SITE-SPECIFIC HERBICIDE (SSH) FOR REDVINE CONTROL IN COTTON Kevin DiCrispino Institute for Technology Development Stennis Space Center, MS Ken Hood Perthshire Farms Gunnison, MS

Abstract

This experiment is intended to develop an image based site-specific method to control redvine in cotton. Three band multispectral imagery was used to establish spectral separability of ground features that may be present in a given field at the time of harvest. Imagery taken just prior to defoliation of the study area was used to delineate areas of redvine infestation. A post harvest site-specific herbicide treatment of dicamba was derived from image products and applied to the study area. Effectiveness of the herbicide treatment will be assessed during the 2003 growing season and appended to this report. Economic analysis of this application will also be pending the 2003 harvest.

Background

Redvine (*Brunnichia ovata*) is a perennial, shrubby vine that occurs as a weed of many agronomic crops of the southern United States (Figure 1). Redvine flourishes in low lying clay soils with high water-holding capacity and is prevalent in the Mississippi delta region (Shaw and Mack, 1991). Redvine occurred most frequently of six perennial species surveyed in the delta region of Mississippi. Greater than 1% of the area surveyed was infested by this weed in 43% of cotton and 31% of soybean fields (Elmore, 1984). In undisturbed areas redvine will climb, by tendrils, on any available supporting structure and produce seed. In cultivated fields the vine rarely produces seed, but propagates from an extensive underground root system (Defelice, 1980). The underground stems are woody and may produce several sprouts, many arising from a common crown. Sub-surface disturbance of the existing root system results in shoot production from root segments. Shoot growth may be dense, which enables redvine to dominate the canopy of a crop and increase its area of dispersal within a field (Shaw et al., 1991). Redvine is particularly problematic to cotton production during harvest, as its vegetative propagules often entangle mechanized pickers. Large dense areas of redvine infestation may not be harvested at all, thus impacting potential cotton yields.

Conventional cultural and chemical practices have been employed to control redvine with limited success. It has been demonstrated that conventional tillage actually increases stem counts and acceptable levels of cultural control can only be achieved with deep tillage by moldboard plowing (Castillo et al., 1998). Chemical control of redvine requires that a substantial concentration of herbicide reach the root system (Shaw et al., 1991). This weed is highly resistant to nonselective herbicides at normal use rates. Current research indicates the best treatment to be a fall application of dicamba (Clarity®--BASF Corp.). A study by Shaw and Mack (1991) was conducted to test application timing of various herbicides for the control of redvine. They report that for all spring-applied treatments, redvine stem reductions did not continue into the following year with the exception of sequential spring and fall applications of dicamba. More effective control was obtained with fall herbicide applications (Shaw et al., 1991). If applied in the fall, when the redvine plants are translocating sugars to their root structures, dicamba can reduce groundcover levels for at least two years (Elkins et al., 1996). A study by Castillo, Keisling, and Oliver (1998), resulted in 96% control of redvine using dicamba, regardless of tillage type. Unlike nonselective, broadspectrum, and environmentally benign herbicides, dicamba is not labeled for 'in season' use in cotton. Therefore, it must be applied after harvest but before the first frost to ensure translocation of the chemical to the root system. It should be noted that dicamba is an expensive chemical input costing approximately \$16/ha (\$40/acre). Given the associated cost and potential environmental impact of this herbicide, development of a precise method of application will be necessary to address redvine problems in cotton production.

Typically, redvine infestation areas have been roughly identified and spot treated by visual scouting of the field, although, aerial photography and Global Positioning/Geographic Information Systems (GPS/GIS) technologies have been utilized to monitor redvine movement (Castillo et al., 1998). Airborne and satellite remotely sensed imagery has the potential not only to monitor weed infestation, but also to drive site-specific herbicide applications by identifying weeds based on the their spectral signature. A study by Richardson et al. (1985) was able to separate johnson grass and pigweed from sorghum, cotton and cantaloupe at the plot level using an airborne video system with narrow band filters in the blue, green, red and NIR regions of the spectrum. Deguise et al. (1999) used an unsupervised classification to successfully select spectral endmembers for canda thistle versus canola using the CASI hyperspectral instrument. ITD-Spectral Visions has performed research in herbicide applications that demonstrates the potential of remote sensing for weed delineation and treatment (Copenhaver et al., 2001b). An Ag2020 plot level experiment conducted in 2000 and 2001 supported the ability to use imagery to separate weeds within soybeans from weed-free soybeans. Results from the study indicated that weed species mixed within soybean rows (giant foxtail, common waterhemp, velvetleaf, shattercane, common lambsquarter) can be separated based on statistical analysis of radiometer data and classifications of remotely sensed imagery. The study also found that several of these weed species could be separated from each other leading to the potential application of additional or specialized herbicide where specific problem weed species exist.

