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REMOTELY SENSED VERSUS GROUND-BASED WEED MAPPING IN COTTON

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Abstract

Remotely sensed images contain site-specific information about conditions in agricultural fields. Researchers have developed several indices that use information extracted from images to represent plant growth status. The normalized difference vegetation index (NDVI) is a commonly used one for agricultural applications. The aim of this study was to identify the relationships among remotely sensed NDVI, weed intensity levels measured at ground level, and plant canopy coverage measured at ground level, all in one cotton field in the Mississippi Delta. Four-band images of the study site were acquired by Geodata Inc. with their GeoVantage® imaging system. The blue band is centered at 450 nm, the green band at 550 nm, the red band at 650 nm, and the near-infrared band at 850 nm. A mosaic image was created from individual scenes with the Erdas Imagine mosaic tool. The resulting image resolution was approximately 0.5 m. A ground-based weed mapping system was developed to measure the weed intensity and distribution in a cotton field. The weed mapping system includes WeedSeeker® PhD600 sensor modules to indicate the presence of weeds, a GPS receiver to provide spatial information, and a data acquisition and processing unit to collect and process the weed data and spatial information. Crop canopy coverage data were collected at approximately the same time as image acquisition and mapping of weed intensity levels. Results indicated that both weed intensity level and crop coverage were significantly correlated with NDVI, and that weed intensity levels should be considered when NDVI is used to predict crop growth and development.

Introduction

Literature Review

The technologies of remote sensing and precision agriculture are, in combination, playing an increasingly important role in agricultural production. Because of their potential for high spatial and spectral resolution, satellite and aircraft images can contain detailed site-specific information about conditions in agricultural fields. They can be used for monitoring crop growth, yield potential, soil conditions, weed intensity, etc. (Thomasson et al., 2003; Broner et al., 2002; Varvel et al., 1999). Spectral reflectances from image data have often been used to calculate vegetation indices that have been related to crop growth status. NDVI (normalized difference vegetation index) is one of the vegetation indices that have been commonly used in remote-sensing applications in agriculture.

Much research has been conducted to predict crop growing conditions with remotely sensed images. Goel et al. (2003a) used hyperspectral image classification to detect weed infestations and nitrogen status in corn. They found it difficult to distinguish between the effects of weeds and nitrogen treatments. However, when one factor was considered at a time, maps indicating weed infestation or nitrogen treatment could be generated with a satisfactory level of accuracy. Goel et al. (2003b) also explored the potential of airborne hyperspectral sensing in the estimation of various corn biophysical parameters and other canopy-related parameters. They found good agreement between observed and predicted values of various parameters. For example, it was observed that NDVI-based models for aerial measurements performed better than the multiple-reflectance-band-based models in predicting corn biophysical parameters. Kostrzewski et al. (2003) tested the ability of a ground-based remote sensing system to separate water and nitrogen stress in cotton using the CV (coefficient of variation) for water and nitrogen stress indices. The CVs of water and nitrogen stress indices increased with water and nitrogen stress, and the CV of stress indices was a more reliable measurement of water and nitrogen status than the mean value of the indices. According to Yang et al. (2001), for cotton, grain sorghum, and corn, airborne multispectral imagery acquired around maximum vegetative development or during early productive development would best describe expected yield or yield variability. Digital images and spectral yield maps could be useful for identification of stress areas that need ameliorative site-specific treatment. Diker et al. (2001) reported their use of aerial images to monitor temporal changes of irrigated corn in northeastern Colorado. The results showed that spatial and temporal variability of corn plant growth and yield could be monitored and perhaps estimated by an integrated use of aerial images, GIS, and ground observations. Plant et al. (1999) investigated the relationships between remotely sensed reflectance data and cotton growth and yield. The results demonstrated that NDVI integrated over time showed a significant correlation with lint yield. The spatiotemporal pattern of NDVI reflected stress factors and was approximately coincident with the onset of measurable water stress.

