USING SATELLITE IMAGERY TO DETECT HERBICIDE INJURY AND IDENTIFICATION OF WEED SPECIES BY SPECTRAL REFLECTANCE PATTERNS

By

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CHAPTER I

USING SATELLITE IMAGERY TO DETECT TRANSIENT INJURY FROM MON 37500 IN HARD RED WINTER WHEAT (*Triticum aestivum* L.)

Using Satellite Imagery to Detect Transient Injury from MON 37500 in Hard Red Winter Wheat (*Triticum aestivum* L.) [1]

JOBY M. PRINCE[2]

Abstract: Field experiments were conducted to evaluate the use of imagery from Landsat Thematic Mapper (TM) satellites to detect herbicide injury in hard red winter wheat (*Triticum aestivum* L.) resulting from commercial applications of MON 37500 or MON 37500 plus an insecticide. Specifically, imagery was used to quantify changes in Normalized Difference Vegetation Index (NDVI), which would indicate a decrease in plant health. Changes in average NDVI between November 12, 1999 and November 28, 1999, for fields treated with MON 37500, MON 37500 plus dimethoate, and untreated fields were determined for fields in Kingfisher County, Oklahoma. Changes in average NDVI between November 28, 1999 to December 14, 1999, for fields treated with MON 37500 plus dimethoate, MON 37500 plus chlorpyrifos, and untreated fields were determined also. The effect of treatment on change in NDVI was determined by an analysis of variance (ANOVA) test on changes in mean normalized difference vegetation index (NDVI) resulting from treatment application. Decreases in mean NDVI were seen during the first time period due to application of MON 37500 only. Changes in NDVI values in the second time period were not statistically different.

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[1] Received for publication ______ and in revised form ______.

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Nomenclature: MON 37500, 1-(4,6-dimethoxypyrimidin-2-yl)-3-(2-ethlsulfonyl-imidazo[1,2-*a*]pyridine-3-yl)sulfonylurea; dimethoate, O,O-dimethyl-S-[(methylcarbamoyl)methyl] phosphorodithioate; chlorpyrifos, O-O-diethyl-O-(3,5,6-trichloro-2-pyridinyl) phosphorothioate; cheat, *Bromus secalinus* L. #[3] SECCE; hard red winter wheat, *Triticum aestivum* L.

Additional index words: Remote sensing, Landsat, cheat, NDVI.

Abbreviations: NDVI, normalized vegetation difference index; TM, thematic mapper; DOQ, digital orthophoto quadrangle.

INTRODUCTION

Annual brome species are widespread throughout the Great Plains (Shinn et al. 1998). Cheat (*Bromus secalinus* L.) is an important annual brome problem in wheat (*Triticum aestivum* L.). Previously, control of cheat with herbicides was difficult because both cheat and wheat are winter annuals with similar growth habits (Greer and Peeper 1990). Cheat remains a problem in production fields because it is either deposited in the combine bin with wheat seed resulting in dockage at the elevator, or discharged from the machine back into the field where it will become a problem the following year.

MON37500 is a sulfonylurea herbicide that targets *Bromus* spp. in winter wheat (Shinn et al. 1998). It has both preemergence and foliar activity (Miller et al. 1999).

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

Environmental conditions may impact herbicide efficacy by changing absorption and translocation of MON 37500 (Olson et al. 1999). These environmental conditions may also result in wheat injury from applications of MON 37500, such as chlorosis of the wheat (Shinn et al. 1998). Although several studies have been conducted to determine the environmental conditions that increase the likelihood of herbicide injury, the results of these studies are mixed. At present, herbicide-environment interactions causing injury symptoms are not well understood.

Shinn et al. (1998) studied the effect of MON 37500 rate and application timing on downy brome (*Bromus tectorum* L.) control in soft white winter wheat. They reported chlorosis of winter wheat with all spring-applied foliar treatments, but no chlorosis with fall applications. Conversely, Blackshaw and Hamman (1998) did not observe injury to winter wheat when MON 37500 was applied preemergence, fall postemergence, or spring postemergence even at twice the labeled rate. Parrish et al. (1995) also found that MON 37500 would not injure winter wheat at three times the labeled rate in a production field, and at sixteen times the labeled rate in a greenhouse.

Geier et al. (1999) evaluated the effects of temperature and soil moisture on wheat injury from MON 37500 in a greenhouse setting. They reported that injury was minor, but increased with preemergence applications under warm conditions and when soil moisture was maintained at 20 percent. They surmised that injury was likely due to increased uptake of the herbicide due to moist conditions. In a similar study, Olson et al. (1999, 2000b) suggested that wheat injury from postemergence application was likely due to temperature fluctuations, which altered MON 37500 absorption.

Miller et al. (1999) proposed that weed control with MON 37500 would be improved by the use of a surfactant and the addition of nitrogen fertilizer. Olson et al. (2000a) examined the effect of MON 37500 on hard red winter wheat when tank-mixed with urea ammonium nitrate (UAN) fertilizer. Leaf burning occurred in both 'Jagger' and '2137' wheat varieties, which was intensified further by the addition of an adjuvant. It was proposed that this injury was due to increased absorption of MON 37500 by the wheat plant caused by the surfactant.

Clearly, injury can, but does not always occur when MON 37500 is applied. Injury may be the result of increased absorption caused by the addition of a surfactant or an increase in temperature or moisture. Injury could also be dependent on application timing.

The objective of this research was to determine whether LandsatTM imagery can be effectively used to detect transient, short-term herbicide injury in hard red winter wheat due to MON 37500. Injury is difficult if not impossible to predict. Currently, satellites such as Landsat capably monitor plant health of crops (Bechdol et al. 2000). Thus it should be expected that it could be used to observe changes in plant health before and after herbicide application. Creating a geodatabase of information based on satellite imagery, regarding MON 37500 applications could provide a library of information to researchers, which may allow them to determine what exact conditions predispose wheat to injury.

MATERIALS AND METHODS

The study area for this project included 45 fields totaling 1830 ha in Kingfisher County, Oklahoma. A database was created which contained information regarding MON 37500 applications for each field. Working from field legal descriptions, field boundaries for treated fields were "heads up" digitized with a Geographic Information System[4] (GIS) using Digital Orthophoto Quadrangles (DOQ) for base maps. The DOQs were downloaded from OKMaps[5], a file transfer site that distributes free DOQs for the entire state of Oklahoma. Field boundaries were verified with cooperators to assure accuracy as the DOQs were acquired by the State of Oklahoma a few years prior to the study. The use of the GIS provided spatially accurate field boundaries with correct geographic locations.

Images were gathered by Landsat satellites five and seven, on November 12, November 28, and December 14, 1999, January 7, February 8, March 27, April 4, and May 30, 2000. The start and end dates were based upon the growing season of winter wheat in Oklahoma. A Landsat satellite has a 16-day orbit and atmospheric conditions are not always optimal on the given day to collect a usable image. These two issues account for the gaps between images. Winter wheat begins to senesce in Oklahoma during May, making measurements after this time period unusable.

These images were georeferenced using the PCI[6] suite of imaging software. Images were obtained from the United States Geological Survey (USGS) as single band data

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[4] SSToolbox©, SST Development Group, Stillwater, Oklahoma, 74075.

[5] Available at ftp://okmaps.onenet.net

[6] PCI Geomatics, Richmond Hill, Ontario, Canada, L4B 1M5

files. The files were imported into the Xpace module to be combined into a single multi-band PCI file. The PCI file was then opened in GCPWorks, another PCI module. Control points were taken using a previously registered Landsat TM image as the base map. At least forty control points were taken for each registration with a root mean square error of 0.05 or less. The resulting file was resampled to a resolution of 30- by 30-m using nearest neighbor techniques. The image was projected into Universal Transverse Mercator (UTM) Zone 14, with North American Datum (NAD) 83. The output files were converted into ERDAS (.lan) format for importing into the GIS for further analysis.

The Image Analysis extension for the GIS was used to extract brightness values for each individual pixel in the portion of each image that was contained within each field boundary. This function creates a point shapefile (.shp)[7] that contains a single record for every pixel in all TM bands.

Using values from the point theme table for the red (R) and near-infrared (NIR) bands a surface was generated with a 0.72 m^2 resolution, using kriging as the interpolation method. Red and NIR were selected because they are traditionally used for vegetation studies that use satellite imagery (Zwiggelaar 1998).

Each surface was corrected for atmospheric reflectance using equations developed by Daniel Itenfisu[8] (Appendix A). This was accomplished quickly using an Avenue[9] script (Appendix B). Using the formatted tables, Normalized Difference Vegetation Index

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[7] Proprietary file format, ESRI, Redlands, California, 92373

[8] Post-doc Fellow, Department of Biosystems and Agricultural Engineering, Oklahoma State University, Stillwater, OK 74078

[9] Proprietary programming language, ESRI, Redlands, California, 92373

(NDVI) was calculated for each pixel in the field for each date. NDVI is expressed mathematically as:

$$\text{NDVI} = \frac{\text{NIR - R}}{\text{NIR + R}}$$

Cooperators were mailed an information packet explaining the research project in detail, a map of their field(s), and a questionnaire (Appendix C). The questionnaire was designed to obtain information regarding the management history of the field. This data was essential to explain spatial variability in the field and account for the causes of changes in NDVI.

Weather information was obtained from the Oklahoma Mesonet service for stations at Kingfisher and Marshall, Oklahoma (Appendix D). All study sites are located between these stations, which are the geographically closest available. None of the study fields were grazed during the period from November 12 to December 14, 1999.

Based on cooperator response and available information from satellites, twenty-three fields were identified as useful for further research over two time periods delineated by the availability of Landsat images (Figures 1 and 2). The first time period selected was November 12 to November 28, 1999. Three treatments were examined in the first time period. The twenty fields used for analysis were treated with MON 37500, MON 37500 plus dimethoate, or were not treated. All applications of MON 37500 alone were made to fields between November 11 and November 16, 1999. All applications of MON 37500 plus dimethoate occurred on November 19, 1999. NDVI values were examined for the start (November 12) and end date (November 28). A full listing of values for each field can be found in Appendix E.

