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Application of Remote Sensing Data to Assess Weed Infestation in Cotton

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Abstract: Field studies were conducted in 2002 at Long View Farm located in east-central Mississippi. Two cotton fields, Field-104 (area 42 ha) and Shop Field (area 65 ha), were selected for the remote sensing of the biophysical properties of the cotton crop. At each field, plots were laid out using previous crop Normalized Difference Vegetation Index (NDVI) into low, medium and high categories. The objective of the study was to determine the potential of spectral analysis of multispectral images and field spectroradiometer data for discriminating morningglory and grasses from cotton canopy. Multispectral images were used to derive NDVI temporal pattern analysis to discriminate weeds from cotton canopy and feature extraction techniques were used to identify and map morningglory on field basis. Images acquired on July 18 and August 28 showed lower NDVI values in the field where weeds were intermixed with cotton plants compared to weed-free cotton canopy. Near infrared band (850 nm) of the multispectral imagery and spectroradiometer ~ 750-1000 nm wavelength region showed promising results for discriminating between weed-free cotton canopy and cotton canopy with morningglory. A spectral extraction process identified and mapped approximately < 50 % of the weeds present in the study area.

Key words: Remote sensing, NDVI, near-infrared, spectral extraction, cotton

INTRODUCTION

Weeds infestation in field crops usually occurs in patches. Therefore blanket application of herbicide on entire field for weed control is neither economical nor environmentally safe. In site-specific farming, within field weeds patches are managed site-specifically. This practice is not only safe for the environment but will also reduce the cost. Therefore accurate detection and mapping is pre-requisite for site-specific weed control. Currently there are two approaches been used to detect and map the weeds in field crops i.e. real-time weed detection and spraying[1] and remote sensing from an aerial platform. However, real-time weed detection is time consuming and labor intensive. While remote sensing to discriminate weeds from crops using an aerial platform has a potential for site-specific weed management.

The potential for using plant reflectance spectra in precision agriculture has been the focus of Alchanatis *et al.*[2]; Beeri *et al.*[3]; Borregaard *et al.*[4]; Goel *et al.*[5]; Moran *et al.*[6]; Qin *et al.*[7]; Vargas *et al.*[8]. Applications investigated include, nutrient management by Jackson *et al.*[9]; Numata *et al.*[10]; Strachan *et al.*[11]; Subhash and Mohanan,[12]; Subhash and Mohanan,[13], monitoring quantity and quality described by Clevers,[14]; Idso *et al.*[15]; Kastens *et al.*[16]; Reyniers *et al.*[17] and the detection of insects and weeds for selective insecticide and herbicide applications denoted by Duppong *et al.*[18]; Heatherly *et al.*[19]; Johnson *et al.*[20]. The reflectance spectra of most green leaves are remarkably alike due to similarities in chemical composition and leaf structure by Neto *et al.*[21]. Plant pigments such as, chlorophylls and carotenoids, have major effects on the reflectance properties of green leaves in the visible wavelengths; whereas the reflectance properties in the Near-Infrared (NIR) are due primarily to differences in leaf structure by Gates *et al.*[22]. Absorption by chlorophylls *a* and *b* dominate the visible wavelengths for most green plants with features occurring at 430 and 670 nm for chlorophylls a and at 460 and 650 nm for chlorophyll b. However, these properties are not entirely responsible for the reflectance of vegetation canopies in remotely sensed imagery because a vegetation canopy is a mosaic of leaves, flowers, stems and shadows against a soil background. So the reflectance properties derived from aerial remote sensing platform of vegetation are primarily due to reflectance at the canopy level, however, the chemical composition of plants can influence these values.

