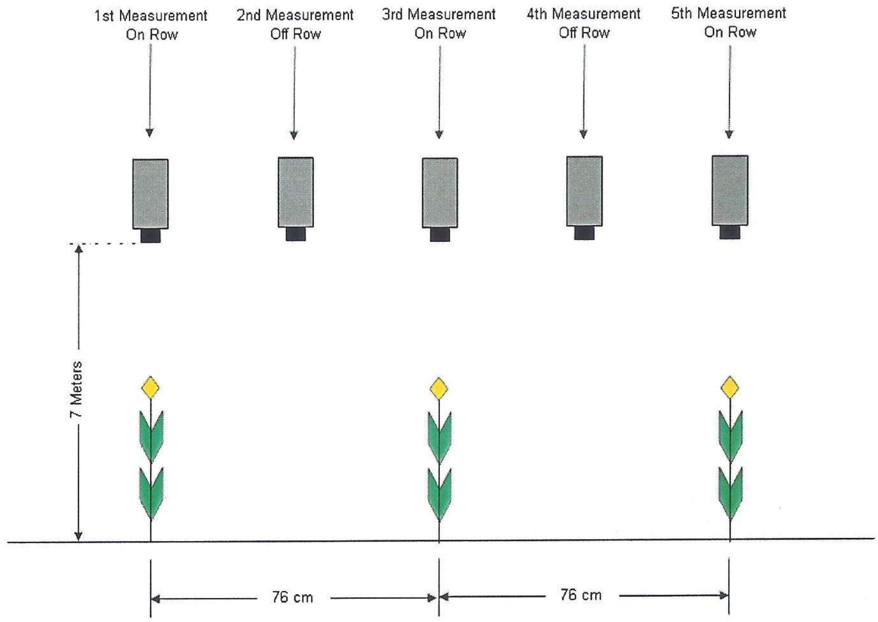

Figure 4.1. Placement of sensor for measurements in each plot showing on-row and off-row placement.

The spectrometer data were collected once for each test, approximately 5 weeks after planting (June 28, 2002) for the PRE early experiment, 4 weeks after planting (July 15, 2002) for the PRE late experiment, 6 weeks after planting for the POST 2001 experiment (June 16, 2001), and 5 weeks after planting for the POST 2002 experiment (June 28, 2002). All data collections occurred on clear days with less than 5% cloud cover near solar noon.

The measurements were converted to reflectance using a scene to reference comparison with linear interpolation between two reference observations using the formula:

$$R_s(\theta,\lambda) = [V_s(\theta,\lambda) - d_s(\lambda)] / V_r^1(\theta,\lambda) * R_r(\theta,\lambda)$$

Where: $V_r^1(\theta,\lambda) = V_{r1}(\theta,\lambda) - d_{r1}(\lambda) + [\{V_{r2}(\theta,\lambda) - d_{r2}(\lambda)\} - \{V_{r1}(\theta,\lambda) - d_{r1}(\lambda)\}]$

$$* \; t_s - t_{r1} / t_{r2} - t_{r1}$$

Where:

$V_s(\theta,\lambda)$ = GER 2600 response over corn canopy for solar illumination angle (θ) and wavelength (λ).

$V_{r1}(\theta,\lambda)$ = GER 2600 response over spectralon reflectance panel collected before corn canopy observation.

$V_{r2}(\theta,\lambda)$ = GER 2600 response over spectralon reflectance panel collected after corn canopy observation.

$R_s(\theta,\lambda)$ = Reflectance of corn canopy for solar illumination angle (θ) and wavelength (λ).

$R_r(\theta,\lambda)$ = Reflectance of spectralon panel for illumination angle (θ) and wavelength (λ).

d_s, d_{r1}, d_{r2} = Dark levels of GER 2600, all = 0.

t_s, t_{r1}, t_{r2} = Time for data collection for corn canopy, reference before and reference after, respectively.

The data were converted into .bip (band interleaved by pixel) image files using Matlab (Figure 4.2). The image files were then analyzed using remote sensing techniques to determine classification effectiveness and treatment separability using MultiSpec. Each of the five observations per plot was represented as a pixel, positioned on-off-on-off-on the rows of corn.

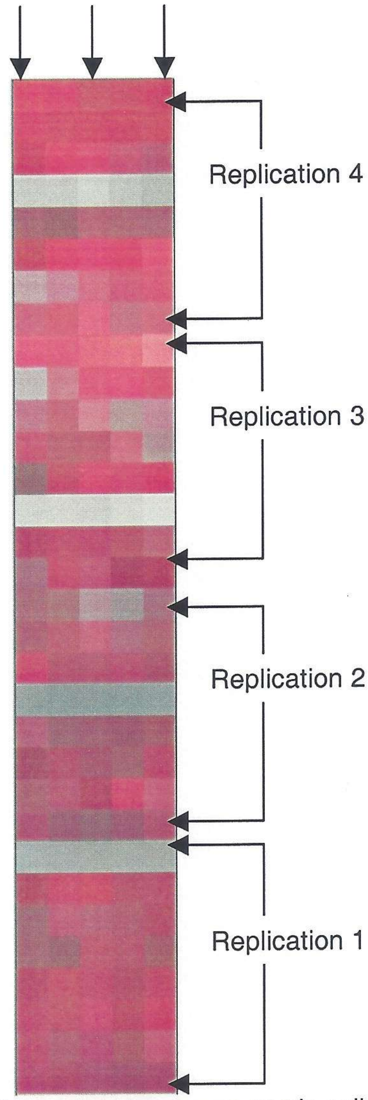

Figure 4.2. Image file created in Matlab using the boom truck collected hyperspectral data. Each row of pixels comprises a treatment. The arrows on the top point to the pixels that are on-row readings, while the second and fourth pixels represent off-row readings.

Several factors were controlled in the MultiSpec classification analysis. First, the number of bands was reduced either (1) to the bands included in the multispectral image bands, a reduction in the number of bands from 640 to 189, or (2) to the bands selected by the SAS STEPDISC procedure. The high dimensionality of the data warranted band reduction to avoid the Hughes phenomenon (Figure 4.3). The Hughes phenomenon is a decrease in the accuracy of statistics estimation as dimensionality increases, which leads to a decline in the accuracy of classification. Although increasing the number of spectral bands or dimensionality potentially provides more information about class separability, this positive effect is diluted by poor parameter estimation. As a result, the classification accuracy first grows and then declines as the number of spectral bands increases (Kuo and Landgrebe, 2001).

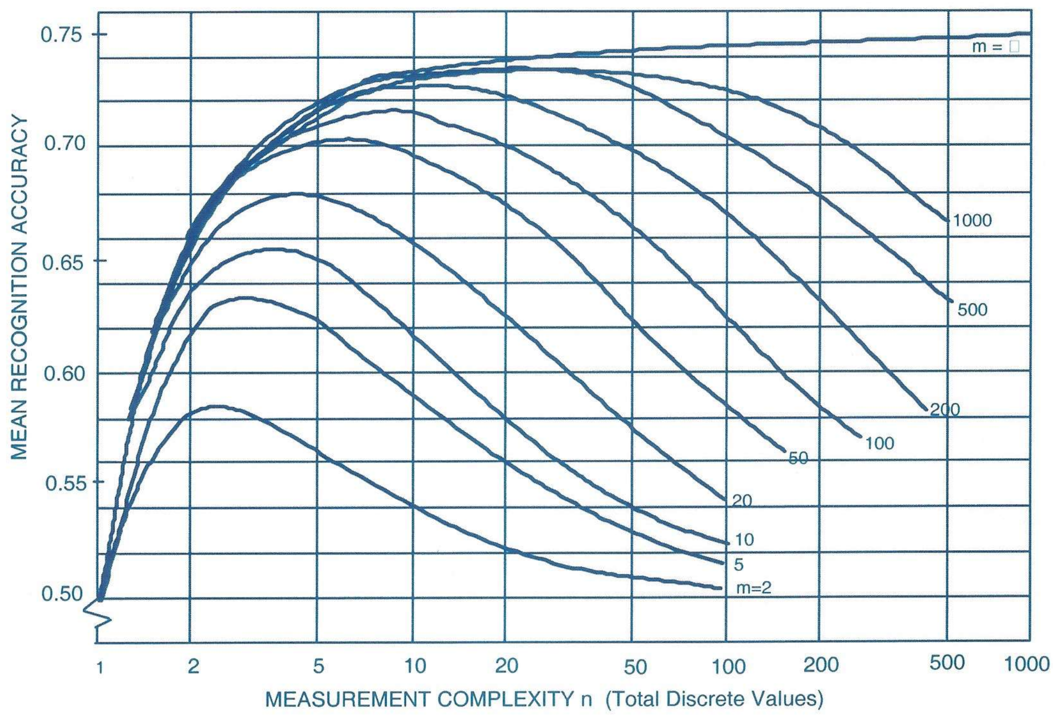

Figure 4.3. Concept of the Hughes Effect with wavelengths on the x-axis, mean recognition accuracy on the y-axis, and number of training samples next to the representative curve. (Landgrebe, 1999)