Changes in NDVI over the time period were calculated as well as percent change in NDVI. Analysis of Variance (ANOVA) was performed on the resultant values using the SAS[10] General Linear Model procedure (Table 1). Each field was also examined for the percent of pixels that experienced a decrease in NDVI between November 12 and November 28. Once percentages were calculated, these values were also entered into SAS and t-tests were performed to examine whether fields treated with MON 37500 or MON 37500 plus dimethoate had statistically significant differences in the percentage of pixels for which NDVI decreased than fields that did not receive treatment.

The second time period selected was November 28 to December 14, 1999. Three treatments were examined in the second time period. The fourteen fields used for analysis were treated with MON 37500 plus dimethoate, MON 37500 plus chlorpyrifos, or were not treated. All applications occurred between November 27 and November 30, 1999. NDVI values were examined for the start and end date. Differences were calculated as well as percent change in NDVI. Analysis of Variance (ANOVA) was performed on the resultant values using the SAS General Linear Model procedure (Table 2). Each field was also examined for the percent of pixels that experienced a decrease in NDVI between November 28 and December 14. Once percentages were calculated, these values were also entered into SAS and t-tests were performed to examine whether fields treated with MON 37500 plus dimethoate or MON 37500 plus chlorpyrifos had statistically significant differences in the percentage of pixels for which NDVI decreased than fields that did not receive treatment.

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[10] SAS Institute Incorporated, Cary, North Carolina, 27513

RESULTS AND DISCUSSION

Response to MON 37500. Six fields were identified that received only MON 37500 between November 11 and November 16, 1999 without the addition of an insecticide (Figure 1). Average NDVI from treated fields increased 13 percent from November 12 to November 28, 1999. Average NDVI from ten untreated check fields in the proximity of the treated fields increased by 27 percent during this time (Table 1). Analysis of the data, using unequal sample size analysis (SAS PROC GLM) suggests that application of MON 37500 reduced the rate of increase in average NDVI ($P = 0.07$) over the 12 to 17 day period following application.

Response to MON 37500 plus dimethoate. Two sets of fields that received MON 37500 plus dimethoate were observed (Figure 1). One set of four fields was treated on November 19 and the change in average NDVI of these fields was compared to the ten untreated fields mentioned above. Average NDVI increased 31 percent in the treated fields from November 12 to November 28, which did not differ significantly ($P = 0.67$) from untreated fields (Table 1). A second set of four fields was sprayed on November 30 and the change in average NDVI was compared to four untreated fields. Average NDVI increased 9 and 11 percent respectively (Table 2), for the treated and untreated fields from November 28 to December 14, suggesting no effect of the herbicide on wheat growth ($P = 0.47$).

Response to MON 37500 plus chlorpyrifos. Four fields that received MON 37500 plus chlorpyrifos on November 28 and 29, 1999 (Figure 2) were observed on November 28 and December 14, 1999 to examine the effect of this tank-mixed combination on the NDVI of wheat (Table 2). Differences in NDVI values between treated and untreated fields were not statistically significant (P = 0.47). Untreated fields had an average increase in NDVI of 11 percent, while fields with MON 37500 plus chlorpyrifos had an average increase in NDVI of 5 percent during the same period.

It has been argued that satellite data is not properly suited for use in weed science due to its poor resolution (Bechdol et al. 2000). However, in a study such as this, where large farm fields are being used instead of small research plots or individual plants, there is a potential to examine large-scale changes in NDVI across a whole field. This study indicates that LandsatTM imagery could be used to detect herbicide injury assuming a certain level of ground truthing and management information could be obtained.

It was observed in this study that increases in mean NDVI are reduced from the use of MON 37500 alone, but not with the addition of an organophosphate insecticide. In fields where only MON 37500 was applied, the rate of NDVI increase was significantly less than for fields that were not treated or were treated with MON 37500 plus an insecticide.

There are four possible explanations for the lower average NDVI increases seen. The first of these is that the herbicide worked properly and decreases in average NDVI are actually due to the dying of cheat plants in the fields. All fields in this study contained cheat, but without ground-truthing it would be impossible to determine if populations of cheat were sufficiently high across the fields to create an observable difference before and after treatment.

A second explanation is that the insecticide controlled infestations of greenbugs (*Schizaphis graminum*), a serious pest for Oklahoma wheat growers. Thus, lower average NDVI gains in the fields treated only with MON 37500 could be the result of greenbug feeding and not herbicide injury. The problem with this explanation is that were this in fact the case, untreated fields should also have shown injury from greenbugs. It is possible that given the distribution patterns of greenbug infestation, many untreated fields also had greenbugs present. As the untreated fields and the MON 37500 treated fields were statistically different, it is difficult to find evidence that suggests that this is the most likely explanation.

Another possible cause for differences in changes in NDVI among the various treatments could be differing weather conditions during application. During the period when MON 37500 alone was being applied, the average daily high was 25 C with average daily lows of 16 C. When MON 37500 plus dimethoate was being applied, average daily highs were down to 8 C with average daily lows down to 1 C (Table 3). Favorable growing conditions when MON 37500 was applied alone could have contributed to wheat injury due to increased absorption or translocation.

Thus, while it is possible that decreases in average NDVI increase could have been caused by greenbugs, there are also reasonable arguments against this explanation. Perhaps weather also played a role in allowing more absorption of herbicide during the period when it was being applied alone. It may also be the case that the herbicide worked properly and the dying cheat caused the NDVI increase to slow. The only other explanation for the decreases seen in this study is that MON 37500 did in fact cause a short-term chlorosis in the fields treated with MON 37500 alone, and that this chlorosis was the direct result of MON 37500 application.

Recommendations for future research would be to perform this study using a field based sensor with better spatial resolution in a more controlled field setting. Landsat obtains data at a spatial resolution of 30- by 30-m or 25- by 25-m, depending on the satellite. This may prove too coarse for many applications of remote sensing to weed science. More ground-truthing should also improve the validity of results and provide more assurance in assessment of herbicide injury.

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Table 1. Average absolute difference and percent change between November 12 and November 28, 1999 for treatments examined.

Treatment	Difference	Change
		%
Untreated	0.101	27.2
MON 37500	0.072[a]	13.3[b]
MON 37500 plus dimethoate	0.110[c]	31.0[d]

[a]P = 0.21, p-value resulting from ANOVA between MON 37500 treated fields versus untreated fields.

[b]P = 0.07, p-value resulting from ANOVA between MON 37500 plus dimethoate treated fields versus untreated fields.

[c]P = 0.73, p-value resulting from ANOVA between MON 37500 treated fields versus untreated fields.

[d]P = 0.67, p-value resulting from ANOVA between MON 37500 plus dimethoate treated fields versus untreated fields.

Table 2. Average absolute difference and percent change between November 28 and December 14, 1999 for treatments examined.

Treatment	Difference	Change
		%
Untreated	0.050	11.1
MON 37500 plus dimethoate	0.030	9.4
MON 37500 plus chlorpyrifos	0.025	5.0

[a]P = 0.18, p-value resulting from ANOVA between MON 37500 plus dimethoate treated fields, MON 37500 plus chlorpyrifos, and untreated fields.

[b]P = 0.47, p-value resulting from ANOVA between MON 37500 plus dimethoate, MON 37500 plus chlorpyrifos, and untreated fields.

Table 3. Selected weather data for November 11 to November 28, 1999 from Marshall and Kingfisher, Oklahoma Mesonet Stations.

	Marshall		Kingfisher	
	Temperature			
Date	High	Low	High	Low
	---C---			
Nov 11	27	8	27	6
Nov 12	27	9	27	8
Nov 13	28	11	27	10
Nov 14	24	8	24	7
Nov 15	22	3	23	3
Nov 16	25	4	26	3
Nov 17	26	7	26	7
Nov 18	24	16	24	15
Nov 19	17	3	17	3
Nov 20	20	1	20	-1
Nov 21	19	4	19	3
Nov 22	21	3	21	2
Nov 23	11	0	11	0
Nov 24	12	-3	11	-2
Nov 25	13	-5	13	-5
Nov 26	21	2	21	0
Nov 27	22	2	20	2

Table 3. continued

Nov 28	14	3	14	2

Figure 1. Layout of fields examined for injury from MON 37500 during November 12 to November 28, 1999