It has been further demonstrated that once the weed extent is determined, information derived from remote sensing can be used for variable rate application of herbicide. Brown and Steckler (1995) demonstrated that a map using mulitspectral imagery could reduce herbicide use by 25 percent. Stafford and Miller (1993) combined ground truth and interpretation of aerial photography to develop a variable rate herbicide application map. A base rate was maintained throughout the field while increased rates were applied where either ground truth or the aerial photograph indicated the presence of weeds. Another research effort by ITD-Spectral Visions in 2001 was able to demonstrate that imagery could be classified into three weed infestation levels and applied with corresponding herbicide levels. Results from this study indicated that weed kill effectiveness and yield were not impacted by the variable applications while herbicide use was reduced by approximately 30% (Copenhaver et al., 2001a).

Project Goal

The short-term goals of this research were to utilize remotely sensed imagery to delineate feature classes for redvine control in cotton. A classification scheme was developed from remotely sensed imagery for the delineation of redvine infestation areas. The resulting classification was then used to generate a prescription for application of site-specific herbicide.

Long-term goals include a test for effectiveness of the treatment to be conducted during the 2003 growing season and also in the following year. In general, all aspects of this research effort are intended to provide cotton producers with an image based method for control of redvine, which will reduce their chemical inputs by facilitating accurate mapping for monitoring weed pressure and custom application of herbicide.

Study Area

The study area, field T167-10 was located on a 20.4 hectare field (50.4 acre) with a history of moderate redvine infestation. This field was planted with cotton (*Gossypium hirsutum*) and is located in the Southeastern United States; Perthshire Farms, Gunnison, Mississippi (Figure 2).

Hypotheses

(1) Mean reflectance for remotely sensed imagery will differ significantly over redvine, cotton, senescing cotton, and bare soil.

H_o: μ_{i} redvine = μ_{i} cotton = μ_{i} senescing cotton = μ_{i} bare soil **H**_A: μ_{i} redvine • μ_{i} cotton • μ_{i} senescing cotton • μ_{i} bare soil Where $_{i}$ = remotely sensed imagery

- (2) An overall classification accuracy for development of herbicide prescriptions will be 90% or better.
 - H_{\circ} : overall classification accuracy < 90% H_{\circ} : overall classification accuracy 90%
- (3) Effective treatment will result in a lesser percent area of redvine infestation in 2003 when compared to the previous 2002 growing season.
 - **H**_•: %redvine area SVH in 2002 % redvine area SVH in 2003
 - H_{A} : % redvine area SVH in 2002 > % redvine area SVH in 2003

Experiment Design

The field selected for study is expected to provide a dispersed spatial distribution of redvine that will be ideal for developing a robust classification scheme. The replicated control design is intended to organize the study area into strips, where treatment and no treatment strips have similar percent coverage of redvine (Figure 3). There were 16 strips in the field, where 11 of the strips received site-specific herbicide treatment, and the remaining 5 control strips received no herbicide treatment. Each strip was 24-row in width (24.384 m, 80 ft) and ran the length of the field (approximately 400 m).

Imagery and Field Data Specifications

<u>Image Data</u>

This experiment relied upon airborne multispectral imagery acquired at 1-meter resolution by the Institute for Technology Development's RDACS camera system. RDACS is a multispectral imaging system with three narrow bands (+/-10nm) centered at 540, 695, and 880 nanometers. Imagery acquired on August 27th was used to generate a stratified random sampling scheme for field data collection and characterization of the features within the study area. Imagery from the 23rd of September was used to generate the final prescription map.