Weed detection through remote sensing: To differentiate/ discriminate spectral response of different types of vegetations is a challenging task. In remote sensing image analysis two approaches have typically been used for identification and mapping weeds by Hatfield and Pinter,[23] in cultivated crops. The first approach is to detect geometric differences between the crops and weeds, such as leaf shape by Perez *et al.*[24] or plant structure by Brown *et al.*[25]. The second approach is based on differences in spectral reflectance by Strachan *et al.*[11]. Since, most of the cultivated crops have a different growth and development pattern than weeds, another approach could be to examine the temporal patterns of vegetation indices by Zwiggelaar,[26] throughout the growing season. Goel *et al.*[5] used a Compact Airborne Spectrographic Imager (CASI) to relate the reflectance obtained in the 72 visible and Near-Infrared (NIR) wavebands (from 409 to 947 nm) to differences associated with combinations of weed control (none, full, grasses only or broadleafs only). They reported the waveband centered at 676-685nm in the red region and 744-830 nm in the near-infra-red region have good potential for distinguishing weeds from corn. Perez *et al.*[24] used near-ground image capturing and processing techniques to detect broad leaved weeds in cereal crops. The color information and shape analysis techniques were used to discriminate between vegetation and soil background and between crop and weeds. The computer algorithm was assessed with human classification. The results indicate that it is feasible to use image processing techniques to estimate and discriminate the relative leaf area of weeds and crop.

The overall objective of this study was to identify and map different types of weeds using remotely sensed multispectral imagery and field spectroradiometer data.

MATERIALS AND METHODS

This field study was conducted at Long View Farm located in east-central Mississippi, in 2002. Two cotton fields, Field-104 (42 ha) and Shop Field (65 ha), were selected for the remote sensing of the biophysical properties of the cotton crop. At each field plots were laid out using previous crop normalized difference vegetation index (NDVI) into low, medium and high categories. A comprehensive bi-weekly data collection process began at the beginning of each growing season, which includes the plant mapping, percent defoliation, stand density, insect damage, disease incidence, weed severity rating and collection of soil and plant tissue samples for fertility and nematode analysis and canopy GAIA Environmental Research (GER 1500) reflectance. The GER 1500 has a spectral range of 350-1050 nm with a bandwidth of 1.5 nm and collects 512 spectral bands. Multispectral aerial imagery data was also acquired throughout the growing season. The data was collected by GeoVantage using a 8-bit real time camera system at a spatial ground resolution of 0.5-m. Spectral resolution width was 80-nm except near-infrared band which was 100-nm and the four bands were centered at 450 nm (band 1 = Blue), 550 nm (band 2 = green), 650 nm (band 3 = red) and 850 nm (band 4 = NIR). A widely used vegetation index is the NDVI. NDVI is an indicator of crop biomass production and canopy vigor:

$$\mathrm{NDVI} = \left(\frac{\mathrm{NIR}_{850} - \mathrm{R}_{650}}{\mathrm{NIR}_{850} + \mathrm{R}_{650}} \right)$$

To identify particular weed specie, the field was surveyed and high concentrated weed patch locations were marked with a GPS system. Two major types of weeds were found in the study area, morningglory (*Ipomea lacunosa*) and Bermudagrass (*Cynodon dactylon)*.

To map weeds in the field based on differences in spectral reflectance between cotton crop and mornininggglory and the Bermudagrass specie, two approaches were used as follows:

- NDVI maps were generated for July 18 and August 28 imagery to discriminate temporal pattern of crop and weed.
- A new technique of feature extraction was used in a Geographic Information System (GIS) environment in which a user creates a feature model by hand-digitizing locations of the features on multispectral image and the software learns based on the user's model and return features in a shape file that closely resemble the features provided.

The above mentioned simplified approaches were used to discriminate and map morningglory and Bermudagrass in the cotton fields.