A leave–one-out covariance (LOOC) matrix was used to estimate the sample covariance for those cases when the number of training samples for a class is equal to the number of channels being used or fewer. This estimator examines the sample covariance and the common covariance estimates, as well as their diagonal forms, to determine which would be most appropriate. The value of the mixing parameter is selected by removing one sample, estimating the mean and covariance from the remaining samples, then computing the likelihood of the sample which was left out, given the mean and covariance estimates. Each sample is removed in turn, and the average log likelihood is computed. Several mixtures are examined by changing the value of the mixing parameter then the value that maximizes the average log likelihood is selected.

Though an estimated covariance matrix is ordinarily singular and therefore not usable when the number of samples used to estimate it is less than or equal to the number of features, the LOOC returns a usable covariance matrix estimate when the number of samples available is at least three or more (Landgrebe and Biehl, 2001). Image classification was run using the quadratic maximum likelihood, Fisher linear discriminant, and correlation classifiers (Figure 4.4).

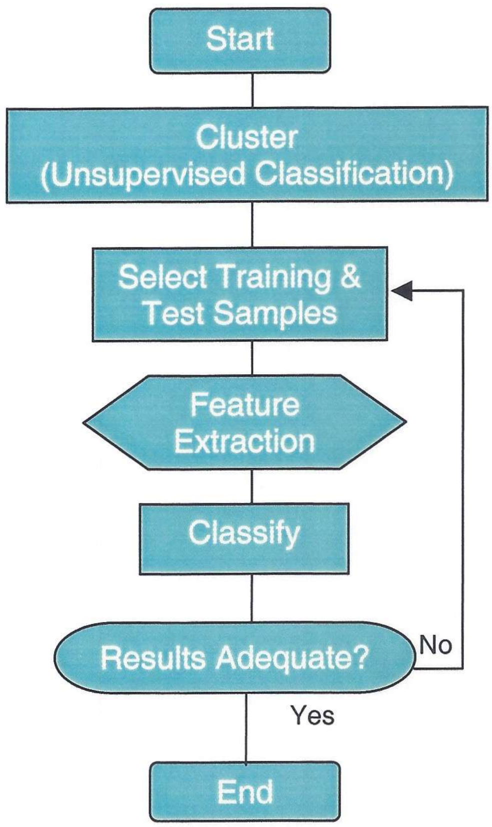

Figure 4.4. Diagram of the classification process used to analyze images in MultiSpec.

Training and test field selection methods for analysis of hyperspectral data in MultiSpec were conducted in two primary ways. The first method to be described is termed the left-right selection method. The data were analyzed by selecting on-off-on three pixels from each treatment as the training set, and the test field was made up of the other two pixels plus the center pixel. Consequently, the center pixel was used to both train and test the classifiers used. The fields were then switched from training to test and from test to training and the classifications were run again. Each treated class was classified in comparison to the untreated class to determine separability of the treatments from the untreated. Classification accuracies using the quadratic maximum likelihood, Fisher linear discriminant, and correlation classifiers were assessed and compared to determine if the sampling method had an effect on classification accuracy.

RESULTS

PRE comparison

In the PRE 2002a test, the quadratic maximum likelihood and correlation classifiers were very comparable from one training class selection to the other. Both classifiers had low Kappa Statistics overall, and had similar reference accuracies for each treatment from one selection method to the other (Table 4.1). Flufenacet + metribuzin had the biggest differences in accuracy when using the two selection methods. Using the left three pixels to train the classifier, classification accuracies were 83, 33, and 83% for Fisher linear discriminant, quadratic maximum likelihood, and correlation classifiers, respectively. The classification accuracies using the right three pixels dropped considerably to 0.0% using the three classification techniques (Table 4.1). Alachlor, atrazine, metolachlor and pendimethalin had the most consistent reference accuracies using the two selection methods. When using the two class selection methods, classification accuracies for alachlor were 92% and 100% using Fisher linear discriminant classification, 33% and 67% using quadratic maximum likelihood, and 75% and 83% using correlation classification (Table 4.1). Classification accuracies for atrazine and pendimethalin differed by less that 9% for Fisher and correlation classification methods when the training classes were changed (Table 4.3). Metolachlor had 92%, 100%, and 58% accuracies using the left three pixels, and 92%, 83%, and 58% accuracies using the right three pixels for Fisher linear discriminant, quadratic maximum likelihood, and correlation classifiers, respectively (Table 4.1). The accuracies were very similar with only quadratic maximum likelihood classification, 16%, differing at all (Table 4.3). Isoxaflutole had different classification accuracies using the left pixels versus the right pixels for all classifiers; however, quadratic maximum likelihood classification had the greatest difference from the left three pixels to the right three pixels selection method with 42% difference in accuracy (Table 4.3).

Classification accuracies for the 2002b test using the two training sample selection methods were almost identical for alachlor, using Fisher linear discriminant and correlation classifiers (Table 4.2). Correlation classification accuracies for metolachlor and quadratic maximum likelihood classification of pendimethalin also were the same using both left and right pixels as training samples. Isoxaflutole classification accuracies differed for every classifier when the training samples were switched. When the left pixels were used, Isoxaflutole had classification accuracies of 83%, 0%, and 75% for Fisher linear discriminant, quadratic maximum likelihood, and correlation classifications, respectively (Table 4.2). Using the right pixels produced accuracies that differed by as much as 42% from the classifications using the left three pixels (Table 4.3). Flufenacet + metribuzin classification accuracies for correlation and Fisher linear discriminant classifications were 16% and 17% different between sample selections (Table 4.3). The difference between the classification using the left and the right training pixels was 66% (Table 4.2). Differences in classification accuracy of other treatments ranged from 9% to 33%. The large discrepancies in classification accuracy show that there are noticeable differences in classification due to sampling of training and test samples that should be taken into consideration. If these are not observed closely, the reported classification accuracies could be misleading and result in a misinterpretation of the data.

The biggest differences in classification accuracy for both tests come when using the quadratic maximum likelihood classifier (Figures 4.5 and 4.6). Flufenacet + metribuzin is the most variable treatment in both tests with high differences in accuracy for each classifier (Table 4.3). Atrazine and metolachlor were the least variable in their classification accuracies, indicating a pixel selection was not a major factor when classifying these treatments. Not including flufenacet + metribuzin in 2002a, the Fisher linear discriminant and correlation classifiers were the least effected by the selection of training pixels (Figures 4.5 and 4.6). This indicates changing training or test classes for these classifiers will not improve or decrease the accuracy of the classification. The small differences for alachlor, atrazine, metolachlor, and pendimethalin show that representative samples were well distributed for the data collected.

Quadratic maximum likelihood classification had lower and more variable classification accuracies than the Fisher linear discriminant and correlation classifiers (Figures 4.5 and 4.6). Fisher linear discriminant and correlation classifiers are not as complex as the quadratic maximum likelihood classifier, therefore, they do not require as many training samples, making them better suited to classifications such as the ones conducted here.