Researchers have attempted to develop herbicide application systems for precision weed control. In general, the systems are either map-based or sensor-based. A map-based system uses weed maps that are created with historic weed data to make application decisions before spraying. The sensor-based system uses data from the sensor for decision making in real time in situ. Lamm et al. (2002) developed a real-time robotic weed control system including machine vision, a controlled illumination chamber, and a precision chemical applicator. The system was able to correctly spray 88.8% of weeds in commercial cotton fields at a speed of 0.45 m/s. Bajwa and Tian (2001) used an airborne digital color-infrared sensor to acquire remotely sensed images for mapping weed density. Multiple regression and artificial neural network approaches were used to build models for weed density prediction. The regression models and artificial neural network models resulted in strong correlations between the predictions and the ground truth ($R^2 \geq 0.82$). Downey et al. (2003) reported the use of an automatic weed mapping location and identification system to map nutshedge in a cotton field. The system had an overall accuracy of about 85% and illustrated the potential for significant labor savings over conventional weed mapping methods. Hummel and Stoller (2002) conducted a multi-year study using a herbicide applicator equipped with Pachen's WeedSeeker® PhD600 single-sensor modules. Their results showed that the savings in the amount of glyphosate used to control weeds in corn and soybeans could be up to 80% in a particular year, and that over time the savings could average about 45%. Antuniassi et al. (2003) also evaluated the performance of the WeedSeeker® PhD600 optical weed detection system. They used four different soil surfaces and eight combinations of weeds with leaf areas between 1.50 and 39.68 cm^2 in their test. The results indicated that the PhD600 system did not detect 100% of weeds if the leaf areas were smaller that 5.32 cm^2. Background surfaces and plant architecture had significant influences on weed detection.

Objectives

The objectives of this study were:

1. To develop a system to collect weed intensity data with the WeedSeeker® PhD600 optical weed detection modules along with spatial information from a GPS receiver.
2. To identify the relationships among airborne multi-spectral imagery and ground truth data of weed intensity and cotton plant canopy coverage in a cotton field in Mississippi's Delta region.

Materials and Methods

Study Site

The study site was a 13-ha commercial cotton field located in Stoneville, Mississippi. The field contains of mixed soil types (Be-Bosket very fine sandy loam, Dk-Dundee silty clay loam, Dp-Dundee very fine sandy loam; and Sd-Sharkey silty clay loam) and has been land formed to a 0.15 m per 100 m slope (drains from West to East). Tillage of the field has been no-till from 2002 to 2003. Cotton was planted in May 2, 2002 and April 29, 2003 for this study.

Development of the System for Weed Intensity Data Collection

A ground-based weed mapping system was developed to measure weed intensity and distribution in a cotton field. The system includes WeedSeeker® PhD600 optical sensor modules for weed detection, a GPS receiver for measuring location, and a data acquisition and processing unit to collect and process weed data and spatial information (Figure 1).

The WeedSeeker® PhD600 sensor is an active optical sensor with its own light source. Its optical and electronic components are housed together in a plastic module (Figure 2). The WeedSeeker® sensor is the key part of the WeedSeeker® selective spray system. The sensor detects the presence of a weed by measuring the reflectance of materials in its view (e.g., weeds and bare ground). If the sensor identifies a weed, it will output an electronic signal to a solenoid valve that activates a nozzle to spray the weed. Thus, there is no spraying on bare ground, and herbicide usage can be significantly reduced.

A four-row hooded sprayer, which was equipped with WeedSeeker® selective spray system, was employed for weed-intensity data collection. There are five hoods in this four-row sprayer (Figure 1). Two WeedSeeker® sensor modules were installed under hood 1 at the middle and left side of the hood, while only one sensor module was installed in hood 5 on the right side of the hood. Three sensor modules were installed in each of the rest of the hoods (Figure 1). In order to measure weed intensity in this study, an external signal wire was introduced into each sensor module for collecting sensor output (Figure 2). The signal wire would read high (about 1.15 VDC) if a weed was detected by the sensor, and it would read low (about 0.11 VDC) if no weed was detected. The sum of the outputs of all 12 WeedSeeker® sensors was used to represent the weed intensity at a specific location in the field. Thus, the weed intensity value varied from about 1.3 to 13.8 Volts. Signal wires of each sensor were connected to the data acquisition unit with four 6-m long cables. The data acquisition unit and the GPS receiver were installed inside the tractor cab. The 12-V battery on the tractor was used to provide power to the system.