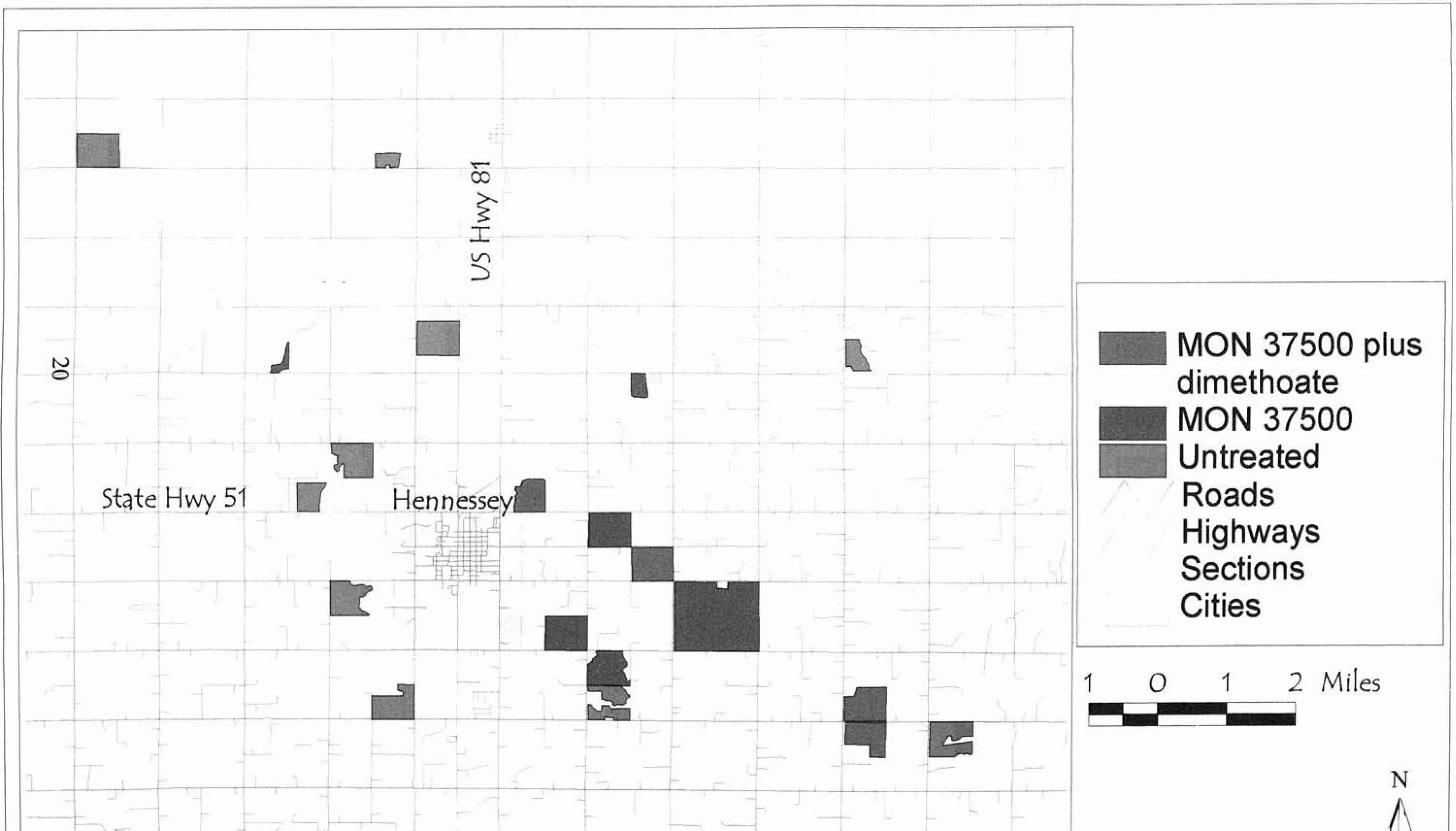
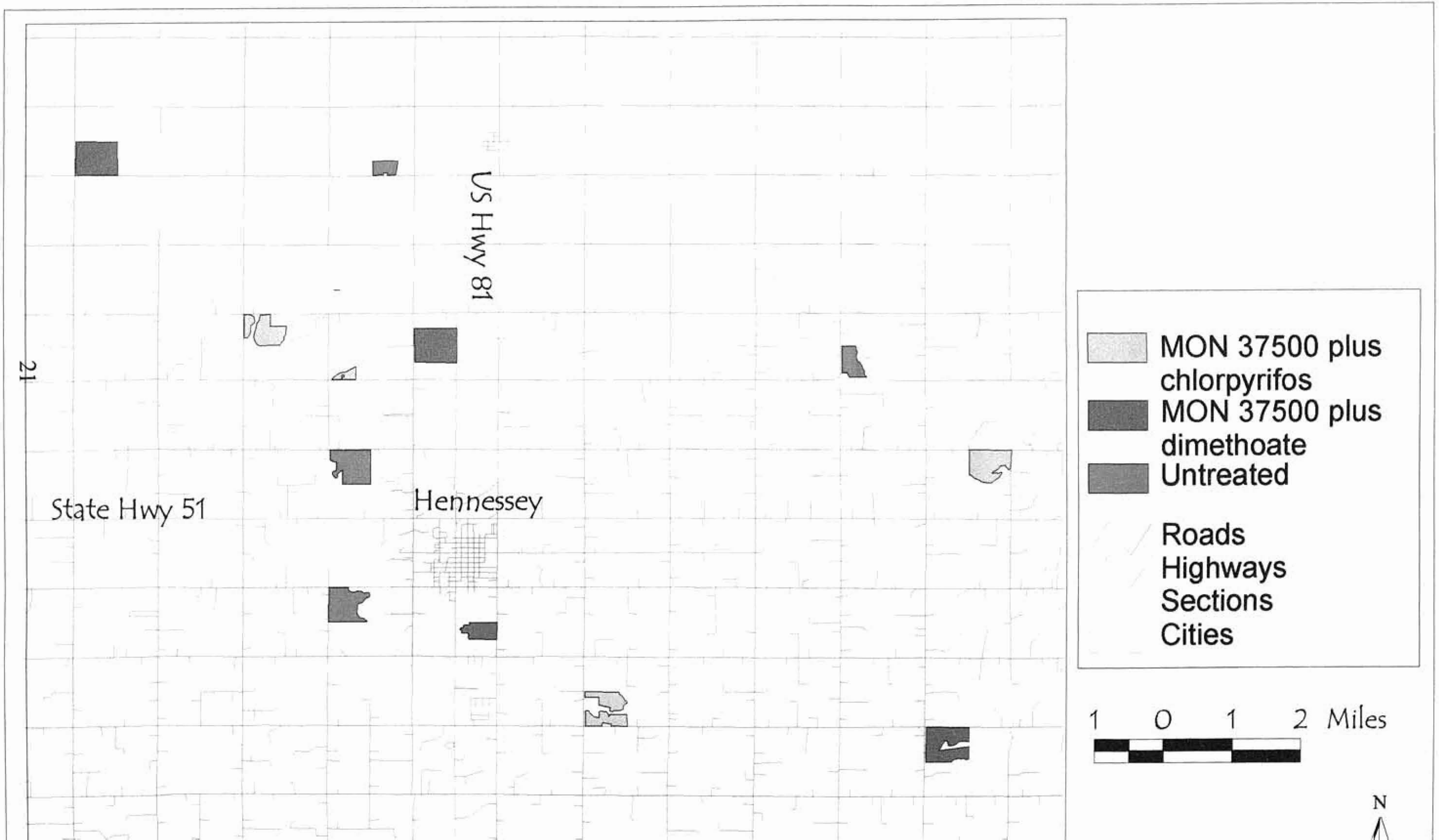


Figure 2. Layout of fields examined for injury from MON 37500 during November 28 to December 14, 1999



CHAPTER II

IDENTIFICATION OF WEED SPECIES BY SPECTRAL REFLECTANCE PATTERNS

Identification of Weed Species By Spectral Reflectance Patterns[1]

JOBY M. PRINCE[2]

Abstract: Field experiments were conducted near Stillwater and Perkins, Oklahoma to identify the spectral reflectance patterns for mono-cultures of hard red winter wheat and three common weeds in wheat, i.e. rye, Italian ryegrass, and henbit. Reflectance readings for all species at various growth stages were collected during February and March using a scanning spectrometer. A calculated index of the normalized difference between 850 and 780 nm was useful for differentiating wheat from rye and wheat from Italian ryegrass, while the reflectance values of 550 and 580 nm were identified as being useful to differentiate wheat from henbit.

Nomenclature: rye, *Secale cereale* L. #[3] SECCE; Italian ryegrass *Lolium multiflorum* Lam. # LOLMU; henbit *Lamium amplexicaule* L. # LAMAM; wheat, *Triticum aestivum* L. 'Jagger'.

Additional index words: remote sensing, precision agriculture, hyperspectral.

Abbreviations: near infrared, NIR; near-infrared shoulder, NIRS; red, R

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[1] Received for publication _______ and in revised form _______.

[2] Graduate Research Assistant, Department of Plant and Soil Sciences, Oklahoma State University, Stillwater, OK 74078

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

INTRODUCTION

Hard red winter wheat, the staple of many farming operations in Oklahoma, is dependent on pesticide applications to maintain production levels (Brown and Steckler 1995). Most herbicides are applied on a whole-field basis (Biller and Schicke 2000; Goudy et al. 2001), but weeds often occur in predictable and detectable patches (Brown and Steckler 1995; Stafford and Miller 1993; Tian et al. 1999; Wang et al. 2001; Woolcock and Cousens 2000; Zwiggelaar 1998). This is particularly true with grass weeds in cereal crops (Wang et al. 2001).

The need to optimize herbicide use in agriculture is driven by real or perceived needs to reduce environmental impacts, reduce pesticide residues in agricultural produce, and reduce input costs (Bostrom and Fogelfors 2002; Paice et al. 1998; Stafford and Miller 1993).

There is evidence that spot-spraying substantially reduces inputs (Rew et al. 1996), but until research can show a significant economic benefit to spot-spraying, it would be unreasonable to expect large scale adoption. Estimates of site-specific spraying in cereals generally suggest a 40 to 60% possible decrease in applied pesticide (Goudy et al. 2001). While equipment to spot-spray based on weed maps has been developed (Paice et al. 1995), the equipment does not generate the required weed population map, an expensive and time-consuming endeavor (Brown et al. 1994; Lass et al. 1996; Tillett et al. 2001). The ability to cost-effectively create accurate weed maps is the missing link in adoption of site-specific weed management (Rew et al. 2001). Currently, savings from reduced herbicide use will likely be offset by increased costs of mapping and special equipment (Rew and Cousens 2001). An alternative approach to this problem is automated weed detection and evaluation (Vrindts et al. 2002). However, until spot spraying of weeds becomes standard practice and technology is developed to make it economically feasible, weed control measures will remain inefficient in terms of both cost and environmental stewardship (Colbach et al. 2000; Wang et al. 2001).