POST comparison

The results of the Fisher linear discriminant classification were very comparable for the two training sample techniques for the 2001 POST data. The reference accuracy for bromoxynil using the left three pixels to train the classifier is lower at 92% than for the right three at 100% (Table 4.4). 2,4-D, dicamba + diflufenzopyr, and nicosulfuron had Fisher classifications of 100% using both class selection methods (Table 4.4). The image analysis classification accuracies for bromoxynil, 2,4-D, dicamba + diflufenzopyr, and nicosulfuron are similar to the accuracies obtained using SAS discriminant analysis techniques. Fisher classification accuracies for atrazine and primisulfuron were the same for both training class selections (Table 4.6).

Quadratic maximum likelihood classification reference accuracies and Kappa Statistics for all treatments were less than 50% for all treatments using the left three pixels to train the classifier (Table 4.4). These low Kappa Statistics indicate the reference and reliability accuracies do not agree well with each other and the overall classification. Classification accuracies using the right three pixels were 67%, 75%, and 75% for atrazine, bromoxynil, and 2,4-D, respectively, while the accuracies using the left three pixels were all 33% or lower, indicating the correlation between classifications is low when using these samples (Table 4.4). Differences in classification accuracy from left to right training pixels differed from 8% to as much as 58% when using the quadratic maximum likelihood classifier (Table 4.6). The quadratic maximum likelihood classifier appears to be more sensitive to changes in training and test samples than the Fisher linear discriminant and correlation classifiers, and more care should be taken to select representative samples for this classifier.

Classification with the correlation classifier returned accuracies greater than 80% for all classes using both left and right pixels to train the classifier (Table 4.4). Reference accuracy and Kappa Statistic results for the Fisher linear discriminant and correlation classifications were all approximately 80% and greater for both training class selections, showing a high level of agreement with the accuracy of the classifiers. These high accuracies show that the selection of samples is not as important for the correlation classifier as it is for the quadratic maximum likelihood classifier.

Classification accuracies for the 2002 data were low in general, with no Kappa Statistics greater than 80%. The low accuracy of the classifications indicates the treatments cannot be separated from the untreated, or the samples are not representative of the treatment.

Fisher linear discriminant classification of dicamba + diflufenzopyr differed only 9% from one method to the other, and there was no difference in reference classification accuracies when using quadratic maximum likelihood and correlation classifiers (Table 4.6). Classification accuracies for atrazine and primisulfuron were virtually the same when using from one method to the other using Fisher, quadratic maximum likelihood, and correlation classification procedures. The largest differences came for bromoxynil when using the quadratic maximum likelihood classifier with a difference of 83% in accuracy (Table 4.6). 2,4-D also had significant differences in classification accuracies when using the three image classifiers. The classification accuracy for the right training pixels was near 100% when using the Fisher linear discriminant and correlation classifiers, however the quadratic maximum likelihood classification was 8% for the same pixels (Table 4.5). When the classes were switched to the left side, quadratic maximum likelihood classification was 100% and the Fisher and correlation classifications were 42% and 33%, respectively (Table 4.5).

Quadratic maximum likelihood classification produced comparable results between the two selection methods for atrazine, dicamba + diflufenzopyr, nicosulfuron, and primisulfuron with differences in accuracy of 17% for atrazine and 0% difference for dicamba + diflufenzopyr, nicosulfuron, and primisulfuron (Table 4.6).

For both years, the greatest difference in accuracies came using the quadratic maximum likelihood classifier (Figures 4.7 and 4.8). The Fisher linear discriminant classifier had the most consistent classification accuracies when the training classes were changed (Figures 4.7 and 4.8).

Excluding 2,4-D, the Fisher linear and correlation classifiers had the most similarities using either class selection method. Therefore, pixel selection is not as important to get high classification accuracies with Fisher linear discriminant and correlation classifiers as it is with quadratic maximum likelihood classification.

The small numbers of training samples available in comparison to the large number of bands used for classification combined with the variation in the five measurements in each plot are the main factors in the varying classification results of the data. The quadratic maximum likelihood classifier, being the most complex of the three classifiers used, requires the most training samples and will experience the most variation with limited training sets. Larger variation in results as a function of differing training sets indicate that conclusions based on them will not be as robust.

List of References

1. Kuo, B.C. and D.A. Landgrebe. 2002. A covariance estimator for small sample size classification problems and its application to feature extraction. IEEE Transactions on Geoscience and Remote Sensing. 40:4: 814-819.

2. Landgrebe, D.A. 1999A. On information extraction principles for hyperspectral data. 4th International Conference on GeoComputation, Fredericksburg, Virginia, USA. July 25-28, 1999.

3. Landgrebe, D.A. 1999B. Information extraction principles for multispectral and hyperspectral image data. In: Information Processing for Remote Sensing. Chen C.H. ed, pp. 1-30, World Scientific Publishing Co., Inc., River Edge, NJ.

4. Landgrebe, D.A. and L.L. Biehl. 2001. An introduction to MultiSpec, version 5.2001. West Lafayette, IN. Purdue Research Foundation.

Table 4.1. Classification accuracy of pair-wise comparisons of preemergence herbicide treatments in corn based on reflectance properties comparing the selection of the left three pixels as training samples and the right three pixels as training samples using bands included in multispectral image bands on Early PRE experiment ground collected reflectance data.

			Herbicide					
Training Pixels	Analysis Procedure		Alachlor	Atrazine	Flufen.+Metr.	Isoxaflutole	Metolachlor	Pendimethalin
	DA [a]	PROC DISCRIM %	100	100	100	75	ND [e]	100
Left 3	FLD [b]	Reference Accuracy %	92	92	83	83	92	100
		Kappa Statistic %	75	76	33	75	83	92
	QML [c]	Reference Accuracy %	33	100	33	42	100	33
		Kappa Statistic %	17	8	17	22	15	25
	CC [d]	Reference Accuracy %	75	50	83	75	58	83
		Kappa Statistic %	50	20	33	50	28	50
Right 3	FLD	Reference Accuracy %	100	83	0	67	92	100
		Kappa Statistic %	83	87	15	75	82	100
	QML	Reference Accuracy %	67	100	0	0	83	25
		Kappa Statistic %	31	44	9	0	31	22
	CC	Reference Accuracy %	83	58	0	83	58	83
		Kappa Statistic %	50	28	14	50	28	50

[a] Discriminant analysis using the PROC STEPDISC and PROC DISCRIM procedures in SAS.
[b] Fisher linear discriminant classification using MultiSpec.
[c] Quadratic maximum likelihood classification using MultiSpec.
[d] Correlation classification (Spectral Angle Mapper) using MultiSpec.
[e] Treatment could not be differentiated from the untreated check using the discriminant analysis procedures in SAS.

Table 4.2. Classification accuracy of pair-wise comparisons of preemergence herbicide treatments in corn based on reflectance properties comparing the selection of the left three pixels as training samples and the right three pixels as training samples using bands included in multispectral image bands on Late PRE experiment ground collected reflectance data.

Training Pixels	Analysis Procedure		Herbicide					
			Alachlor	Atrazine	Flufen.+Metr.	Isoxaflutole	Metolachlor	Pendimethalin
	DA [a]	PROC DISCRIM %	ND [e]	ND	ND	ND	ND	ND
Left 3	FLD [b]	Reference Accuracy %	67	67	75	83	67	58
		Kappa Statistic %	42	67	79	63	67	67
	QML [c]	Reference Accuracy %	33	25	17	0	50	33
		Kappa Statistic %	3	6	3	0	30	3
	CC [d]	Reference Accuracy %	50	33	42	75	67	50
		Kappa Statistic %	13	0	17	29	40	21
Right 3	FLD	Reference Accuracy %	67	83	92	58	92	92
		Kappa Statistic %	54	54	71	67	46	63
	QML	Reference Accuracy %	42	58	83	42	75	33
		Kappa Statistic %	17	44	33	11	71	8
	CC	Reference Accuracy %	50	50	58	53	67	67
		Kappa Statistic %	17	0	8	21	18	17

[a] Discriminant analysis using the PROC STEPDISC and PROC DISCRIM procedures in SAS.
[b] Fisher linear discriminant classification using MultiSpec.
[c] Quadratic maximum likelihood classification using MultiSpec.
[d] Correlation classification (Spectral Angle Mapper) using MultiSpec.
[e] Treatment could not be differentiated from the untreated check using the discriminant analysis procedures in SAS.