Originally, the experiment called for the ground truth image and prescription base image to be of the same date in order to reduce classification error resulting from natural changes in the field over time. Due to severe weather events in the weeks prior to, during, and after defoliation, image acquisition was not possible within the targeted window. Field T167-10 was defoliated on September 24th and harvested 7 days later on the 2nd of October. Imagery was acquired over the study area on September 23rd, one day before defoliants were applied by airplane. Ground truth data were collected on August 29th for spectral analysis of the feature classes pertinent to this study. This august data set was also used as ground truth for the classification image much reduced in vegetation, as the chemical defoliants would have head 10-14 days to prepare the field for picking. An image taken at this time would predominate in bare soil type features, with only the most resistant vegetation apparent in the field (presumably the redvine).

Post defoliation and pre-harvest days are the dates that define the optimal window of opportunity for this project. The normal time period associated with this window will be 10-14 days. Field T167-10 was harvested 7 days after defoliation. This deviation from normal practices was due to severe weather associated with Tropical Storm Isidor and Hurricane Lili. The field was defoliated just before the arrival of the remnants of Isidor, and hurriedly picked just before rain from Lili arrived. These consecutive weather events, having both occurred at a critical time in the growing season, will likely be the most significant factors affecting the 2002 cotton harvest in the Mississippi delta region.

<u>Field Data</u>

Field data were collected with a World Navigator GPS (Teletype) to include field boundaries and treatment strips, along with point and polygon data, for development of training sets for classification. Stratified random points generated across a 10 class equal area NDVI were used in support of the image classification and error assessment, where 15 points were collected in each NDVI class.

The point data were collected in a 3x3 meter grid. The sample area was broken into 9 subareas (or cells) 1x1 meter in size. Each sample point was characterized for the majority feature class present, and at points where redvine were present, the approximation density was recorded as shown in figure 4.

Ground truth data were collected on 08/29/02 after the crop had begun to "cut out". "Cut-out" is a generally imprecise term suggesting the transition out of rapid vegetative growth into a state where all photosynthate and translocatable mineral nutrients are allocated to boll growth, and, vegetative growth and development (including fruit initiation) end. "Cut-out" is usually thought of as the time of achievement of the harvestable boll load. It is commonly indicated by the decreasing number of nodes above (first position) white flower = 5 (Baker, personal communication, 2002). In addition, cut out is referred to as a point during the growing season where the field peaks in vegetative vigor. This is usually apparent in imagery as thick canopies of vegetation begin to decline in vigor and reflectance from soil features increases in the absence of shadowing leafs. This was selected as the ideal time to capture imagery that would contain all of the targeted feature classes for spectral analysis.

Methodology

Imagery was acquired over the field during defoliation as weather permitted. Images from August 27th and September 23rd were used to establish spectral separability between feature classes and to generate a prescription for herbicide.

Image Processing Procedures

- 1. Bands were band-to-band registered. The RDACS sensor has 3 separate Kodak cameras, each with a filter to allow the energy of the appropriate wavelength to reach the its CCD array. As a result, the image frames are not co-registered. The band-to-band registration process was performed to spatially register the bands to each other.
- 2. Radiometric calibration was performed on the imagery. This process uses pseudo-invariant features that were near the experiment field as reference for the calibration process. These features included asphalt, gravel and concrete bridges. Spectroradiometer reflectance measurements of the pseudo-invariant features were taken and were used to transform the raw 8-bit Digital Numbers (DNs) to percent reflectance in the imagery. A linear regression was performed between the digital numbers of the pseudo invariant features retrieved from the imagery and the true percent reflectance measurement

for each pseudo invariant feature. The linear regression equation was calculated and applied to the imagery to convert the data to percent reflectance.

- 3. Imagery was georeferenced to a combination of Digital Ortho Quarter Quads (1:12,000 National Mapping Accuracy Standard) and GPS reference points acquired around the study area. The process used nearest-neighbor resampling and the output data was projected to the Universal Transverse Mercator (UTM) coordinate system and WGS84 datum. All data and analysis was performed in UTM. However, the final prescriptions were unprojected to lat/long coordinates to accommodate the applicator software.
- 4. All non-field areas, including field edges and roads among the fields, were masked out of the image scene, leaving only pixels within the experiment field.
- 5. A normalized difference vegetation index (NDVI) was generated from the image data.
- 6. The imagery was degraded from 1 to 3 meter resolution to overlay with ground truth data collected with 3x3 meter grid.
- 7. Various classifiers were applied to image data and NDVI images were classified according to threshold values as determined by statistical analysis.
- 8. Prescription spray grids were generated from the classification images.