Current satellite and aerial technologies capably distinguish among major categories of land cover – soils, crops, and weeds - with high levels of accuracy (Biller and Schicke 2000; Felton and McCloy 1992; Lamb et al. 1999; Stafford and Miller 1993; Vrindts et al. 2002; Wang et al. 2001). Aerial imagery can be a valuable tool in weed mapping where only one species is of interest or when there is no desire to distinguish among species (Rew and Cousens 2001).

Green, red, and near infrared (NIR) are commonly used wavebands for characterizing plants using remote sensing (Zwiggelaar 1998). Green is used frequently to quantify chlorophyll or other plant pigments. Daughtry et al. (2000) developed a strategy for detecting leaf cholophyll in corn (*Zea mays* L.) using hyperspectral aerial imagery. They used several indexes, which included a green value centered at 550 nm, with a 6 nm width. Five hundred fifty nm is a common wavelength for green reflectance. Called the "green hump" (Sims and Gamon 2002), or green reflectance peak (Everitt et al. 1984), it represents the minimum chlorophyll absorption point in the visible spectrum (Haboudane et al. 2002), and the upper end of anthocyanin absorption (Zwiggelaar 1998). The "green hump" is strongly related to crop variables such as leaf area index (Thenkabail et al. 2000). Daughtry et al. (1998) found that 550 nm permitted detection of *Cannabis sativa* (L). from surrounding background plants and provided the most difference of all bands studied.

Spectral information in the red and NIR portions of the spectrum also holds the potential for discrimination among crop species (Zwiggelaar 1998). Maximum absorbance in the red waveband is between 660 and 680 nm (Sims and Gamon 2002), with 670 nm being the chlorophyll absorption peak (Haboudane et al. 2002; Zwiggelaar 1998). The red region provides the most information about plants when used in conjunction with NIR values. Daughtry and Walthall (1998) have recommended the use of the slope from red to NIR for species discrimination. Red and NIR are used frequently in the formation of indexes. Both the normalized difference vegetation index (NDVI) and the ratio vegetation index (RVI) use these portions of the spectrum to distinguish soil from plant or to remove the effect of shadows or soil background present in an image (Zwiggelaar 1998).

NIR has been reported to be useful for discriminating between crop and weed species (Zwiggelaar 1998). Differences are due to the internal structure of the plant such as number of cell layers, size of cells and orientation of cell walls, but also on external factors such as the presence of leaf hairs or wax (Feyaerts and Gool 2001; Zwiggelaar 1998). Discrimination of plants by internal structure is specific to NIR only (Zwiggelaar 1998). The portion from 780 to at least 900 nm is called the NIR plateau or NIR shoulder (Everitt et al. 1984), which changes only marginally between crops. Eight hundred fifty nm is often thought of as the center of the NIR shoulder (Thenkabail et al. 2000).

Felton and McCloy (1992) used visible and NIR wavelengths to discriminate green plants from soil background. Biller and Schicke (2000) used an optoelectronic sensor with two photodiodes, both fitted with band-pass filters that only allowed red light at 650 nm and NIR radiation at 850 nm to be measured, to rapidly discriminate between plant and soil. Information from the NIR portion of the spectrum can separate weeds from soil during early season development, which is a key time for postemergence herbicide application (Varner et al. 2000). Despite their abilities to detect weeds from a soil background, current satellite sources of remote sensing information are inadequate in their role of providing information for species separation (Bechdol et al. 2000; Brown et al. 1994; Thenkabail et al. 2000). This has pushed the use of hyperspectral imagery with narrow band values obtained with aerial or ground-based sensors (Blackburn 1998; Daughtry and Walthall 1998).

It has been argued that in a production agriculture field it is not enough to detect weed patches; individual species must be identified (Varner et al. 2000). Several researchers have advocated use of "weed classes" such as broadleaf species or grass species, which would be controlled with the same herbicide, but where individual species are not distinguished (Brown et al. 1994; Feyaerts and Gool 2001; Vrindts et al. 2002). In a system where both grass and broadleaf spp. are present, or where all species cannot be controlled with the same herbicide, grouping is not an optimal approach. Thus, in most situations, species identification will be necessary to identify satisfactory postemergence treatments. It should be expected then that effective use of remote sensing in weed science will rely on databases of information, which include spectral response patterns of individual weed species (King et al. 2000).

Spectral reflectance properties of plants are determined by chemical and physical properties. The spectral reflectances of different plant species are often very similar and can overlap (Tillett et al. 2001; Zwiggelaar 1998). The possibility of weed/crop discrimination has been listed by many professionals in the field as a key area of future research (Bechdol et al. 2000; Thanapura et al. 2000; Zwiggelaar 1998). Advances in the area of hyperspectral imaging have allowed researchers to quantify individual photosynthetic pigments within vegetation. This information should aid in the discrimination of species based on spectral properties (Blackburn 1998).

There are periods when spectral differences in plants are heightened, such as during anthesis or when the crop has senesced and the weed is green (Stafford and Miller 1993). Much attention has been given to selection of weed species for study based upon color characteristics. Peters et al. (1992) used coarse-resolution (1100 m by 1100 m) multispectral data from the Advanced Very High Resolution Radiometer (AVHRR) to detect the distribution and relative density of broom snakeweed [*Gutierrezia sarothrae* (Pursh) Britt. & Rusby]. The basis for their research was a maturity color differential between broom snakeweed and surrounding species. The characteristic early season green flush of broom snakeweed could not be detected, however, due to slightly distorted georeferencing of test sites. Lack of adequate ground-truthing left the results unquantifiable. Everitt et al. (1992) also examined the possibility for weed differentiation based on a maturity color differential. Their objective was to use aerial photography and video imagery to detect goldenweed infestations on rangelands. They concluded that conventional color aerial photography could be used to detect and monitor the spread of common goldenweed [*Isocoma coronopifolia* (Gray) Greene] and Drummond goldenweed [*Haplopappus drummondii* (T. & G.) Greene] when these plants were in anthesis, but did not seek to differentiate between the two species.

The development of spectral reflectance patterns is a key area of interest in current research on species discrimination (Noble and Crowe 2001). Differences in spectral reflectance patterns at only a few key wavelengths could permit differentiation of species (Brown et al. 1994; Feyaerts and Gool 2001; Lamb et al. 1999; Lee et al. 1999; Zwiggelaar 1998). The spectral reflectance pattern of yellow starthistle (*Centaurea solstitialis* L.) was measurably different from other rangeland species at anthesis because of its bright yellow inflorescence (Lass et al. 1996). In similar fashion, Lass and Callahan (1997) researched the potential to differentiate yellow hawkweed (*Hieracium pratense* Tausch.) from surrounding pasture species. They concluded that at anthesis, spectroradiometric measurements indicate the spectral reflectance pattern of yellow hawkweed was distinct from surrounding plants in the yellow-green wavelengths.

Species studied. Among the species selected for this study, at the reproductive stage only henbit produces an inflorescence that is distinctly non-green. The stems and leaves are often purplish in color, and the flower has a pink to purple corolla (Stubbendieck et al. 1995). Wheat growers easily identify its purple inflorescence and feel an urgency to control the weed despite the finding by Scott et al. (1995) that even at large densities, henbit does not affect wheat yield.

Italian ryegrass is listed as one of the 10 most troublesome weeds in wheat in 10 of the 13 southern states (Ritter and Menbere 2002). It is highly competitive with wheat, and will become dominant in a field if not controlled (Peeper et al. 2000; Ritter and Menbere 2002). It is easily distinguishable to the human eye because it has shiny, dark green leaves with prominent veins (Whitson 1996). This results in an apparent higher magnitude of reflectance that should be detectable with a sensor.

Even at low densities Italian ryegrass will reduce wheat yield substantially (Hashem et al. 2000; Olofsdotter and Streibig 2001) by causing severe lodging and harvest complications (Ritter and Menbere 2002). Within a few years it is anticipated that many wheat crops in north central Oklahoma will fail due to Italian ryegrass. Farmers in southern Oklahoma have already shifted away from wheat because they cannot economically control the weed. It is expected that this trend will spread (Peeper et al. 2000). This situation is further complicated by the emergence of herbicide-resistant Italian ryegrass biotypes, which leave growers with limited options for chemical control (Anderson and Staska 1994; Bravin et al. 2001; Peeper et al. 2000). Certainly this situation warrants improved herbicide efficiency because of relatively high input costs and the need to manage resistance.

Rye (*Secale cereale* L.) is another serious weed in wheat production for which growers have few control options. The only herbicide registered for rye control in wheat is glyphosate applied with a rope wick applicator once the rye has grown taller than the wheat (Anonymous 2000; Roberts et al. 2001). Earlier rye control may require species discrimination using remote sensing.

Wang et al. (2001) examined the spectra of hard red winter wheat at 3 weeks and 6 weeks from planting with the goal of discrimination from three common wheat-field weed species; kochia [*Kochia scorparia* (L.) Schrad.], redroot pigweed (*Amaranthus retroflexus* L.), and flixweed [*Descurainia sophia* (L.) Webb ex Prantl]. They detected differences between the wheat and weeds as a group using an optical sensor. A step beyond general class discrimination, Varner et al. (2000) researched the possibility of differentiating between soybean [*Glycine max* (L.) Merr.] and common cockleburs (*Xanthium strumarium* L.). Using hyperspectral imagery it was possible to distinguish between the species with at least 78 percent accuracy. They advised that this type of research should be repeated for other species that cause problems for soybean growers. Research focused on obtaining this type of information for weeds that infest wheat should also be performed if remote sensing will ever be of use to Oklahoma wheat producers. Therefore, the objective of this research was to analyze spectra for selected weed species that are a problem for wheat growers in Oklahoma.