Table 4.3. Differences in classification accuracy of pair-wise comparisons of preemergence herbicide treatments in corn based on reflectance properties comparing the selection of the left three pixels as training samples and the right three pixels as training samples using bands used in multispectral images on Early PRE experiment ground collected reflectance data.

						Herbicide		
Training Pixels	Analysis Procedure		Alachlor	Atrazine	Flufen.+Metr.	Isoxaflutole	Metolachlor	Pendimethalin
Left	FLD[a]	Reference Accuracy %	8	8	83	17	0	0
		Kappa Statistic %	8	11	18	0	2	8
	QML[b]	Reference Accuracy %	33	0	33	42	17	8
		Kappa Statistic %	6	37	8	22	16	8
	CC[c]	Reference Accuracy %	8	8	83	8	0	0
		Kappa Statistic %	0	8	19	0	0	0
Right	FLD	Reference Accuracy %	0	17	17	25	25	33
		Kappa Statistic %	13	13	8	4	20	4
	QML	Reference Accuracy %	8	33	67	42	25	0
		Kappa Statistic %	14	39	31	11	42	6
	CC	Reference Accuracy %	0	17	17	22	0	17
		Kappa Statistic %	4	0	8	8	22	4

[a] Fisher linear discriminant classification using MultiSpec.
[b] Quadratic maximum likelihood classification using MultiSpec.
[c] Correlation classification (Spectral Angle Mapper) using MultiSpec.

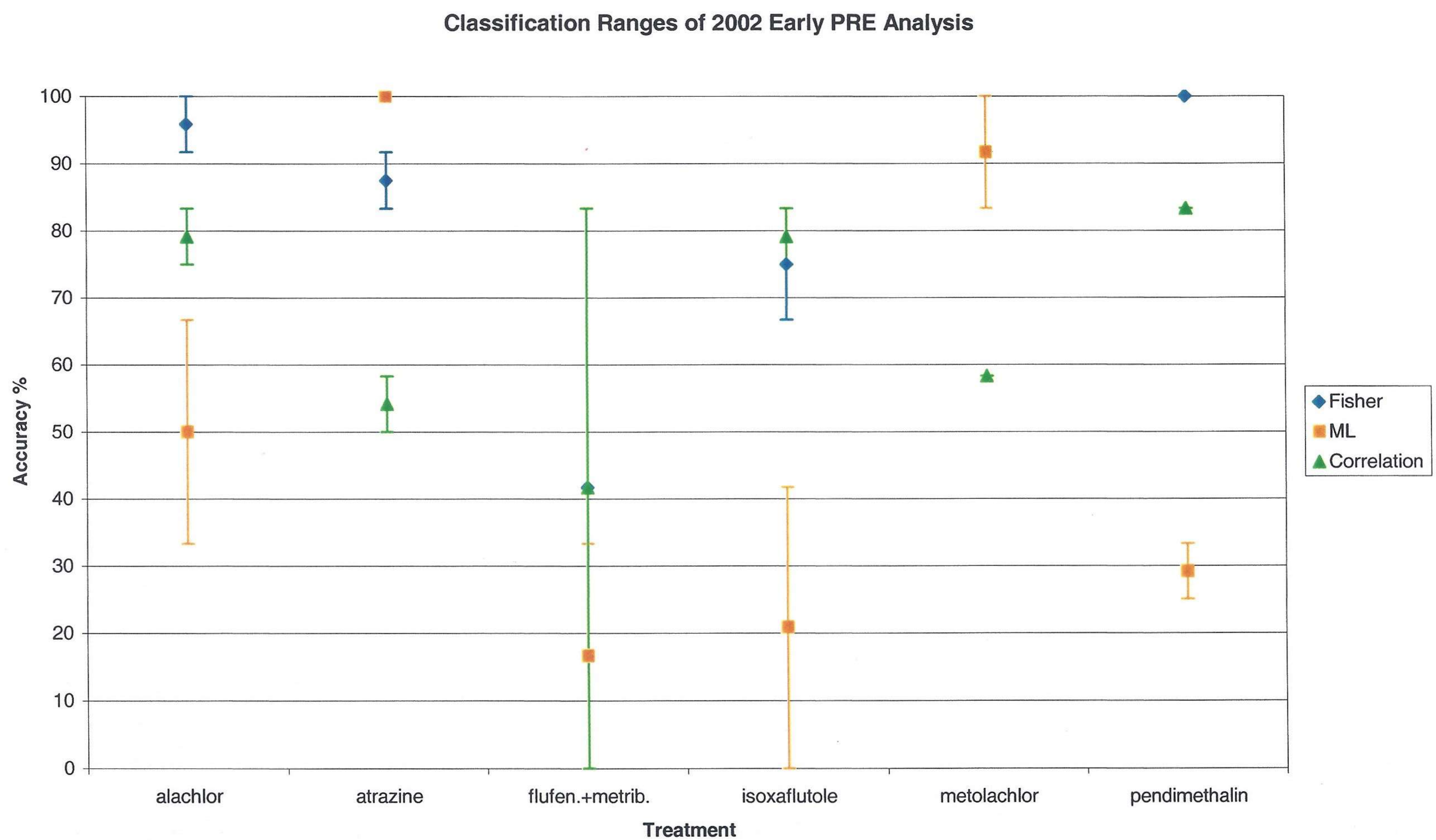

Figure 4.5. Classification accuracy ranges of pair-wise comparisons using pre-emergence herbicide treatments in corn to compare reflectance properties using the left-right selection method for wavelengths included in the multispectral image on 2002 Early Exp. ground collected reflectance data. Average classification accuracy for each treatment using each classifier is plotted, using error bars to indicate the range of the left and right accuracies.