The data acquisition and processing system was based on a single-board-computer (SBC) with a 16.5-cm flat panel display (NEC TFT) (Figure 3). The SBC included a 233-MHz processor with standard PC interfaces and was operated with a +5-VDC power supply. The system has one serial port, a PCMCIA controller, and a 16-channel 12-bit analog–to-digital converter (ADC). The analog signals from the 12 WeedSeeker® sensors were input to the ADC and then collected and analyzed by the SBC. The serial port of the system was employed to record spatial information from the GPS receiver in real time. Weed intensity and spatial information are displayed on a color screen and stored in a PCMCIA memory card. The GSA and RMC sentences from the receiver are used to provide PDOP (position dilution of precision), location, and speed data. Location data are differentially-corrected with the signal from the nearest U.S. Coast Guard beacon station, but a more accurate private signal could easily be used instead. The system's data acquisition box reads data directly from the DGPS receiver. Data that include weed intensity and spatial information could be downloaded from the PCMCIA card of the data acquisition system to a laboratory computer and processed with GIS software such as ArcView® or Arc/Info. Weed intensity maps were able to be created to show the weed distribution within a field. The C programming language was used for the system operation code.

Data Collection

Field measurements included weed intensity as measured with the weed mapping system, manual measurements of crop canopy coverage, and remotely sensed images from which NDVI was calculated. Dates when field measurements were made are given in Table 1. In 2002, weed intensity and canopy coverage data were collected only once, but images were collected twice. In 2003, all field measurements were collected twice. The sensitivity level of the WeedSeeker® controller was set to 3 during weed intensity data collection. The travel speed of the sprayer was about 8 km/h. Weed intensity data from the WeedSeeker® sensors and spatial data from a Trimble AgGPS132 receiver were collected once per second.

Cotton plant growth conditions, including plant height and crop canopy coverage, were measured and recorded at 32 sampling locations within the 13–ha experimental field (Figure 9). Crop canopy coverage is the percentage of plant vegetation in view (as opposed to bare ground, crop residue, weeds, etc.) when one is looking straight down on the field. This was measured from the leading edge of the plant canopy on one row to the leading edge of the canopy on the next row. It was known that the row spacing was 0.97 m, so crop canopy coverage could be calculated by dividing the difference between row spacing and the canopy width by the row spacing.

Four-band images of the study site were acquired by Geodata Inc. with their GeoVantage® imaging system. Flying altitude was approximately 1300 m. A mosaic image was created from individual scenes with tools available in Erdas Imagine software. The resulting image resolution was approximately 0.5 m. The blue band of the images was centered at 450 nm, the green at 550 nm, the red at 650 nm, and the near-infrared (NIR) at 850 nm. NDVI was calculated on a pixel-by-pixel basis by dividing the difference between the NIR and red digital numbers by the sum of NIR and red digital numbers; i.e., NDVI = (NIR – red) / (NIR + red).

Data Analysis

The weed map data consisted of a series of locations (latitude and longitude) with a weed intensity value. Image digital numbers were extracted for each weed intensity location as follows. Square windows with sides of 1 m were constructed around each weed intensity location. An average, weighted by the area of the portion of each pixel in the window, was calculated with software written in the C++ programming language (see equation below).

$$Wt\_average = \frac{\sum pix\_value * pixel\_area\_in\_buffer}{buffer\_area}$$

Where

Wt_average: Average of pixel values weighted for the actual area of each pixel in the sample area;
Pix_value: Digital number of pixel;
Pixel_area_in_buffer: Actual area of the pixel that lies within the sample area;
Buffer_area: Sampling area around sample location.

Values of the *Wt_average* for each of the four image bands were combined with the weed intensity data. Using the same method as described above, both image digital numbers and weed intensities were extracted around each canopy coverage sampling point with a 10 m by 10 m square buffer.

After extracting image data, each record in the dataset included latitude, longitude, speed, weed intensity, and image values for bands 1 to 4. Then, NDVI was calculated at each weed intensity location by dividing the difference between the NIR and red weighted-average digital numbers by the sum of NIR and red weighted-average digital numbers; i.e., NDVI = (NIR – red) / (NIR + red). For the purpose of having visual comparisons, weed intensity maps, NDVI maps, and crop canopy coverage maps were created with ArcView®.

Data including crop coverage, weed intensity, and NDVI were analyzed with the REG procedure in SAS®. Parameter coefficients and coefficients of determination (R^2) were obtained in the regression analyses and used to compare linear relationships between crop canopy coverage and NDVI, crop canopy coverage and weed intensity, and crop canopy coverage and NDVI plus weed intensity.