MATERIALS AND METHODS

During the 2001-2002 winter wheat growing season, randomized complete block design experiments with four replicates were established at experiment stations near Perkins and Stillwater, OK. Each plot measured 3 m by 3 m. Treatments were monocultures of wheat, rye, Italian ryegrass, and henbit. Pure cultures were selected to develop spectral reflectance patterns for each species without interference of other species or soil background. Soil at Perkins was a Teller sandy loam (fine-loamy, mixed, active, thermic Udic Argiustoll) with pH 6.1 and 1.1% organic matter. The soil at Stillwater was a Norge sandy clay loam (fine-silty, mixed, active, thermic Udic Paleustoll) with pH 6.5 and 1.8% organic matter.

The experiments were fertilized with 190 kg/ha of 19-19-19 (NPK) fertilizer on September 13, 2001 and top dressed with 154 kg/ha of 46-0-0 (NPK) on January 16, 2002. Additionally, plots were sprayed on December 11, 2001 with dimethoate applied at 0.42 kg/ha as a preventative measure.

On October 4, 2001, 'Jagger' wheat, 'Oklon' rye and 'Marshall' Italian ryegrass were hand spread into a conventionally prepared seedbed. Seed was incorporated with two passes of a spike-toothed harrow. Seeding rates were 132 kg/ha for wheat, and 116 kg/ha for rye and Italian ryegrass. Wheat was hand seeded to achieve a uniform canopy and to mask soil background. Henbit was allowed to infest the appropriate plots, but, as an understory species, did not develop in other plots.

Spectral data were acquired on February 22, March 14, and March 28, 2002. This time frame was selected because it is the period when many producers apply postemergence herbicides to their wheat, thus a key time for weed detection. A hard freeze in early March and rains in late March limited opportunities to collect data. Complete weather data for both sites is in Appendix F.

Reflectance was measured using an SD2000 fiber optic scanning spectrometer[4]. The spectrometer measured reflectance in 0.39 nm increments using two channels. The first channel measured reflectance in wavelengths from 177.33 to 879.98 nm, and the second channel measured reflectance in wavelengths from 640.78 to 1275.73 nm. The two data sets were matched in a spreadsheet[5] at 700 nm to form a continuous spectral reflectance curve with the values from 177.33 to 700 nm coming from the first channel's output, and the following portion from the second channel's output. The spectrometer sent data to an on-board laptop computer through a PCMCIA card. Spectral data were displayed using the spectrometer's proprietary software, and saved as delimited text files.

The sensor was attached to a hood, which housed four light bulbs – two 120 watt flood lights and two 125 watt infrared lights. The hood was tractor-mounted via a three-point hitch. The tractor was not driven into or through the plots in order to avoid damaging the plants. The tractor was backed up to each plot and the hood lowered into each plot until

[4] OceanOptics, Dunedin, Florida, 34698

[5] Microsoft Excel, Microsoft Corporation, Redmond, Washington, 98073

it touched the ground, blocking out external light sources. Reflected light was then captured with the spectrometer software program. Reflectance was recorded from two sites within each plot on each date, with the exception of henbit, where the number of samples was two or three depending on availability.

Delimited text files were converted to spreadsheet for all calculations. To remove noise spectral samples were processed using dark readings, and reflectance calculated with a barium sulfate standard. The resultant total reflectance was smoothed using a third order low-pass filter, mathematically expressed as:

$$[Ref_{i-2} + 2 * Ref_{i-1} + 5 * Ref_{i} + 2 * Ref_{i+1} + Ref_{i+2}] / 11$$

The wavebands selected were centered on 480 (blue), 550 (green), 580 (yellow), 670 (red), 780 (near infrared), and 850 (near infrared) nm. Other bands examined included 640, 840, and 1000 nm which had previously been recognized as useful for remote sensing in grains (Kondratyev and Fedchenko 1979). Wavebands measured +/- 5 nm on each center. Values used were from the smoothed data set. These waveband values were used alone and in combination as indexes. Indexes included examining slopes, ratios, and normalized differences. Other values for the specific color waveband were examined by adjusting each value up and down by 10 nm while still using the values at +/- 5 nm band. A 3nm width band approach was also attempted using original band values.

Statistical analysis in the form of t-tests was performed on selected wavebands and indexes. Average values for each species were used to perform two-tailed t-tests with the weed species compared to wheat. Ratios examined included 850/670, 780/670, 550/670, and 850/780. Slopes examined included 780 to 850, 670 to 780, and 550 to 670. Slopes were calculated as the difference in reflectance divided by the difference in nm.

Normalized differences examined included the pairs 850 and 780, 780 and 670, 670 and 550, plus 850 and 670.

Although several researchers advocated the use of the DISCRIM procedure for SAS[6] (Nobel and Crowe 2001; Vrindts et al. 2002), this procedure was not performed due to a limitation imposed by the data set size. PROC DISCRIM computes discriminate analysis functions, which classify observations into groups on the basis of quantitative variables.

RESULTS AND DISCUSSION

A scanning spectrometer was used to develop spectral reflectance patterns to discriminate between wheat and rye, wheat and Italian ryegrass, and wheat and henbit. The first date of data collection, February 22, coincides with the time when tillers are becoming strongly erect, but the first stem node is still not visible. Wheat plants at Perkins were approximately 20 cm tall on average, as were rye and Italian ryegrass. Plants at Stillwater were approximately 13 cm tall on average. By the March 28 collection date, plants at Perkins were approaching 43 cm, while plants at Stillwater were approximately 30 cm tall. The third collection date coincides with the period when the second node of the stem should be visible on the wheat plant. Henbit ranged from 10 to 15 cm over the data collection period, with the most robust blooms on the March 28 collection date. Rye and Italian ryegrass had not produced an inflorescence, while henbit was always at anthesis.

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[6] SAS Institute Incorporated, Cary, North Carolina, 27513

The original wavebands selected, 480 (blue), 550 (green), 580 (yellow), 670 (red), 780 (near infrared), and 850 (near infrared) nm were used for all calculations examined to develop conclusions about this project. Values for wavebands 10 nm above or below the selected wavebands were examined but not used for calculations because there were no significant ($P > 0.10$) differences between the original wavebands and the values at +/- 10 nm. Additionally, a 3 nm width band was also examined and abandoned due to non-significant differences ($P > 0.10$) with the 10 nm band width.

Wheat versus Rye. Although several significant differences ($P = 0.05$) existed between rye and wheat reflectance for each NIR band, the use of the normalized difference between 850 and 780 nm more frequently yielded the most significant differences ($P = 0.01$) with the most consistency (Table 1). NIR discriminates plants on the basis of internal structure and external features, rather than color (Feyaerts and Gool 2001; Zwigglear 1998). Perhaps this is why it was most useful in discriminating two species that look very similar in color. Normalizing the data may have also contributed to the success in discrimination as normalizing spectral data is often used to compensate for sensor calibration, sensor noise, and other factors.

Species detection was best at Perkins regardless of date. All ratios examined provided excellent discrimination ($P = 0.01$) between rye and wheat at Perkins, but were not useful at Stillwater. Growth of both species was more vigorous at Perkins, so this may be responsible for difficulties in finding similarities across both locations.

While differences were observed at Stillwater, they were not as frequent and the results were not consistent with results at Perkins. By March 28, no differences between wheat and rye could be detected ($P = 0.10$) for any specific wavebands or slopes examined.

Significant differences were seen only in t-tests performed on all examined ratios (P = 0.10) and normalized differences between the pairs 850 and 780 nm, 780 and 670 nm, plus 670 and 550 nm. However, by March 28, stem elongation is occurring and producers will not drive across their fields to apply herbicide for fear of damaging the wheat plants. Therefore, the inability to differentiate wheat from rye by this late date may not be a serious problem, as producers would not control the rye even if it could be identified with a sensor.

Wheat versus Italian ryegrass. Although significant differences (P = 0.05) were often seen between Italian ryegrass and wheat reflectance for each NIR band, the use of the normalized difference between 850 and 780 nm as well as the ratio of 850 to 780 nm yielded significant differences (P= 0.01) in all plots for all dates and locations (Table 2). This is likely due to the shiny cuticle present on Italian ryegrass, which is not found on wheat blades. The cuticle produces a higher reflectance in the NIR, which was clearly detectable with the spectrometer. Significant differences (P = 0.10) were seen sporadically for other indexes examined, but none were as consistent as indexes which involved the selected NIR bands.

A significant finding when examining differences in Italian ryegrass and wheat is that using normalized differences of reflectance from both species allows for absolute discrimination between species. The reflectance of Italian ryegrass was always higher than wheat reflectance with no overlap in numbers across dates or locations. Additionally, in 5 out of 6 collection periods (March 28 from Stillwater being the exception) all NIR reflectance ratios for Italian ryegrass are higher than reflectances for wheat. This could replace the need to use fuzzy logic systems and would make use of absolute thresholds instead.

Wheat versus Henbit. Two wavebands were identified as useful in differentiating henbit from wheat. These wavebands were 580 and 550 nm. Both of these wavebands yielded significant differences ($P = 0.01$) from wheat with high consistency for both locations and all dates (Table 3). As henbit has purplish stems and blooms the use of the green waveband seems appropriate to detect a difference between species. This is potentially due to the masking of green in the henbit caused by the presence of purple inflorescence and purplish stems. Although significant differences ($P = 0.10$) existed in other indexes, none were consistent across dates and locations.

As was the case with Italian ryegrass, the use of 550 nm in discriminating henbit from wheat could rely on absolute thresholds and not fuzzy logic because there is no overlap between henbit reflectance values and wheat reflectance values at 550 nm.

Performing research in remote sensing in many ways is like being given a box of spare parts with no picture of the final product on the side. Everyone is pulling out the parts and trying to make something out of them, but no one agrees on what the final product should look like. It makes research in remote sensing difficult, but also exciting. It is like being at the forefront of something which holds the potential to change how agriculturalists make decisions. Spectral reflectance patterns are just another "part" in the box.