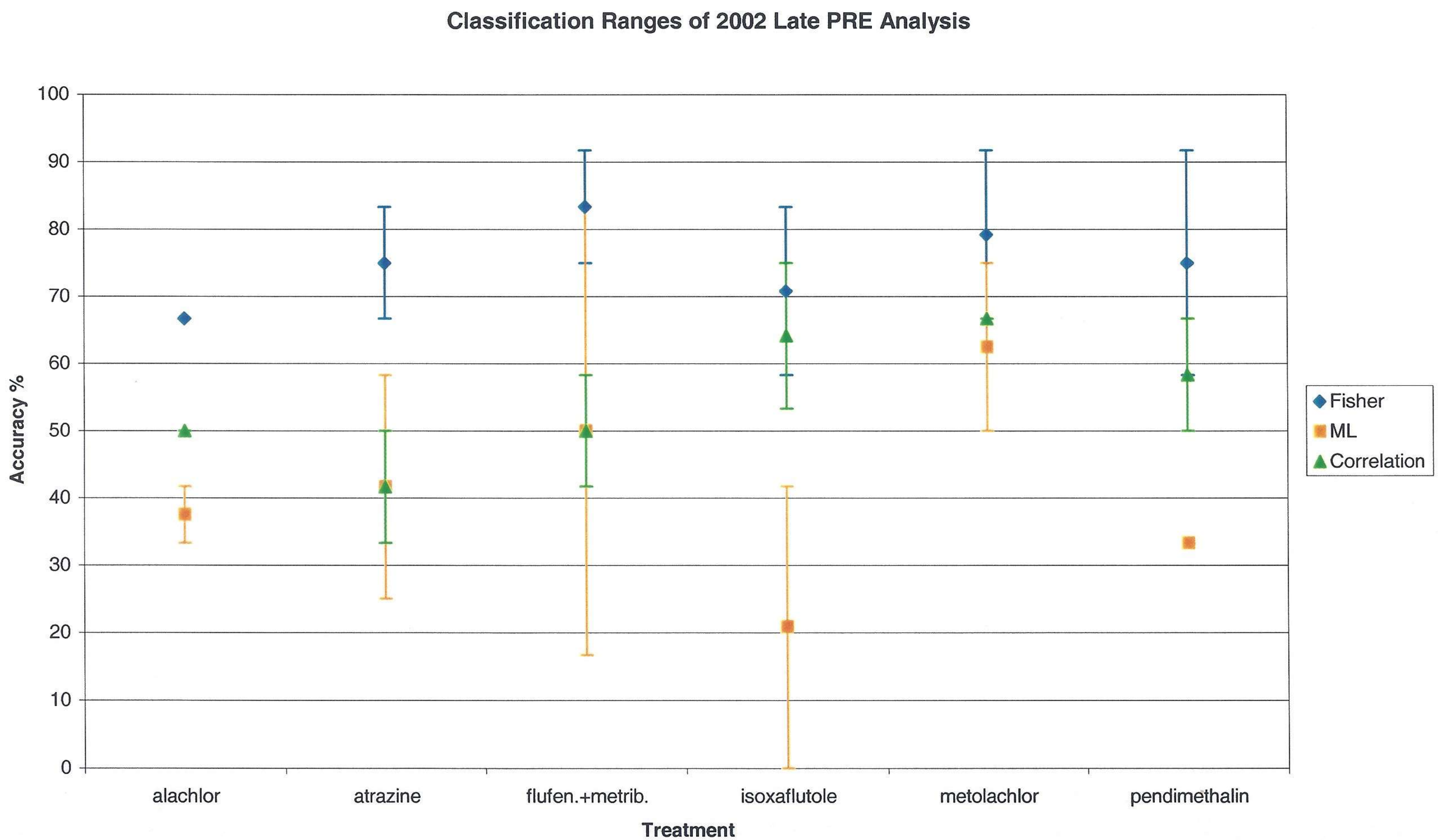

Figure 4.6. Classification accuracy ranges of pair-wise comparisons using pre-emergence herbicide treatments in corn to compare reflectance properties using the left-right selection method for wavelengths included in the multispectral image on 2002 Late Exp. ground collected reflectance data. Average classification accuracy for each treatment using each classifier is plotted, using error bars to indicate the range of the left and right accuracies.

Table 4.4. Classification accuracy of pair-wise comparisons of postemergence herbicide treatments in corn based on reflectance properties comparing the selection of the left three pixels as training samples and the right three pixels as training samples using bands included in multispectral image bands on POST 2001 ground collected reflectance data.

			Herbicide					
Training Pixels	Analysis Procedure		Atrazine	Bromoxynil	2,4-D	Dicam.+Diflu.	Nicosulfuron	Primisulfuron
	DA [a]	PROC DISCRIM %	NS [e]	100	100	100	100	NS
Left 3	FLD [b]	Reference Accuracy %	83	92	100	100	100	92
		Kappa Statistic %	87	96	96	100	100	86
	QML [c]	Reference Accuracy %	25	33	17	42	25	17
		Kappa Statistic %	33	31	19	44	33	6
	CC [d]	Reference Accuracy %	83	83	100	83	83	83
		Kappa Statistic %	87	92	100	92	81	79
Right 3	FLD	Reference Accuracy %	83	100	100	100	100	92
		Kappa Statistic %	81	100	100	100	100	92
	QML	Reference Accuracy %	67	75	75	25	58	8
		Kappa Statistic %	75	56	67	14	68	3
	CC	Reference Accuracy %	83	92	92	100	100	92
		Kappa Statistic %	81	100	96	100	100	88

[a] Discriminant analysis using the PROC STEPDISC and PROC DISCRIM procedures in SAS.
[b] Fisher linear discriminant classification using MultiSpec.
[c] Quadratic maximum likelihood classification using MultiSpec.
[d] Correlation classification (Spectral Angle Mapper) using MultiSpec.
[e] Treatment could not be separated from the untreated check using the discriminant analysis procedures in SAS.

Table 4.5. Classification accuracy of pair-wise comparisons of postemergence herbicide treatments in corn based on reflectance properties comparing the selection of the left three pixels as training samples and the right three pixels as training samples using bands included in multispectral image bands on POST 2002 ground collected reflectance data.

Training Pixels	Analysis Procedure		Atrazine	Bromoxynil	2,4-D	Herbicide Dicam.+Diflu.	Nicosulfuron	Primisulfuron
	DA[a]	PROC DISCRIM %	ND[e]	ND	100	75	ND	ND
Left 3	FLD[b]	Reference Accuracy %	67	75	42	83	92	83
		Kappa Statistic %	45	58	42	67	42	42
	QML[c]	Reference Accuracy %	100	83	100	100	100	0
		Kappa Statistic %	1	44	-31	-3	1	-22
	CC[d]	Reference Accuracy %	75	75	33	83	75	83
		Kappa Statistic %	33	50	42	67	33	42
Right 3	FLD	Reference Accuracy %	67	83	92	92	58	67
		Kappa Statistic %	45	58	79	63	38	29
	QML	Reference Accuracy %	83	0	8	100	100	0
		Kappa Statistic %	21	0	3	19	0	0
	CC	Reference Accuracy %	67	75	100	83	58	75
		Kappa Statistic %	50	46	79	67	43	29

[a] Discriminant analysis using the PROC STEPDISC and PROC DISCRIM procedures in SAS.
[b] Fisher linear discriminant classification using MultiSpec.
[c] Quadratic maximum likelihood classification using MultiSpec.
[d] Correlation classification (Spectral Angle Mapper) using MultiSpec.
[e] Treatment could not be differentiated from the untreated check using the discriminant analysis procedures in SAS.

Table 4.6. Difference in classification accuracy of pair-wise comparisons of postemergence herbicide treatments in corn based on reflectance properties comparing the selection of the left three pixels as training samples and the right three pixels as training samples using bands used in multispectral images on POST 2001 ground collected reflectance data.

Training Pixels	Analysis Procedure		Atrazine	Bromoxynil	2,4-D	Herbicide Dicam.+Diflu.	Nicosulfuron	Primisulfuron
2001	FLD [a]	Reference Accuracy %	0	8	0	0	0	0
		Kappa Statistic %	6	4	4	0	0	6
	QML [b]	Reference Accuracy %	33	42	58	17	33	8
		Kappa Statistic %	34	25	47	31	34	3
	CC [c]	Reference Accuracy %	17	8	8	17	17	8
		Kappa Statistic %	19	8	4	8	19	8
2002	FLD	Reference Accuracy %	0	8	50	8	33	17
		Kappa Statistic %	0	0	38	4	5	13
	QML	Reference Accuracy %	17	83	92	0	0	0
		Kappa Statistic %	19	44	33	22	1	22
	CC	Reference Accuracy %	8	0	67	0	17	8
		Kappa Statistic %	17	4	38	0	9	13

[a] Fisher linear discriminant classification using MultiSpec.
[b] Quadratic maximum likelihood classification using MultiSpec.
[c] Correlation classification (Spectral Angle Mapper) using MultiSpec.