RESULTS AND DISCUSSION

Figure 1 shows marked (filled red triangle) locations of the morningglory and Bermudagrass weeds on top of the multispectral image taken on July 18, 02. The high concentrated patches of weeds are distinctive as green color as compared to the reddish cotton canopy

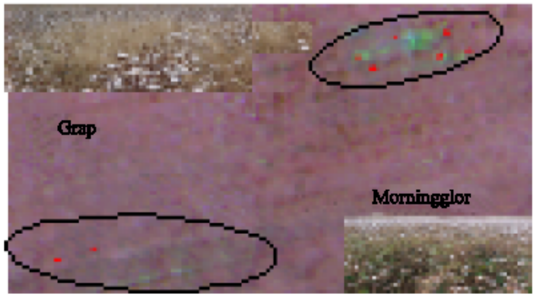

Fig. 1: Multispectral Imagery taken on July 18 showing marked area of Morningglory and bermudagrass

background. To show the difference in growth pattern between weeds and cotton canopy, NDVI maps were derived from July 18 and August 28 multispectral imagery using those two marked areas in the field. The Digital Number (DN) based NDVI ranged from 0.09 to 0.27 for July 18 and 0.04 to 0.24 for August 28 multispectral images. The lowest NDVI values were recorded for areas with dense dominant bermudagrass stand patch whereas the surrounding healthy cotton canopy has a distinctive light green to dark green color. Comparing the two NDVI maps one can notice the distinctive pattern of growth between weeds and cotton crop and this behavior can be used as tool for separating the species (Fig. 2).

To show the effectiveness of multispectral image spectra, pixels DN values were extracted which included: Marked weed (Bermudagrass and morningglory) areas (Fig. 1) of the field, healthy cotton canopy, bare soil and water. The blue (450 nm), green (550 nm) and red (650 nm) were not effective in discriminating between weed-free cotton canopy and cotton canopy with weeds of either Morningglory or stand of bermudagrass, while as expected, the same wavelengths showed a distinctive pattern over soil and water. DN values derived from the NIR band (850 nm) over the cotton canopy clearly differed from morningglory, bermudagrass, bare soil and water (Fig. 3). The NIR's DN values were distinctively higher for cotton canopy without any weeds than over morningglory mixed with cotton canopy, or bare soil and water. This could be due to the fact the morningglory intermixed with the cotton canopy have much less reflectance in the chlorophylls-absorption region (550- 650 nm) and much higher reflectance in the NIR region. However, the weeds reduced the NIR reflectance.

Figure 4 shows the comparison of average field spectroradiometry spectra of cotton canopy, cotton canopy with *Alternaria* disease symptoms + morningglory, soil + debris and cotton canopy infested with heavy morningglory. Cotton canopy infested with either weeds (morningglory and/or Bermudagrass) or *Alternaria* disease clearly differed from cotton canopy without weeds, which was easily differentiated primarily based on percentage reflectance values between 750 nm-1000 nm wavelength region. The highest percentage reflectance spectra was in the order of cotton canopy without any weeds, cotton canopy with medium intensity (rated 3 on the scale from 0-5, whereas 5 is considered as the highest intensity of morningglory intermixed with cotton canopy) of weeds + *Alternaria* disease symptoms on cotton leaves, bare soil and followed by cotton canopy intermixed with heavy intensity (rated 5) of morningglory. Alteraria leaf spot caused by *alternaria macrospora,* a fungus that infect the cotton leaves, brackets and bolls. Cotton is fairly tolerant in the dry weather conditions, but under high humidity or rainfall, which was the study during 2002 growing season, spores are produced that are windblown or splashed on cotton plants. Red lesions appeared where spores have germinated and grown into host tissue. Figure 4 clearly illustrates the effects of severe symptoms of *Alternaria* disease symptoms, which reduces the spectral reflectance of cotton in the NIR region,