While this study has shown that differences between selected species are statistically significant at specific wavebands, the findings are hardly the end to what remote sensing can do for weed science, but rather a beginning. The spectral characteristics examined in this study account for what would happen if pure cultures were present. In a field setting, weed species would be mixed with crops or could have interference from soil background. In order to make spectral reflectance patterns useful to end users such as growers, more research needs to be done on how reflectances change in mixed cultures and what can be done to overcome problems presented by overlapping species and other outside interference.

The development of "smart" sensors that can sense the presence of weeds in a production agriculture field and spot spray only those areas where weeds are present holds the potential to decrease pesticide inputs while also decreasing a grower's production costs. Discrimination between species is key to the successful implementation and design of a selective herbicide placement system that employs the use of a smart sensor. Spectral reflectance patterns are simply a primary step in what may be a long developmental process. Research in the area of spectral reflectance patterns could provide a database to engineers which may facilitate the design of such sensors. If engineers are informed of what wavebands are useful in discrimination of species, they can design sensors which target specific portions of the spectrum and show statistically significant differences between species. In short, a database of spectral reflectance patterns of specific species would keep engineers from "reinventing the wheel".

In this study, early data collection was not performed because of a desire to look at reflectance after canopy closure. Recommendations for future research in spectral reflectance patterns are more data collection early in the growing season and data collection targeted at specific developmental stages in the wheat and weed growth. The data collection dates in this study were chosen out of convenience and availability. Had they been targeted at specific stages of growth, repeatability would be much easier as dates would be specific and not arbitrary.

While much research has already been done in the area of remote sensing, it is still not enough to provide a significant number of marketable applications that growers can use. Until research can show growers the benefit of remote sensing, it will remain an academic endeavor. However, it is only through research that the final product will be seen.

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Table 1. Average values for wavebands and indexes of wheat reflectance for all collection dates at Perkins and Stillwater.

	Perkins			Stillwater		
Parameter	Feb 22	Mar 14	Mar 28	Feb 22	Mar 14	Mar 28
Wavebands						
850	0.5873	0.5142	0.3556	0.6819	0.4896	0.3602
780	0.5808	0.4979	0.3538	0.6701	0.4836	0.3611
670	0.0420	0.0851	0.0604	0.0533	0.0632	0.0485
580	0.0735	0.1370	0.1042	0.0805	0.1122	0.0893
550	0.0950	0.1599	0.1257	0.0975	0.1356	0.1091
480	0.0365	0.1107	0.0512	0.0408	0.0570	0.0431
Slopes						
780-850	0.5790	0.5071	0.3505	0.6723	0.4827	0.3550
670-780	0.5804	0.4972	0.3532	0.6696	0.4830	0.3607
550-670	0.0412	0.0838	0.0593	0.0525	0.0620	0.0476
Ratios						
850/670	14.28	6.31	6.19	12.95	7.87	7.62
780/670	14.12	6.12	6.17	12.73	7.78	7.64
550/670	2.27	1.92	2.14	1.85	2.17	2.29
850/780	1.01	1.03	1.01	1.02	1.01	1.00

Table 1. continued

Normalized Differences						
850-780	0.0056	0.0166	0.0027	0.0086	0.0062	*0.0013*
780-670	0.8640	0.7069	0.7065	0.8529	0.7689	0.7640
670-550	*0.3868*[a]	*0.3096*	*0.3553*	*0.2960*	*0.3665*	*0.3874*
850-670	0.8654	0.7154	0.7081	0.8552	0.7715	0.7636

[a] Italicized values are negative.

Table 2. Average values for wavebands and indexes of rye reflectance with observed significance levels of t-tests comparing the average reflectance of rye to wheat at Perkins and Stillwater.

	Perkins			Stillwater		
Parameter	Feb 22	Mar 14	Mar 28	Feb 22	Mar 14	Mar 28
Wavebands						
850	0.6638**[a]	0.05553**	0.3562	0.8289***	0.5687***	0.3557
780	0.6654**	0.5591***	0.1247	0.8583***	0.5643***	0.3630
670	0.0371	0.0588***	0.0789***	0.1110*	0.0727**	0.0407
580	0.0779	0.1170**	0.0703***	0.2118*	0.1265**	0.0846
550	0.1072*	0.1535	0.1102**	0.2643*	0.1525***	0.1093
480	0.0428***	0.1085	0.0372***	0.2205	0.0671***	0.0451
Slopes						
780-850	0.6543**	0.5473**	0.3545	0.8167***	0.5606***	0.3505
670-780	0.6651**	0.5585***	0.1240	0.8572***	0.5636***	0.3626
550-670	0.0362	0.0575***	0.0247***	0.1088*	0.0714**	0.0398
Ratios						
850/670	18.17***	9.57***	13.46***	9.99*	7.93	9.05*
780/670	18.23***	9.64***	6.57***	10.02*	7.87	9.24*
550/670	2.93***	2.63***	1.80***	2.13	2.12	2.72***

Table 2. continued

850/780	0.10***	0.99***	0.97***	0.97	1.01	0.98***
Normalized Differences						
850-780	_0.0015_***[b]	_0.0032_***	_0.0154_***	_0.0165_***	0.0038	_0.0102_***
780-670	0.8947***	0.8089***	0.8560***	0.7843*	0.7722	0.7977*
670-550	_0.4884_***	_0.4473_***	_0.5680_***	_0.3512_	_0.3566_	_0.4593_***
850-670	0.8944***	0.8080***	0.8519***	0.7710	0.7738	0.7940

[a]* significant at P = 0.10; ** significant at P = 0.05; *** significant at P = 0.01.

[b] Italicized values are negative.

Table 3. Average values for wavebands and indexes of Italian ryegrass reflectance with observed significance levels of t-tests comparing the average reflectance of Italian ryegrass to wheat at Perkins and Stillwater.

	Perkins			Stillwater		
Parameter	Feb 22	Mar 14	Mar 28	Feb 22	Mar 14	Mar 28
Wavebands						
850	0.5674	0.4626***[a]	0.3454	0.6569	0.4820	0.3447***
780	0.5472	0.4324**	0.1234	0.6161**	0.4526**	0.3384***
670	0.0599***	0.1022**	0.1137	0.0725***	0.0930***	0.0508
580	0.0947***	0.1477	0.1052	0.0899***	0.1284***	0.0860
550	0.1162***	0.1637	0.1279	0.100	0.1400	0.1036
480	0.0418**	0.1148	0.0500	0.0386*	0.0603	0.0383**
Slopes						
780-850	0.5596	0.4564***	0.3438	0.6481	0.4827	0.3399***
670-780	0.5467	0.4315***	0.1224	0.6154**	0.4830**	0.3380***
550-670	0.0590***	0.1009**	0.0614	0.0716***	0.0620***	0.0499
Ratios						
850/670	9.56***	4.61**	5.90	9.11***	5.25***	6.83
780/670	9.22***	4.32***	2.98	8.54***	4.93***	6.71*
550/670	1.95***	1.62**	1.28	1.39***	1.52***	2.05**

Table 3. continued

850/780	1.04***	1.07***	1.02***	1.07***	1.07***	1.02***
Normalized Differences						
850-780	0.0181***	0.0339***	0.0103***	0.0322***	0.0315***	0.0091***
780-670	0.8947***	0.6171***	0.7041	0.7896***	0.6600***	0.7394*
670-550	*0.3204****[b]	*0.2339***	*0.3729*	*0.1617****	*0.2037****	*0.3429**
850-670	0.8084***	0.6379***	0.7094	0.8014***	0.6774***	0.7433

[a]* significant at P = 0.10; ** significant at P = 0.05; *** significant at P = 0.01.

[b] Italicized values are negative.

Table 4. Average values for wavebands and indexes of henbit reflectance with observed significance levels of t-tests comparing the average reflectance of henbit to wheat at Perkins and Stillwater.

	Perkins			Stillwater		
Parameter	Feb 22	Mar 14	Mar 28	Feb 22	Mar 14	Mar 28
Wavebands						
850	0.5698	0.5206	0.4501***[a]	0.7195	0.5199	ND[b]
780	0.5479	0.5059	0.4497***	0.6859	0.5037	ND
670	0.0428	0.0550**	0.0399**	0.0427**	0.0441**	ND
580	0.0606*	0.0825***	0.0667***	0.0606***	0.0741***	ND
550	0.0713**	0.1015***	0.0882***	0.0693***	0.0909***	ND
480	0.0349	0.0907***	0.0405***	0.0420***	0.0314***	ND
Slopes						
780-850	0.5620	0.5134	0.4437***	0.7097	0.5127	ND
670-780	0.5474	0.5054	0.4494***	0.6855	0.5033	ND
550-670	0.0422	0.0542**	0.0392***	0.0422**	0.0434**	ND
Ratios						
850/670	13.46	9.48**	11.36***	16.88***	11.78***	ND
780/670	12.94	9.21**	11.35***	16.10***	11.41***	ND
550/670	1.68***	1.85	2.22	1.63	2.06	ND

Table 4. continued

850/780	1.04***	1.03	1.00	1.05***	1.03**	ND
Normalized Differences						
850-780	0.0198***	0.0143	0.0005	0.0239***	0.0159**	ND
780-670	0.8534	0.8036*	0.8362***	0.8823**	0.8389***	ND
670-550	*0.2512****[c]	*0.2967*	*0.3767*	*0.2372**	*0.3465*	ND
850-670	0.8588	0.8086*	0.8364***	0.8875***	0.8435***	ND

[a]* significant at P = 0.10; ** significant at P = 0.05; *** significant at P = 0.01.

[b] ND – insufficient data for calculations.

[c] Italicized values are negative.