In addition to these statistical analyses, the artificial neural network (ANN) methodology was chosen to identify relationships between weed intensity and image data. The 2003 data were used to train a feed-forward back-propagation ANN. The NevProp software was used for creating, training, and testing the ANN. Reflectances (digital numbers) from the four original image bands were used as inputs and were represented as real number values. Weed intensity was the output and was broken down into six categories (Table 2). Once the weed intensity categories had been selected, each category was encoded in binary format and was represented by a particular output unit in a group of six output units (Table 2). When a weed intensity value fell within particular range, then the output unit that represents that range was set to 1 to indicate true. The remaining five output units were set to 0 (false) to indicate that the weed intensity did not fall in any other range. A total of 15,179 data inputs and their associated outputs were used. Of all the data patterns, 80% were used for ANN training. To test the ANN, 20% of the dataset was set aside for only testing.

Results and Discussion

Relationship Among Crop Canopy Coverage, Weed Intensity, and NDVI

Figures 4, 5, 6, and 7 show the relationships at various dates between weed intensity as measured with the weed mapping system and NDVI calculated from the images. It was observed that there was not a generally strong correlation between weed intensity and NDVI. However, the figures indicate the generally significant positive correlation between them, and for the measurements made on 07/14/03, the correlation was fairly good (R^2=0.45). These results imply that weed intensity in the field had some relationship with remotely sensed images.

Results of the analyses to determine relationships between crop canopy coverage and NDVI, crop canopy coverage and weed intensity, and crop canopy coverage and NDVI plus weed intensity are given in Table 1. For all comparisons except June 2003, crop canopy coverage was significantly correlated with NDVI plus weed intensity. However, none of relationships were particularly strong ($0.20 \leq R^2 \leq 0.53$). The crop canopy coverage was most closely correlated with NDVI and with NDVI plus weed intensity in July 2002. The R-square values were 0.48 and 0.53, respectively. In June 2003, the crop canopy coverage had no significant relationship with weed intensity and NDVI. This is likely due to the early growth stage of the cotton plants, which would tend to cause NDVI to be very low and thus result in very noisy data. It was found that the models that have NDVI and weed intensity as independent variables also did a better job at estimating crop canopy coverage than did the models that have only NDVI as an independent variable. This indicates that weed intensity information was a useful additional predictive variable when NDVI was being used to predict plant growth and development. Figure 8 is a plot of actual crop canopy coverage versus predicted crop canopy coverage. The predicted crop canopy coverage determined with the model including both NDVI and weed intensity as independent variables had a stronger correlation with the actual crop canopy coverage (R^2=0.73) than that predicted with the model including only NDVI as an independent variable (R^2=0.69).

Map Comparison

Figure 9 includes weed intensity and crop canopy coverage maps created with data collected on 07/10/02. The NDVI maps resulting from both July 2002 images are shown in Figure 9 as well. Figure 10 includes color-infrared images corresponding to the NDVI maps in Figure 9. It can be observed that a similar pattern exists in the maps and images of Figures 9 and 10. Weed intensity at the top of the weed intensity map was heavier than in the rest of the field. Crop canopy coverage and NDVI also tended to be greater in this portion of the field. However, in the middle of the field from west to the east, a strip on the weed intensity map exhibited high weed intensity, while in the same part of the field NDVI was high but crop canopy coverage was not.

Figures 11 and 12 include maps created with data collected in late June and on 14 July 2003, respectively. It was observed that the crop canopy coverage map in both figures did not match the NDVI map well in terms of relative magnitude. But if the pattern of the crop canopy coverage map were visually combined with the pattern of the weed intensity map, a pattern very similar to that of the NDVI map would appear. This result makes sense because both crop coverage and weed intensity apparently relate to NDVI.

Artificial Neural Network Analysis

Table 3 shows the percentage of output predictions that were correct after training and testing the neural network. More specifically, the accuracy was the percentage of network predicted output patterns that match the expected output patterns. The network never achieved an accuracy greater than 40%. It appears that no matter the number of epochs used for training, the neural network never learned to accurately predict weed intensity from the provided NDVI data. The results of the ANN analysis roughly matched those from the SAS analysis. NDVI could not be used directly for weed intensity prediction in this study, because crop canopy coverage has a significant relationship with NDVI as well.