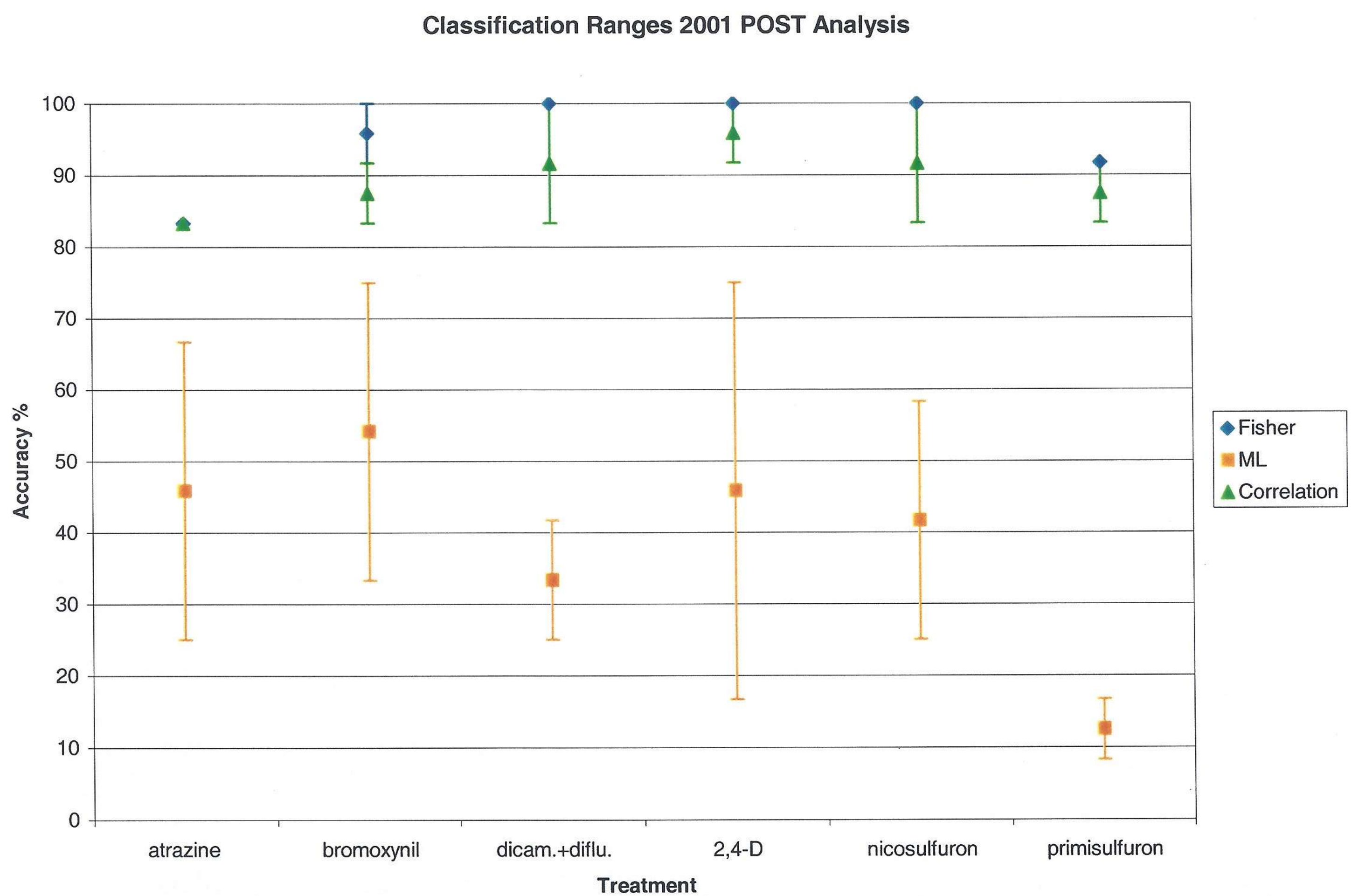

Figure 4.7. Classification accuracy ranges of pair-wise comparisons using postemergence herbicide treatments in corn to compare reflectance properties using the left-right selection method for wavelengths included in the multispectral image on 2001 POST ground collected reflectance data. Average classification accuracy for each treatment using each classifier is plotted, using error bars to indicate the range of the left and right accuracies.

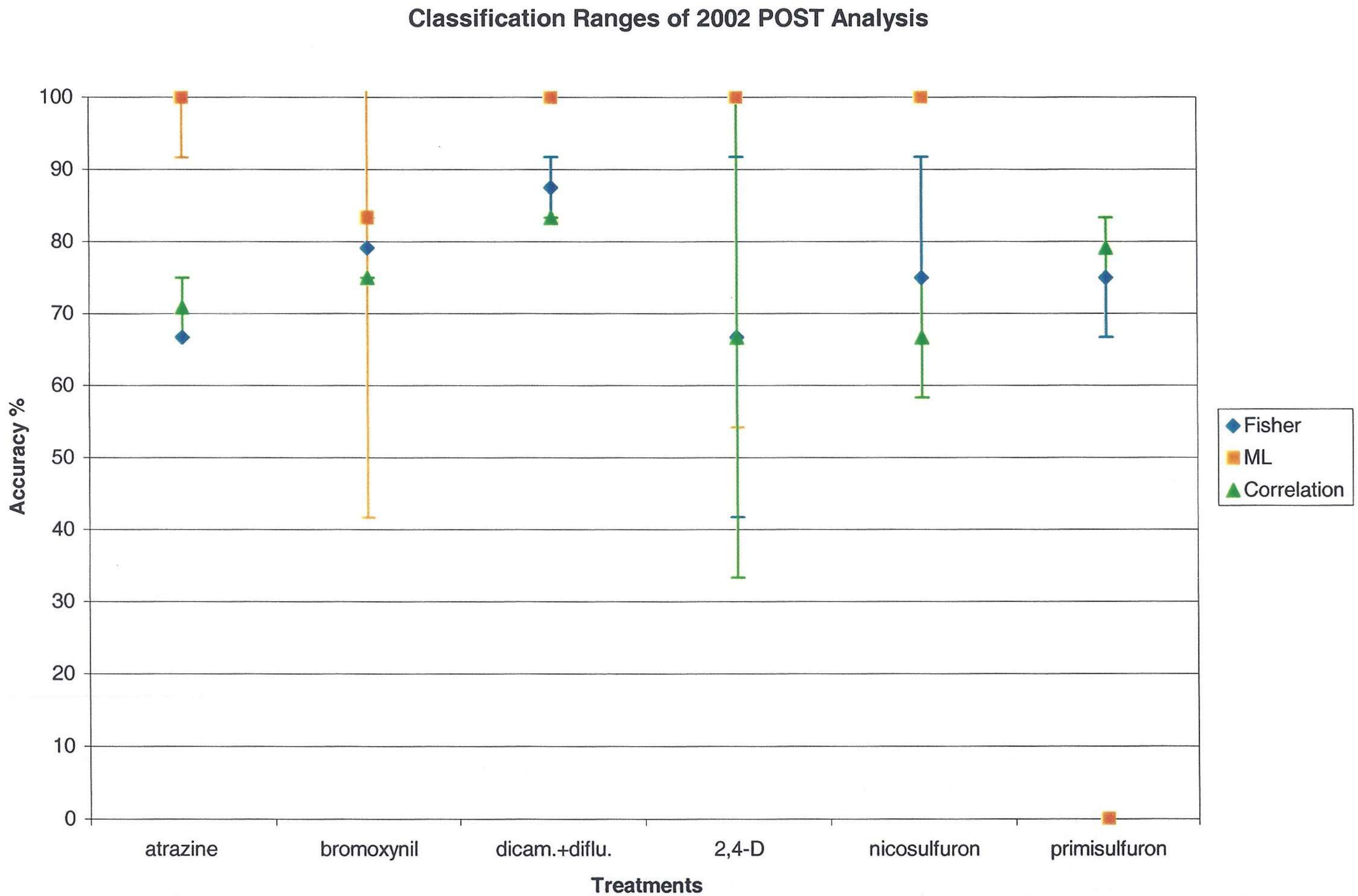

Figure 4.8. Classification accuracy ranges of pair-wise comparisons using postemergence herbicide treatments in corn to compare reflectance properties using the left-right selection method for wavelengths included in the multispectral image on 2002 POST ground collected reflectance data. Average classification accuracy for each treatment using each classifier is plotted, using error bars to indicate the range of the left and right accuracies.

APPENDIX

Table 2.2. Classification accuracy of pair-wise comparisons of preemergence herbicide treatments used in corn based on reflectance properties using various analysis techniques with bands included in multispectral image bands on ground collected reflectance data.