APPENDIX

```
  imgFTab.SetValue(rv4,r,math4)
 end
end
imgFTab.SetEditable(false)

redband = imgFTab.FindField("REFV3")
nirband = imgFTab.FindField("REFV4")
ndvifld = imgFTab.FindField("ndvi")

imgFTab.SetEditable(true)
if (imgFTab.IsEditable) then
 for each r in 0..(imgFTab.getnumRecords -1)
  red = imgFTab.ReturnValue(redband,r)
  nir = imgFTab.ReturnValue(nirband,r)

  mathndvi = ((nir - red)/(nir + red))

  imgFTab.SetValue(ndvifld,r,mathndvi)
 end
end
imgFTab.SetEditable(false)

kgs = imgFTab.FindField("Ekg_ha")
lbs = imgFTab.FindField("Elb_ac")
bu = imgFTab.FindField("Ebu_ac")

imgFTab.SetEditable(true)
 if (imgFTab.IsEditable) then
  for each r in 0..(imgFTab.getnumRecords -1)
   health = imgFTab.ReturnValue(ndvifld,r)
     mathkgha = (165.9 * (2.7183^(4.0443 * health)))
   imgFTab.SetValue(kgs,r,mathkgha)

   funkymetricunit = imgFTab.ReturnValue(kgs,r)
     mathlbac = ((funkymetricunit * 2.2) / 2.47)
   imgFTab.SetValue(lbs,r,mathlbac)

   lubbage = imgFTab.ReturnValue(lbs,r)
     mathbuac = (lubbage / 60)
   imgFTab.SetValue(bu,r,mathbuac)

  end
 end
imgFTab.SetEditable(false)
```

Appendix A. Values used for atmospheric correction for Landsat images.

Image date	Band	Gain	Bias	K factor
November 12, 1999	R	0.6192157	-5	0.0036371
	NIR	0.6372549	-5.1	0.0054017
November 28, 1999	R	0.6192157	-5	0.0039792
	NIR	0.6372549	-5.1	0.0059099
December 14, 1999	R	0.6192157	-5	0.0042572
	NIR	0.6372549	-5.1	0.0063228

Appendix B. Avenue script written to correct atmospheric reflectance in Landsat images.

```
theDoc = av.Getactivedoc
imgtheme = theDoc.getactivethemes.get(0)

imgFTab = imgtheme.getftab

bv3 = imgftab.findfield("Band3")
if (bv3 = nil) then
 MsgBox.Info ("Error: Please select an image point theme.", "Yield Estimate
Calculator")
return false
end
bv4 = imgftab.findfield("Band4")
if (bv4 = nil) then
 MsgBox.Info ("Error: Please select an image point theme.", "Yield Estimate
Calculator")
return false
end

checkit = imgFTab.FindField("REFV3")
checkagain = imgFTab.FindField("REFV4")
if (checkit <> nil) then
 MsgBox.Info ("Error: Reflectance Value Field REFV3 Already Exists in Table", "Yield
Estimate Calculator")
 return false
elseif (checkagain <> nil) then
 MsgBox.Info ("Error: Reflectance Value Field REFV4 Already Exists in Table", "Yield
Estimate Calculator")
 return false
end

rv3 = field.make("REFV3",#FIELD_DOUBLE,8,6)
rv4 = field.make("REFV4",#FIELD_DOUBLE,8,6)
ndvi = field.make("NDVI", #FIELD_DOUBLE,8,6)
kgha = field.make("Ekg_ha", #FIELD_DOUBLE,8,2)
lbac = field.make("Elb_Ac", #FIELD_DOUBLE,8,2)
buac = field.make("Ebu_Ac", #FIELD_DOUBLE,8,0)

years = {"November 12, 1999","November 28, 1999","December 14, 1999","January 7,
2000","February 8, 2000","March 27, 2000","April 4, 2000","May 30, 2000"}
whatyear = MsgBox.ChoiceAsString(years, "Please Select a Year:", "Yield Estimate
Calculator")

if (whatyear = nil) then
 return false
```

```
end

fldList = {}
fldList.Add (rv3)
fldList.Add (rv4)
fldList.Add (ndvi)
fldList.Add (kgha)
fldList.Add (lbac)
fldList.Add (buac)

imgFTab.SetEditable(true)
if (imgFTab.IsEditable) then
  imgFTab.AddFields(fldList)
  for each r in 0..(imgFTab.getnumRecords -1)
    value3 = imgFTab.ReturnValue(bv3,r)
    value4 = imgFTab.ReturnValue(bv4,r)

    if (whatyear = "November 12, 1999") then
      math3 = ((value3 * 0.6192157 - 5) * 0.0036371)
      math4 = ((value4 * 0.6372549 - 5.1) * 0.0054017)
    elseif (whatyear = "November 28, 1999") then
      math3 = ((value3 * 0.6192157 - 5) * 0.0039792)
      math4 = ((value4 * 0.6372549 - 5.1) * 0.0059099)
    elseif (whatyear = "December 14, 1999") then
      math3 = ((value3 * 0.6192157 - 5) * 0.0042572)
      math4 = ((value4 * 0.6372549 - 5.1) * 0.0063228)
    elseif (whatyear = "January 7, 2000") then
      math3 = (((value3 * 0.006486 - 0.012) / 0.067) * 0.044471)
      math4 = (((value4 * 0.011683 - 0.02341) / 0.128) * 0.066133)
    elseif (whatyear = "February 8, 2000") then
      math3 = (((value3 * 0.006488 - 0.01212) / 0.067) * 0.039244)
      math4 = (((value4 * 0.011683 - 0.02353) / 0.128) * 0.05836)
    elseif (whatyear = "March 27, 2000") then
      math3 = (((value3 * 0.006488 - 0.01219) / 0.067) * 0.027043)
      math4 = (((value4 * 0.011683 - 0.02341) / 0.128) * 0.040216)
    elseif (whatyear = "April 4, 2000") then
      math3 = ((value3 * 0.6192157 - 5) * 0.0025305)
      math4 = ((value4 * 0.9654902 - 5.1) * 0.0037584)
    elseif (whatyear = "May 30, 2000") then
      math3 = (((value3 * 0.006486 - 0.01196) / 0.067) * 0.023288)
      math4 = (((value4 * 0.011669 - 0.02074) / 0.128) * 0.034632)
    end

    imgFTab.SetValue(rv3,r,math3)
```

```
   imgFTab.SetValue(rv4,r,math4)
  end
end
imgFTab.SetEditable(false)

redband = imgFTab.FindField("REFV3")
nirband = imgFTab.FindField("REFV4")
ndvifld = imgFTab.FindField("ndvi")

imgFTab.SetEditable(true)
if (imgFTab.IsEditable) then
 for each r in 0..(imgFTab.getnumRecords -1)
  red = imgFTab.ReturnValue(redband,r)
  nir = imgFTab.ReturnValue(nirband,r)

  mathndvi = ((nir - red)/(nir + red))

  imgFTab.SetValue(ndvifld,r,mathndvi)
 end
end
imgFTab.SetEditable(false)

kgs = imgFTab.FindField("Ekg_ha")
lbs = imgFTab.FindField("Elb_ac")
bu = imgFTab.FindField("Ebu_ac")

imgFTab.SetEditable(true)
 if (imgFTab.IsEditable) then
  for each r in 0..(imgFTab.getnumRecords -1)
   health = imgFTab.ReturnValue(ndvifld,r)
     mathkgha = (165.9 * (2.7183^(4.0443 * health)))
   imgFTab.SetValue(kgs,r,mathkgha)

   funkymetricunit = imgFTab.ReturnValue(kgs,r)
     mathlbac = ((funkymetricunit * 2.2) / 2.47)
   imgFTab.SetValue(lbs,r,mathlbac)

   lubbage = imgFTab.ReturnValue(lbs,r)
     mathbuac = (lubbage / 60)
   imgFTab.SetValue(bu,r,mathbuac)

  end
 end
imgFTab.SetEditable(false)
```

Appendix C. Questionnaire given to wheat producers to obtain information regarding the management of a field in the study.

Section 1. Planting and Harvest Information

What varieties are planted in this field?

On what date was this field planted?

What was the average yield for this field?

On what date was this field harvested?

Section 2. Management Information

Was this field grazed? If so, during what days?

Did this field experience any disease problems such as wheat rusts or soil borne diseases such as Soil Borne Mosaic Virus?

How long has this field been in wheat production?

What other chemicals was this field treated with and when?

Appendix D. Weather data from Marshall and Kingfisher, Oklahoma Mesonet stations for November and December 1999.

	Marshall Station			Kingfisher Station		
	Temperature			Temperature		
Date	Low	High	Rain	Low	High	Rain
	-----------C---------		cm	-----------C---------		cm
November 1	8	21	0.03	8	21	0.00
November 2	2	13	0.00	1	12	0.00
November 3	1	18	0.00	1	19	0.00
November 4	1	24	0.00	1	23	0.00
November 5	8	19	0.00	8	19	0.00
November 6	14	26	0.00	13	26	0.00
November 7	11	27	0.00	12	26	0.00
November 8	12	25	0.00	11	24	0.00
November 9	14	24	0.00	13	24	0.00
November 10	8	26	0.00	8	24	0.00
November 11	8	27	0.00	6	27	0.00
November 12	9	27	0.00	8	27	0.00
November 13	11	28	0.03	10	27	0.00
November 14	8	24	0.00	7	24	0.00
November 15	3	22	0.00	3	23	0.00
November 16	4	25	0.00	3	26	0.00
November 17	7	26	0.00	7	26	0.00