Statistical Analysis

The ground truth data were assembled within a GIS software package (Esri ArcView). Digital values were extracted from the 8/27/02 imagery over data points with a 1.5m radius at each data point. For each feature class, mean reflectances for each bands green, red, and NIR, were extracted from the RDACS multispectral imagery (Figures 5&6). The redvine feature class was sorted into 3 density groupings (Low Redvine•33%, Med Redvine•66%, High Redvine>66%). The average reflectance of high, medium, and low redvine, cotton, senescing cotton, and bare soil points were tested using the GLM analysis of variance in SAS.

To determine thresholds for NDVI classification, band ratios and indices, were calculated for each data point over the September 23rd imagery. Error matrices were generated to measure the accuracy of the classification images.

Results

To establish spectral speparability in the August 27th imagery, mean reflectances for green, red, NIR, NDVI, and GNDVI were analyzed for significant differences between each feature class (Table 1, Figures 5&6).

Within the green band (540nm) healthy cotton, senescing cotton, soil, and high density redvine are significantly different from each other at a minimum alpha level of 0.05 (Table 1). The redvine density groupings do not demonstrate good separability from each other in this band. The green band is successful in distinguishing healthy cotton from higher densities of redvine (P<0.007). This band was the only band that could distinguish High Redvine. This result matches visual observations made in the field. At full canopy, thick redvine patches were easily discernable with the naked eye. The redvine was apparent as it grew over the crop because of its brighter green color.

Analysis of the red band (695nm) produced results similar to those for the green band, however, in the red band there was no indication that High Redvine and Healthy categories were separable. Both the red and the green band successfully separate High Redvine from Senescing and Soil categories. The latter two categories will presumably be the dominant features within the post defoliant image.

The NIR band (880nm) distinguished redvine from senescing cotton. Unlike the red and green bands, the NIR band was able to differentiate High Redvine and Med Redvine categories from the Senescing cotton (P<0.001 and 0.0336, respectively). The red and green bands were both successful at distinguishing High Redvine from Senescing, but the NIR demonstrates potential to distinguish both High Redvine and Med Redvine from the Senescing category.

The NDVI values calculated from the 08/27/02 imagery produced similar results to those of its band inputs (NIR and Red). In contrast to those of the red band, NDVI results indicate separability between High Redvine and Low Redvine (P<0.0992). This may prove useful for distinguishing between densities of redvine.

GNDVI analysis results demonstrated the same separability (P<0.0344) between Healthy and High Redvine categories, as did the green band. However, there was no indication that GNDVI could separate any redvine category from senescing cotton. As previously mentioned, the dominating features in an image intended for this type of redvine application will likely be soil and senescing cotton.

In order to establish spectral separability between feature classes the high density redvine data set (High Redvine) should be considered the relevant redvine component of the study. This High Redvine grouping consists of data points where redvine density was recorded to be greater than 66 percent. The results show that all vegetation categories could be separated from one another by some component of image analysis. The green band separated all of the important categories: Healthy, Se-

nescing, Soil, and High Redvine. Mean reflectance from remotely sensed imagery differs significantly over redvine, healthy cotton, senescing cotton, and bare soil.

NDVI thresholding and Isodata classification schemes were explored to characterize the redvine infestation within the study area to derive a thematic map that would be used to generate a prescription for treatment of redvine. Due to the disparity between the dates of the ground data and the image data, feature classes within the field had changed over time. To compensate for these changes, the feature classes recorded for the ground data were grouped as Other and Redvine and used for image thresholding and error assessment.

The 09/23/02 image was pre-processed and classified using the isodata classifier to output 50 classes (Figure 7). The resulting classes were combined according to polygon data acquired around redvine during the ground data collection. Point data were used to generate an error matrix for the classification. The overall accuracy reported was 64.86% (Table 2). The producers accuracy for the redvine class was determined to be 45.83%. Producers accuracy indicates how well training set pixels of the given feature are classified. It should be noted that the redvine grouping in the ground truth data set contains redvine points of varying densities mixed with other feature classes. A particular point for redvine may have any combination of healthy and/or senescing cotton, along with soil features mixing within the sample point. Assessment of the classification imagery indicated that low and medium densities of redvine were being allocated to the same classes as the dominant feature senescing cotton.