Conclusions

A weed mapping system was developed with the WeedSeeker® PHD600 sensor module as a weed detector. The system was able to simultaneously collect and process weed intensity data from 12 WeedSeeker® sensor modules and spatial information from a GPS receiver. The mapping system was tested in a commercial cotton field over two years. Weed intensity data that were collected with the system were analyzed along with remote-sensing and crop growth data. Weed intensity was somewhat correlated with NDVI, and NDVI was also correlated with crop canopy coverage. It was observed in this study that both weed intensity and crop canopy had significant relationships with remotely sensed images. Weed intensity should need to be taken into consideration as remotely sensed reflectance data from a field are used to predict crop growth and development.

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References

Antuniassi, U. R., M. D. S. Nery, W. P. A. Carvalho, E. R. S. Ruiz, and M. J. D. Leon. 2003. Performance Evaluation of an optical sensor for weed detection. *ASAE Paper No. 031160.* St. Joseph, Mich.: ASAE.

Bajwa, S. G. and L. F. Tian. 2001. Aerial CIR remote sensing for weed density mapping in a soybean field. *Transaction of the ASAE*, Vol(6): 1965-1974.

Broner, I., W. Bausch, D. Westfall, and R. Khosla. 2002. Decision support for crop management using remote sensing. *In: Proc. World Congress of Computers in Agriculture and Natural Resources*, Iguacu Falls, Brazil. pp. 339-346.

Diker, K., W. C. Bausch, and D. F. Heermann. 2001. Monitoring temporal changes of irrigated corn by aerial images. *ASAE Paper No. 011144.* St. Joseph, Mich.: ASAE.

Downey D., D. K. Giles, and D. C. Slaughter. 2003. Ground based vision identification for weed mapping using DGPS. *ASAE Paper No. 031005.* St. Joseph, Mich.: ASAE

Goel, P. K., S. O. Prasher, J.-A. Landry, R. M. Patel, and A. A. Viau. 2003a. Hyperspectral image classification to detect weed infestations and nitrogen status in corn. *Transactions of the ASAE*, Vol. 46(2): 539-550.

Goel, P. K., S. O. Prasher, J.-A. Landry, R. M. Patel, A. A. Viau, and J. R. Miller. 2003b. Estimation of corn biophysical parameters through airborne and field hyperspectral remote sensing. *Transactions of the ASAE*, Vol. 46(4): 1235-1246.

Hummel, J. W. and E. W. Stoller. 2002 On-the-go weed sensing and herbicide application for the northern cornbelt. *ASAE Paper No. 021021.* St. Joseph, Mich.: ASAE.

Kostrzewski, M., P. Waller, P. Guertin, J. Haberland, P. Colaizzi, E. Barnes, T. Thompson, T. Clarke, E. Riley, and C. Choi. 2003. Ground-based remote sensing of water and nitrogen stress. *Transactions of the ASAE*, Vol. 46(1): 29-38.

Lamm, R. D., D. C. Slaughter, and D. K. Giles. 2002. Precision weed control system for cotton. *Transaction of the ASAE,* Vol. 45(1): 231-238.

Plant, R. E., D. S. Munk, B. R. Robert, R. L. Vargas, D. W. Rains, R. L. Travis, and R. B. Hutmacher. 2000. Relationships between remotely sensed reflectance data and cotton growth and yield. *Transactions of the ASAE*, Vol. 43(3): 535-546.

Thomasson, J. A., J. Wooten, S. Gogineni, and R. Sui. 2003. Multitemporal Remote Sensing for Predicting Cotton Yield. *In: Proc. 2003 Beltwide Cotton Conferences*, Memphis, TN: National Cotton Council of America.

Varvel, G. E., M. R. Schlemmer, and J. S. Schepers. 1999. Relationships between spectral data from an aerial image and soil organic matter and phosphorus levels. Precision Agric., Intl. J. Adv. Precision Agric. 1(3): 291-300.

Yang, C., J. M. Bradford, and C. L. Wiegand. 2001. Airborne multispectral imagery for mapping variable growing conditions and yields of cotton, grain sorghum, and corn. *Transation of the ASAE*, Vol. 44(6): 1983-1994.

Table 1. Relationship among crop canopy coverage, NDVI and weed intensity.