November 18	16	24	0.00	15	24	0.00
November 19	3	17	0.00	3	17	0.00
November 20	1	20	0.00	-1	20	0.00
November 21	4	19	0.00	3	19	0.00
November 22	3	21	0.00	2	21	0.00
November 23	0	11	0.43	0	11	1.02
November 24	-3	12	0.00	-2	11	0.00
November 25	-5	13	0.00	-5	13	0.03
November 26	2	21	0.00	0	21	0.00
November 27	2	22	0.00	2	20	0.00
November 28	3	14	0.00	2	14	0.00
November 29	1	14	0.00	-1	13	0.00
November 30	-1	16	0.00	-4	16	0.00
December 1	8	19	0.00	8	19	0.00
December 2	10	21	0.91	9	21	2.24
December 3	3	17	0.03	3	16	0.28
December 4	2	8	4.39	2	8	4.06
December 5	-4	5	0.10	-4	5	0.03
December 6	-5	12	0.00	-5	11	0.00
December 7	3	15	0.00	3	14	0.00
December 8	5	19	1.35	6	18	1.24
December 9	-1	9	3.99	1	9	3.15

Appendix D. continued

December 10	-3	11	0.00	-4	12	0.00
December 11	1	9	0.00	-1	9	0.00
December 12	-1	11	0.00	0	11	0.03
December 13	-4	12	0.00	-4	12	0.00
December 14	1	9	0.15	2	9	0.08
December 15	-3	11	0.00	-3	11	0.00
December 16	-3	13	0.00	-3	13	0.00
December 17	1	11	0.00	1	10	0.00
December 18	0	8	0.00	-1	8	0.00
December 19	-1	7	0.03	-1	7	0.00
December 20	-6	4	0.00	-5	3	0.00
December 21	-6	7	0.00	-6	7	0.00
December 22	-5	6	0.00	-3	7	0.00
December 23	-4	13	0.00	-3	14	0.00
December 24	-3	8	0.00	-3	7	0.00
December 25	-4	17	0.00	-4	17	0.00
December 26	-3	12	0.00	-3	13	0.00
December 27	-4	10	0.00	-3	10	0.00
December 28	-5	12	0.03	-4	21	0.00
December 29	-2	21	0.00	-3	21	0.00
December 30	-1	16	0.00	-1	16	0.00
December 31	-4	17	0.00	-3	16	0.00

Appendix E. Differences in average NDVI values and percent changes in average NDVI values between start and end dates for all fields included in the study.

Image Dates	Field	Difference	Change
			%
Nov. 11 – Nov. 28	Untreated check 1	0.105922	34.6
Nov. 11 – Nov. 28	Untreated check 2	0.154181	37.1
Nov. 11 – Nov. 28	Untreated check 3	0.078370	13.1
Nov. 11 – Nov. 28	Untreated check 4	0.107734	36.1
Nov. 11 – Nov. 28	Untreated check 5	0.167937	38.5
Nov. 11 – Nov. 28	Untreated check 6	0.044071	6.5
Nov. 11 – Nov. 28	Untreated check 7	0.041961	6.3
Nov. 11 – Nov. 28	Untreated check 8	0.162636	54.4
Nov. 11 – Nov. 28	Untreated check 9	0.021976	18.0
Nov. 11 – Nov. 28	Untreated check 10	0.128896	34.8
Nov. 11 – Nov. 28	MON 37500 treated 1	0.074435	11.3
Nov. 11 – Nov. 28	MON 37500 treated 2	0.068027	12.3
Nov. 11 – Nov. 28	MON 37500 treated 3	0.085229	14.4
Nov. 11 – Nov. 28	MON 37500 treated 4	0.084567	19.0
Nov. 11 – Nov. 28	MON 37500 treated 5	0.071506	15.1
Nov. 11 – Nov. 28	MON 37500 treated 6	0.050680	8.7
Nov. 11 – Nov. 28	MON 37500 plus dimethoate treated 1	0.102068	25.1
Nov. 11 – Nov. 28	MON 37500 plus dimethoate treated 2	0.112400	39.5
Nov. 11 – Nov. 28	MON 37500 plus dimethoate treated 3	0.105453	27.2

Nov. 11 – Nov. 28	MON 37500 plus dimethoate treated 4	0.123467	32.1
Nov. 28 – Dec.14	Untreated check 1	0.036473	8.9
Nov. 28 – Dec.14	Untreated check 2	0.033793	5.9
Nov. 28 – Dec.14	Untreated check 3	0.040291	6.0
Nov. 28 – Dec.14	Untreated check 4	0.089410	23.7
Nov. 28 – Dec.14	Untreated check 6	0.002863	0.0
Nov. 28 – Dec.14	Untreated check 7	0.016985	2.4
Nov. 28 – Dec.14	MON 37500 plus dimethoate treated 5	0.039722	8.6
Nov. 28 – Dec.14	MON 37500 plus dimethoate treated 6	0.048354	21.5
Nov. 28 – Dec.14	MON 37500 plus dimethoate treated 7	0.019452	3.2
Nov. 28 – Dec.14	MON 37500 plus dimethoate treated 8	0.011888	0.0
Nov. 28 – Dec.14	MON 37500 plus chlorpyrifos treated 1	0.017888	2.6
Nov. 28 – Dec.14	MON 37500 plus chlorpyrifos treated 2	0.021438	3.9
Nov. 28 – Dec.14	MON 37500 plus chlorpyrifos treated 3	0.031677	7.8
Nov. 28 – Dec.14	MON 37500 plus chlorpyrifos treated 4	0.028400	5.7

Appendix F. Weather data from Stillwater and Perkins, Oklahoma Mesonet stations for February and March, 2002.

	Stillwater Station			Perkins Station		
	Temperature			Temperature		
Date	Low	High	Rain	Low	High	Rain
	------------C------------		cm	------------C------------		cm
Feb 1	-6	5	0.00	-6	5	0.00
Feb 2	-7	-15	0.00	-4	9	0.00
Feb 3	-1	12	0.00	1	12	0.00
Feb 4	-4	7	0.00	-3	7	0.00
Feb 5	0	3	0.51	-1	2	0.36
Feb 6	-1	2	0.76	-1	1	0.71
Feb 7	-2	111	0.00	1	11	0.15
Feb 8	-1	18	0.03	0	17	0.00
Feb 9	2	12	0.00	2	12	0.00
Feb 10	-3	6	0.00	-2	6	0.00
Feb 11	-8	13	0.00	-7	12	0.00
Feb 12	-4	12	0.00	-2	12	0.00
Feb 13	-3	11	0.00	-1	11	0.00
Feb 14	-3	15	0.00	-1	14	0.00
Feb 15	-3	12	0.05	0	12	0.13
Feb 16	-3	18	0.00	-2	18	0.00
Feb 17	-4	19	0.00	-2	19	0.00

Feb 18	8	19	0.00	7	18	0.00
Feb 19	7	20	0.79	7	19	0.64
Feb 20	1	18	0.00	2	18	0.00
Feb 21	-1	14	0.00	3	13	0.00
Feb 22	-4	14	0.00	-3	14	0.00
Feb 23	3	22	0.00	4	21	0.00
Feb 24	2	24	0.00	3	24	0.00
Feb 25	-6	4	0.00	-6	4	0.00
Feb 26	-9	-3	0.00	-9	-2	0.00
Feb 27	-12	6	0.00	-12	5	0.00
Feb 28	-6	13	0.00	-6	13	0.00
Mar 1	-6	9	0.00	-6	9	0.00
Mar 2	-11	-6	0.00	-11	-6	0.00
Mar 3	-14	-2	0.00	-14	-2	0.00
Mar 4	-14	13	0.66	-14	13	0.66
Mar 5	-3	18	0.00	-3	18	0.00
Mar 6	6	20	0.00	6	20	0.00
Mar 7	2	24	0.00	2	24	0.00
Mar 8	1	22	0.20	1	22	0.20
Mar 9	-5	7	0.00	-5	7	0.00
Mar 10	-7	14	0.00	-7	14	0.00
Mar 11	2	16	0.00	2	16	0.00

Mar 12	-1	20	0.00	-1	20	0.00
Mar 13	7	27	0.00	7	27	0.00
Mar 14	9	28	0.00	9	28	0.00
Mar 15	1	10	0.00	1	10	0.00
Mar 16	-1	9	0.00	-1	9	0.00
Mar 17	4	17	0.00	4	17	0.00
Mar 18	7	13	2.77	7	13	2.77
Mar 19	8	12	1.17	8	12	1.17
Mar 20	3	16	0.00	3	16	0.00
Mar 21	-3	5	0.00	-3	5	0.00
Mar 22	-7	6	0.00	-7	6	0.00
Mar 23	-2	19	0.00	-2	19	0.00
Mar 24	6	24	0.00	6	24	0.00
Mar 25	-1	6	0.00	-1	6	0.00
Mar 26	-4	12	0.00	-4	12	0.00
Mar 27	0	21	0.00	0	21	0.00
Mar 28	11	28	0.00	11	28	0.00
Mar 29	12	21	0.00	12	21	0.00
Mar 30	11	17	0.00	11	17	0.00
Mar 31	2	21	0.00	2	21	0.00

VITA 2

Joby Michelle Prince

Master of Science

Thesis: USING SATELLITE IMAGERY TO DETECT HERBICIDE INJURY AND IDENTIFICATION OF WEED SPECIES BY SPECTRAL REFLECTANCE PATTERNS

Major Field: Plant and Soil Science

Biographical:

Personal Data: Born in Enid, Oklahoma, January 25, 1978, the daughter of Mack and Donna Prince.

Education: Graduated from Cherokee High School, Cherokee, Oklahoma, in May 1996; received Bachelor of Science degree in Plant and Soil Sciences from Oklahoma State University, May 2001. Completed requirements for the Master of Science degree in Plant and Soil Sciences at Oklahoma State University in August, 2002.

Experience: Raised in rural Cherokee, Oklahoma; undergraduate at Oklahoma State University, August 1996 to May 2001; employed by SST Development Group as an intern, 1999 to 2001; performed independent undergraduate research in remote sensing on a grant from the OSU Wentz Foundation, 1999 to 2001; graduate research assistant, Department of Plant and Soil Sciences, May 2001 to present.

Professional Organizations: Soil and Water Conservation Society.