Statistical analysis of ground truth data demonstrated an 80% accuracy when classifying the point data for redvine with a NDVI threshold level > -0.125. The NDVI image was output to a GRID file and reclassified, where values > -0.125 were coded as 'redvine' and lesser values were coded as 'other' (Figure 8). The ground data were compared to the image data by building a confusion matrix (Table 3).

The NDVI thresholding classification map generated an overall accuracy of 62.16% and a producers accuracy of 45.83% for redvine. After visual examination of the classification with the redvine points overlaid, it was apparent that many redvine points where positioned near the borders of the classes but not close enough to be considered part of the class. This is most likely attributable to GPS error. This research project called for the classification ground truth to utilize a GPS with submeter accuracy, but as previously mentioned the mission was cancelled due to severe weather events around the window of opportunity for image acquisition and ground truth collection. With low accuracies and limited ground truth data, another time constraint came into play. The application of Clarity® (BASF Corp.) must take place after harvest but before the first frost in order to effectively translocated to the root crown of the redvine. The first frost in Gunnison Mississippi usually arrives by mid to late October.

The field was harvested on 10/02/02. With similar reported accuracies, the classification maps were presented to the producer and it was agreed that the NDVI thresholding classification was to be the one applied to the field. A prescription map for the treatment strips was generated from the NDVI Classification (Figure 9). 'Spray' polygons were coded to put out Clarity® at a rate of 2qts/acre (4.67L/Ha) as directed by the manufacturer. The chemical was tank mixed with water to be applied at 20 gallons per acre. On 10/18/02 the prescription was applied to the field with a Melroe Spray Coupe fitted with Raven Industries' Viper Controller. An as-applied map was generated to report the actual rates as they were put out in the field. (Figure 10).

Effectiveness of the application will be determined in 2003. A ratio of percent coverage redvine will be assessed in 2003 for SSH strips and No Herbicide strips to determine if there is a significant difference between treatments and between treatments and years. In order to analyze effectiveness between growing seasons, a T-test of proportion will be conducted to determine if the herbicide was successful in controlling the redvine.

Economic Analysis

An economic analysis will be performed at the conclusion of the 2003 growing season based on net returns where:

Gross Revenue = Yield * Price of crop Herbicide Costs = Treatmet Acres * Herbicide Price Net Return = Gross Revenue – Herbicide Costs – Imaging Costs

Yield will be reported by yield monitors equipped with GPS during the 2003 harvest and economic analysis will be guided by agriculture economists at Mississippi State University.

Conclusions

Remotely sensed imagery can be used to separate healthy cotton, senescing cotton, bare-soil, and redvine. Analysis of the ground data collected on 08/29/02 demonstrated that healthy cotton, senescing cotton, and soil are easily separated in all

bands and indices that were examined. High densities of redvine showed significant differences from the non-redvine features within the green band. The NIR band has demonstrated the potential to separate high densities of redvine from senescing cotton.

The vegetation indices generated from the 08/27/02 image did not return results as good as those of the above mentioned bands. However, NDVI generated from the 09/23/02 image returned the best result after analysis of the ground data using 'redvine' and 'other' groupings of the sample points. This result may be attributable to the field having less healthy cotton to be allocated into the redvine classes and vice versa.

Future Work Recommendations

A favorable assessment of effectiveness in 2003, as well as a favorable economic analysis would suggest that further work be done in this area of research. A refinement of the ground data sampling design could result in more informative spectral separability results and higher classification accuracies. Although given the network type physiology of the redvine root system, it may be that lower densities of redvine do not need to be sprayed. Presumably there may be some lower level of redvine density, where cost of treatment outweighs the immediate benefit of the results.