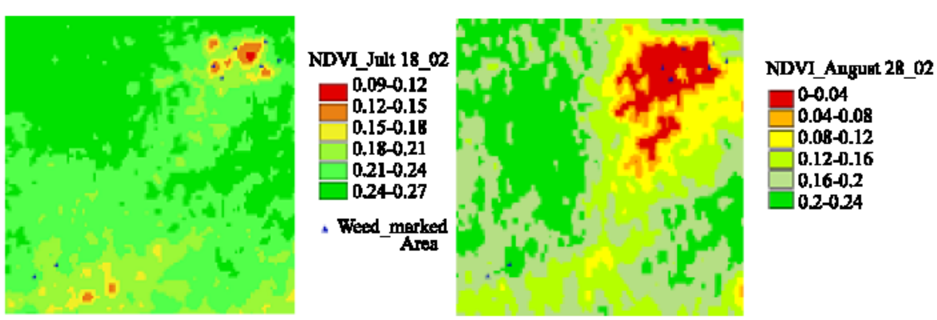

Fig. 2: NDVI based discrimination between cotton canopy, morningglory + cotton canopy and bermudagrass

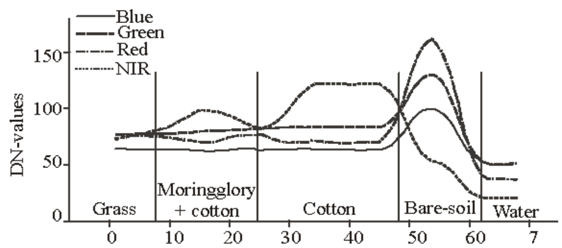

Fig. 3: Comparison of the digital numbers of blue (450 nm), green (550 nm), red (650) and NIR (850) of Bermudagrass, morningglory + cotton canopy, cotton canopy, bare soil and water. Multispectral Image was taken on July 18 over marked area of morningglory and bermudagrass in Fig. 2

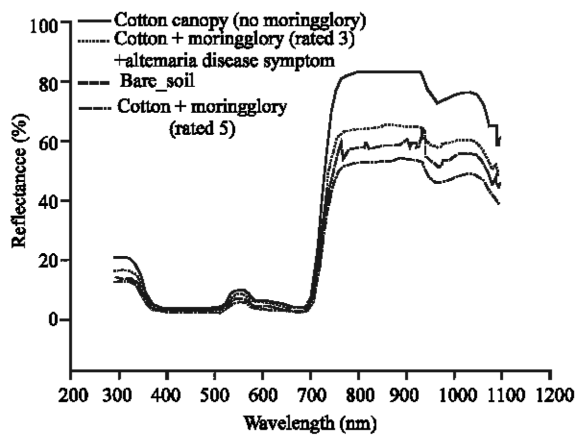

Fig. 4: Comparison of average field spectroradiometer spectra of cotton canopy, cotton canopy with Alternaria disease symptoms + morningglory, soil+debris and cotton canopy infested with heavy morningglory

Fig. 5: Feature based discrimination of morningglory and bermudagrass from cotton canopy using multispectral image taken on July 18, 02

compared to healthy crop.

The above results indicate that morningglory and *Alternaria* disease symptoms on cotton leaves reduced the percentage reflectance in the NIR band significantly. Behavior of the weeds during the month of July can be used as a tool to differentiate different vegetation species in the field. To achieve the second objective of this study, feature extraction process was used in the GIS environment in which a feature model was created by hand-digitizing locations of the morningglory and Bermudagrass on the multispectral image and the software learned based on the model input and return features in a shape file that closely resemble the features provided. This methodology was applied on the July 18 multispectral imagery (Fig. 5). The key point to successfully extract the pixels location where weeds are intermixed with cotton canopy is to locate and train the software. The resultant map shows the location of morningglory and Bermudagrass in the 104-Field and shop-Field. By this methodology approximately 50% of the weeds were mapped, due to difficulty in locating a pure pixel location of morningglory in the image (Fig. 5).

CONCLUSION

This study indicated that the near-infrared band was most effective for weed detection in cotton field. Spectral extraction method identified about 50% weeds in cotton. We also found that remote sensing utilizing temporal pattern of NDVI is a valuable index to discriminate crops from weeds. This procedure can be used for target application of herbicides according to the spatial distribution of weeds.

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