			Herbicide					
Exp.	Analysis	Procedure	Alachlor	Atrazine	Flufen.+Metr.	Isoxaflutole	Metolachlor	Pendimethalin
Early	DA[a]	PROC DISCRIM %	100	100	100	75	ND[e]	100
	FLD[b]	Reference Accuracy %	96	88	42	75	92	100
		Reliability Accuracy %	80	89	31	83	96	93
		Kappa Statistic %	79	82	24	75	83	96
	QML[c]	Reference Accuracy %	50	100	17	21	92	29
		Reliability Accuracy %	95	70	50	50	66	100
		Kappa Statistic %	28	26	13	11	23	26
	CC[d]	Reference Accuracy %	79	54	42	79	58	83
		Reliability Accuracy %	73	65	31	73	67	71
		Kappa Statistic %	50	24	24	50	28	50
Late	DA	PROC DISCRIM %	ND	ND	ND	ND	ND	ND
	FLD	Reference Accuracy %	67	83	92	58	92	92
		Reliability Accuracy %	73	67	65	78	58	65
		Kappa Statistic %	54	54	71	67	46	63
	QML	Reference Accuracy %	42	58	83	42	75	33
		Reliability Accuracy %	71	70	71	71	90	80
		Kappa Statistic %	17	44	33	11	71	8
	CC	Reference Accuracy %	50	50	58	56	67	67
		Reliability Accuracy %	50	46	35	58	53	53
		Kappa Statistic %	17	0	8	21	18	17

[a] Discriminant analysis using the PROC STEPDISC and PROC DISCRIM procedures in SAS.
[b] Fisher linear discriminant classification using MultiSpec.
[c] Quadratic maximum likelihood classification using MultiSpec.
[d] Correlation classification (Spectral Angle Mapper) using MultiSpec.
[e] Treatment could not be differentiated from the untreated check using the discriminant analysis procedures in SAS.

Table 2.3. Classification accuracy of pair-wise comparisons of preemergence herbicide treatments used in corn based on reflectance properties using various analysis techniques with bands used in SAS analysis from the early experiment ground collected reflectance data.

Exp.	Analysis	Procedure	Herbicide Alachlor	 Atrazine	 Flufen.+Metr.	 Isoxaflutole	 Metolachlor	 Pendimethalin
Early	DA [a]	PROC DISCRIM %	100	100	100	75	ND [e]	100
	FLD [b]	Reference Accuracy %	71	71	75	71	ND	63
		Reliability Accuracy %	71	74	68	69	ND	69
		Kappa Statistic %	40	46	40	38	ND	35
	QML [c]	Reference Accuracy %	71	83	75	75	ND	63
		Reliability Accuracy %	71	91	65	60	ND	79
		Kappa Statistic %	40	66	32	28	ND	66
	CC [d]	Reference Accuracy %	58	58	42	75	ND	71
		Reliability Accuracy %	61	58	43	78	ND	72
		Kappa Statistic %	19	15	0	54	ND	44
Late	DA	PROC DISCRIM %	ND	ND	ND	ND	ND	ND
	FLD	Reference Accuracy %	46	58	50	71	ND	50
		Reliability Accuracy %	58	47	54	77	ND	56
		Kappa Statistic %	4	9	10	48	ND	10
	QML	Reference Accuracy %	54	63	54	58	ND	54
		Reliability Accuracy %	37	60	50	74	ND	72
		Kappa Statistic %	-4	26	-4	45	ND	31
	CC	Reference Accuracy %	67	54	54	75	ND	67
		Reliability Accuracy %	67	43	59	60	ND	67
		Kappa Statistic %	33	-7	15	25	ND	33

[a] Discriminant analysis using the PROC STEPDISC and PROC DISCRIM procedures in SAS.
[b] Fisher linear discriminant classification using MultiSpec.
[c] Quadratic maximum likelihood classification using MultiSpec.
[d] Correlation classification (Spectral Angle Mapper) using MultiSpec.
[e] Treatment could not be differentiated from the untreated check using the discriminant analysis procedures in SAS.

Table 2.4. Classification accuracy of pair-wise comparisons of preemergence herbicide treatments used in corn based on reflectance properties using various image analysis techniques and SAS analysis on aerial image data.

			Herbicide					
Exp.	Analysis	Procedure	Alachlor	Atrazine	Flufen.+Metr.	Isoxaflutole	Metolachlor	Pendimethalin
Early	DA [a]	PROC DISCRIM %	ND [e]	ND	75	ND	ND	ND
	FLD [b]	Reference Accuracy %	16	48	77	61	73	75
		Reliability Accuracy %	32	43	54	70	46	53
		Kappa Statistic %	9	-1	26	48	3	27
	QML [c]	Reference Accuracy %	68	73	72	84	48	91
		Reliability Accuracy %	51	47	47	61	43	53
		Kappa Statistic %	41	20	26	54	3	38
	CC [d]	Reference Accuracy %	24	36	56	48	63	20
		Reliability Accuracy %	22	35	62	78	42	22
		Kappa Statistic %	-24	-17	25	45	-9	-24
Late	DA	PROC DISCRIM %	ND	ND	ND	ND	ND	ND
	FLD	Reference Accuracy %	52	45	67	28	47	24
		Reliability Accuracy %	45	35	57	60	55	82
		Kappa Statistic %	7	-24	36	19	18	19
	QML	Reference Accuracy %	68	59	33	76	53	56
		Reliability Accuracy %	45	45	53	50	56	66
		Kappa Statistic %	18	6	42	10	27	44
	CC	Reference Accuracy %	65	51	73	28	55	8
		Reliability Accuracy %	46	37	55	81	55	60
		Kappa Statistic %	3	-20	31	27	22	8

[a] Discriminant analysis using the PROC STEPDISC and PROC DISCRIM procedures in SAS.
[b] Fisher linear discriminant classification using MultiSpec.
[c] Quadratic maximum likelihood classification using MultiSpec.
[d] Correlation classification (Spectral Angle Mapper) using MultiSpec.
[e] Treatment could not be differentiated from the untreated check using the discriminant analysis procedures in SAS.

Table 3.5. Classification accuracy of pair-wise comparisons, using the average accuracy of left and right test pixel classifications, of post-emergence herbicide treatments in corn based on reflectance properties using various analysis techniques and bands included in multispectral image bands on ground collected reflectance data.

			Herbicide					
Year	Analysis	Procedure	Atrazine	Bromoxynil	2,4-D	Dicam.+Diflu.	Nicosulfuron	Primisulfuron
2001	DA [a]	PROC DISCRIM %	ND [e]	100	100	100	100	ND
		Reference Accuracy %	83	96	100	100	100	92
	FLD [b]	Reliability Accuracy %	91	100	96	100	100	92
		Kappa Statistic %	84	98	98	100	100	89
		Reference Accuracy %	46	54	46	33	42	13
	QML [c]	Reliability Accuracy %	100	100	100	100	100	100
		Kappa Statistic %	54	43	43	29	51	4
		Reference Accuracy %	83	88	96	92	92	88
	CC [d]	Reliability Accuracy %	96	98	100	100	96	88
		Kappa Statistic %	84	96	98	96	91	83
2002	DA	PROC DISCRIM %	ND	ND	100	75	ND	ND
		Reference Accuracy %	67	79	67	88	75	75
	FLD	Reliability Accuracy %	67	68	81	82	66	58
		Kappa Statistic %	45	58	61	65	40	36
		Reference Accuracy %	92	42	54	100	100	0
	QML	Reliability Accuracy %	56	31	75	58	50	0
		Kappa Statistic %	11	22	-14	8	1	-11
		Reference Accuracy %	71	75	67	83	67	79
	CC	Reliability Accuracy %	63	62	78	74	65	61
		Kappa Statistic %	42	48	61	67	38	36

[a] Discriminant analysis using the PROC STEPDISC and PROC DISCRIM procedures in SAS.
[b] Fisher linear discriminant classification using MultiSpec.
[c] Quadratic maximum likelihood classification using MultiSpec.
[d] Correlation classification (Spectral Angle Mapper) using MultiSpec.
[e] Treatment could not be differentiated from the untreated check using the discriminant analysis procedures in SAS.