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Table I. Statistic	Table 1. Statistical analysis of 08/27/02 mean reflectance using GLM test procedure.							
	Healthy	Senescing	Soil	High Redvine	Med Redvine	Low Redvine		
Healthy								
Senescing	0.0057							
Soil	< 0.0001	< 0.0001						
HighRedvine	0.0007	0.0398	< 0.0001					
Med Redvine	<mark>0.6352</mark>	<mark>0.6496</mark>	< 0.0001	<mark>0.1704</mark>				
Low Redvine	0.0233	<mark>0.6913</mark>	< 0.0001	<mark>0.1447</mark>	<mark>0.5621</mark>			
			Red Bai	nd				
	Healthy	Senescing	Soil	High Redvine	Med Redvine	Low Redvine		
Healthy								
Senescing	< 0.0001							
Soil	< 0.0001	< 0.0001						
HighRedvine	<mark>0.3339</mark>	0.0484	< 0.0001					
Med Redvine	<mark>0.7624</mark>	<mark>0.2040</mark>	< 0.0001	<mark>0.8215</mark>				
Low Redvine	0.0063	<mark>0.5309</mark>	< 0.0001	0.2140	<mark>0.3345</mark>			
			NIR Bai	nd				
	Healthy	Senescing	Soil	High Redvine	Med Redvine	Low Redvine		
Healthy								
Senescing	< 0.0001							
Soil	< 0.0001	< 0.0001						
HighRedvine	<mark>0.5773</mark>	< 0.0001	< 0.0001					
Med Redvine	<mark>0.7167</mark>	0.0336	< 0.0001	<mark>0.9628</mark>				
Low Redvine	< 0.0001	<mark>0.4124</mark>	< 0.0001	0.0031	0.0881			
			NDVI					
	Healthy	Senescing	Soil	High Redvine	Med Redvine	Low Redvine		
Healthy								
Senescing	< 0.0001							
Soil	< 0.0001	< 0.0001						
HighRedvine	<mark>0.4765</mark>	0.0130	< 0.0001					
Med Redvine	<mark>0.7783</mark>	<mark>0.1579</mark>	< 0.0001	<mark>0.9117</mark>				
Low Redvine	0.0033	<mark>0.5060</mark>	< 0.0001	0.0992	<mark>0.2779</mark>			
GNDVI								
	Healthy	Senescing	Soil	High Redvine	Med Redvine	Low Redvine		
Healthy	•			-				
Senescing	< 0.0001							
Soil	< 0.0001	< 0.0001						
HighRedvine	0.0344	<mark>0.6142</mark>	< 0.0001					
Med Redvine	0.6812	0.2838	< 0.0001	0.4622				
Low Redvine	0.0027	<mark>0.9456</mark>	< 0.0001	0.7079	0.3233			
Croon Bond								

Table 1. Statistical analysis of 08/27/02 mean reflectance using GLM test procedure.

If P value < 0.1 there is a significant difference.

Table 2. Isod	lata Classification	Error Matrix					
Ground Truth (Pixels)							
Class	Redvine pts	Other pts	Total				
Redvine	11	39	50				
Other	13	85	98				
Total	24	124	148				
Ground Truth (Percent)							
Class	Redvine pts	Other pts	Total				
Redvine	46	31	34				
Other	54	<mark>69</mark>	66				
Total	100	100	100				
		Overall Accuracy = $(96/148)$ 65%					
			Producers Accuracy				

Table 3. NDVI Classification Error Matrix								
Ground Truth (Pixels)								
Class	Redvine pts	Other pts	Total					
Redvine	11	43	54					
Other	13	81	94					
Total	24	124	148					
Ground Truth (Percent)								
Class	Redvine pts	Other pts	Total					
Redvine	46	35	36					
Other	54	<mark>65</mark>	64					
Total	100	100	100					
		Overall Accuracy = $(92/148)$ 62%						





(Map courtesy of North Carolina State University for the Southern Weed Science Society Weed Identification Committee)

Figure 1. Geographic distribution of redvine.



Figure 2. Study Area.



Figure 3. Experiment Design.



Figure 4. Ground Truth Sampling Unit.



Figure 5. Mean NDVI & GNDVI values per feature class.



Figure 6. Ground data spectra from August 27th imagery.



Figure 7. September 23 imagery and classification map.



Figure 8. NDVI Classification Map.



Figure 9. Prescription Map for Herbicide over Classification Map.



Figure 10. As-applied Map.