Table 3.6. Classification accuracy of pair-wise comparisons, using rep 3 to test the classifier, of postemergence herbicide treatments in corn based on reflectance properties using various analysis techniques and bands included in multispectral image bands on ground collected data.

			Herbicide					
Year	Analysis	Procedure	Atrazine	Bromoxynil	2,4-D	Dicam.+Diflu.	Nicosulfuron	Primisulfuron
2001	DA[a]	PROC DISCRIM %	ND[e]	100	100	100	100	ND
		Reference Accuracy %	0	100	100	100	100	40
	FLD[b]	Reliability Accuracy %	0	100	100	100	100	50
		Kappa Statistic %	55	100	100	100	100	42
		Reference Accuracy %	0	20	100	100	80	0
	QML[c]	Reliability Accuracy %	0	100	100	100	100	0
		Kappa Statistic %	27	14	100	55	46	7
		Reference Accuracy %	0	40	100	100	100	20
	CC[d]	Reliability Accuracy %	0	100	100	100	100	50
		Kappa Statistic %	43	55	100	100	100	49
2002	DA	PROC DISCRIM %	ND	ND	100	75	ND	ND
		Reference Accuracy %	40	20	40	40	20	60
	FLD	Reliability Accuracy %	67	25	67	67	20	43
		Kappa Statistic %	32	45	60	65	-15	40
		Reference Accuracy %	100	40	100	60	0	0
	QML	Reliability Accuracy %	50	40	50	38	0	0
		Kappa Statistic %	0	37	-17	20	-26	-11
		Reference Accuracy %	80	0	40	40	20	40
	CC	Reliability Accuracy %	80	0	67	50	20	33
		Kappa Statistic %	65	35	70	35	-15	30

[a] Discriminant analysis using the PROC STEPDISC and PROC DISCRIM procedures in SAS.
[b] Fisher linear discriminant classification using MultiSpec.
[c] Quadratic maximum likelihood classification using MultiSpec.
[d] Correlation classification (Spectral Angle Mapper) using MultiSpec.
[e] Treatment could not be differentiated from the untreated check using the discriminant analysis procedures in SAS.

Table 3.7. Classification accuracy of pair-wise comparisons of post-emergence herbicide treatments in corn based on reflectance properties using various analysis techniques and bands used in 2001 SAS analysis on ground collected reflectance data.

Year	Analysis Procedure		Herbicide					
			Atrazine	Bromoxynil	2,4-D	Dicam.+Diflu.	Nicosulfuron	Primisulfuron
2001	FLD [a]	Reference Accuracy %	ND [d]	100	100	100	100	ND
		Reliability Accuracy %	ND	100	100	100	96	ND
		Kappa Statistic %	ND	100	100	100	94	ND
	QML [b]	Reference Accuracy %	ND	92	96	100	100	ND
		Reliability Accuracy %	ND	100	100	100	100	ND
		Kappa Statistic %	ND	96	97	99	95	ND
	CC [c]	Reference Accuracy %	ND	92	96	100	100	ND
		Reliability Accuracy %	ND	100	100	100	96	ND
		Kappa Statistic %	ND	94	98	100	94	ND
2002	FLD	Reference Accuracy %	ND	63	54	75	54	ND
		Reliability Accuracy %	ND	60	52	69	58	ND
		Kappa Statistic %	ND	37	29	40	12	ND
	QML	Reference Accuracy %	ND	71	33	75	96	ND
		Reliability Accuracy %	ND	77	45	63	58	ND
		Kappa Statistic %	ND	56	21	25	12	ND
	CC	Reference Accuracy %	ND	79	96	79	88	ND
		Reliability Accuracy %	ND	81	84	79	77	ND
		Kappa Statistic %	ND	65	75	65	50	ND

[a] Fisher linear discriminant classification using MultiSpec.
[b] Quadratic maximum likelihood classification using MultiSpec.
[c] Correlation classification (Spectral Angle Mapper) using MultiSpec.
[d] Treatment could not be differentiated from the untreated check using the discriminant analysis procedures in SAS.

Table 3.8. Classification accuracy of pair-wise comparisons of post-emergence herbicide treatments in corn based on reflectance properties using various analysis techniques and bands used in 2002 SAS analysis on ground collected reflectance data.

			Herbicide					
Year	Analysis Procedure		Atrazine	Bromoxynil	2,4-D	Dicam.+Diflu.	Nicosulfuron	Primisulfuron
2001	FLD [a]	Reference Accuracy %	ND [d]	ND	100	67	ND	ND
		Reliability Accuracy %	ND	ND	100	88	ND	ND
		Kappa Statistic %	ND	ND	69	50	ND	ND
	QML [b]	Reference Accuracy %	ND	ND	100	54	ND	ND
		Reliability Accuracy %	ND	ND	100	89	ND	ND
		Kappa Statistic %	ND	ND	100	38	ND	ND
	CC [c]	Reference Accuracy %	ND	ND	79	67	ND	ND
		Reliability Accuracy %	ND	ND	79	60	ND	ND
		Kappa Statistic %	ND	ND	63	21	ND	ND
2002	FLD	Reference Accuracy %	ND	ND	58	67	ND	ND
		Reliability Accuracy %	ND	ND	56	67	ND	ND
		Kappa Statistic %	ND	ND	31	29	ND	ND
	QML	Reference Accuracy %	ND	ND	46	83	ND	ND
		Reliability Accuracy %	ND	ND	61	69	ND	ND
		Kappa Statistic %	ND	ND	28	36	ND	ND
	CC	Reference Accuracy %	ND	ND	83	54	ND	ND
		Reliability Accuracy %	ND	ND	67	60	ND	ND
		Kappa Statistic %	ND	ND	36	15	ND	ND

[a] Fisher linear discriminant classification using MultiSpec.
[b] Quadratic maximum likelihood classification using MultiSpec.
[c] Correlation classification (Spectral Angle Mapper) using MultiSpec.
[d] Treatment could not be differentiated from the untreated check using the discriminant analysis procedures in SAS.

Table 3.9. Classification accuracy of pair-wise comparisons of post-emergence herbicide treatments in corn based on reflectance properties using various analysis techniques and analysis on aerial multispectral reflectance data.

Year	Analysis Procedure		Herbicide					
			Atrazine	Bromoxynil	2,4-D	Dicam.+Diflu.	Nicosulfuron	Primisulfuron
2001	DA[a]	PROC DISCRIM %	75	100	100	100	75	75
	FLD[b]	Reference Accuracy %	69	92	100	91	92	57
		Reliability Accuracy %	65	72	96	76	75	67
		Kappa Statistic %	41	66	97	72	67	39
	QML[c]	Reference Accuracy %	65	93	100	92	87	60
		Reliability Accuracy %	67	79	97	80	76	73
		Kappa Statistic %	46	81	98	82	68	50
	CC[d]	Reference Accuracy %	61	69	100	89	80	53
		Reliability Accuracy %	60	61	96	71	65	47
		Kappa Statistic %	30	43	97	60	47	-6
2002	DA	PROC DISCRIM %	NS[e]	NS	75	NS	NS	NS
	FLD	Reference Accuracy %	68	81	87	65	9	5
		Reliability Accuracy %	50	62	76	54	47	29
		Kappa Statistic %	10	33	68	29	2	7
	QML	Reference Accuracy %	8	8	87	52	4	4
		Reliability Accuracy %	30	33	75	54	60	17
		Kappa Statistic %	-9	17	72	38	3	11
	CC	Reference Accuracy %	16	61	87	60	27	40
		Reliability Accuracy %	43	75	76	82	69	52
		Kappa Statistic %	-8	41	68	53	18	10

[a] Discriminant analysis using the PROC STEPDISC and PROC DISCRIM procedures in SAS.
[b] Fisher linear discriminant classification using MultiSpec.
[c] Quadratic maximum likelihood classification using MultiSpec.
[d] Correlation classification (Spectral Angle Mapper) using MultiSpec.
[e] Treatment could not be differentiated from the untreated check using the discriminant analysis procedures in SAS.