Date	Dependent variable	Independent variable	Model	R^2	P value
weed intensity: 7/10/02 canopy coverage: 7/10/02 NDVI: 7/02/02	canopy coverage (cov)	NDVI	cov=72*NDVI+74.6	0.23	0.005
		weed intensity	cov=13.9*weed-96.2	0.37	0.0002
		NDVI, weed intensity	cov=18.8*NDVI+11.9*weed-70.9	0.38	0.0009
weed intensity: 7/10/02 canopy coverage: 7/10/02 NDVI: 7/17/02	canopy coverage (cov)	NDVI	cov=98.4*NDVI+59.2	0.48	<0.0001
		weed intensity	cov=13.9*weed-96.2	0.37	0.0002
		NDVI, weed intensity	cov=72.1*NDVI+6.6*weed-15.8	0.53	<0.0001
weed intensity: 6/24/03 canopy coverage: 6/20/03 NDVI: 6/21/03	canopy coverage (cov)	NDVI	cov=28.8*NDVI+42.1	0.06	0.1703
		weed intensity	cov=0.47*weed+35.5	0.04	0.2689
		NDVI, weed intensity	cov=23*NDVI+0.2*weed+39.7	0.07	0.3670
weed intensity: 7/14/03 canopy coverage: 7/14/03 NDVI: 7/14/03	canopy coverage (cov)	NDVI	cov=70.1*NDVI+50.9	0.39	0.0001
		weed intensity	cov=1.6*weed+33.2	0.20	0.0112
		NDVI, weed intensity	cov=117.4*NDVI-1.8*weed+68.6	0.47	0.0002

Table 2. Weed Intensity category and encoding.

Category	Weed Intensity Range	Encoded
High Low	1 -- 3.083	**1** 0 0 0 0 0
Low Low	> 3.083 --5.167	0 **1** 0 0 0 0
Low Medium	> 5.167 -- 7.250	0 0 **1** 0 0 0
High Medium	> 7.250 --9.333	0 0 0 **1** 0 0
Low High	>9.333 --11.417	0 0 0 0 **1** 0
High High	>11.417 -- 13.500	0 0 0 0 0 **1**

Table 3. ANN test result.

Number of Epochs	Test Accuracy (%)
100	0
250	30.6
500	40.0
1000	39.3
1500	22.9
2000	3.4

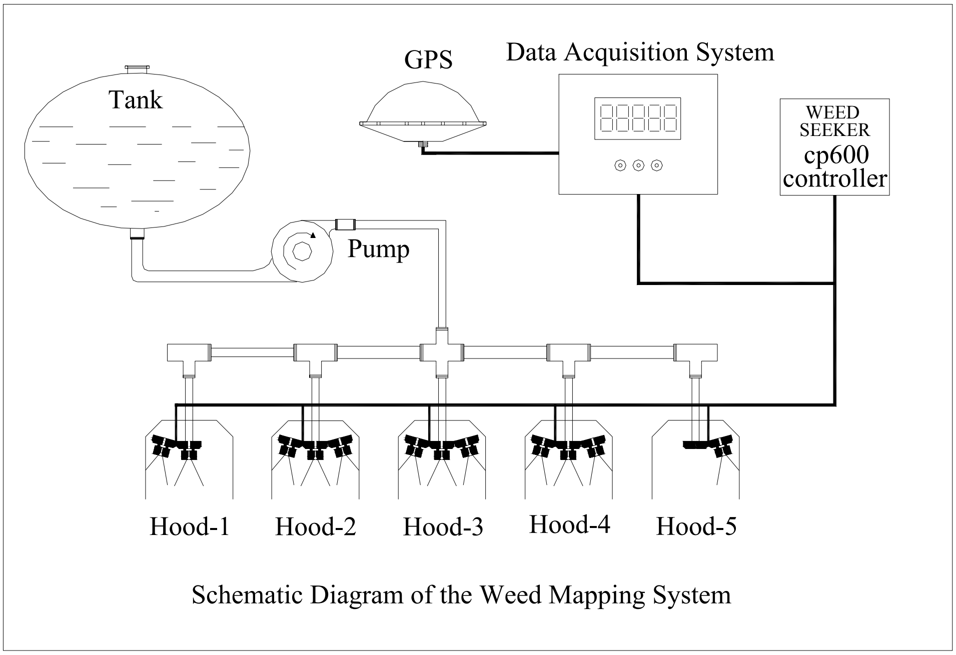

Figure 1. Configuration of the weed mapping system.

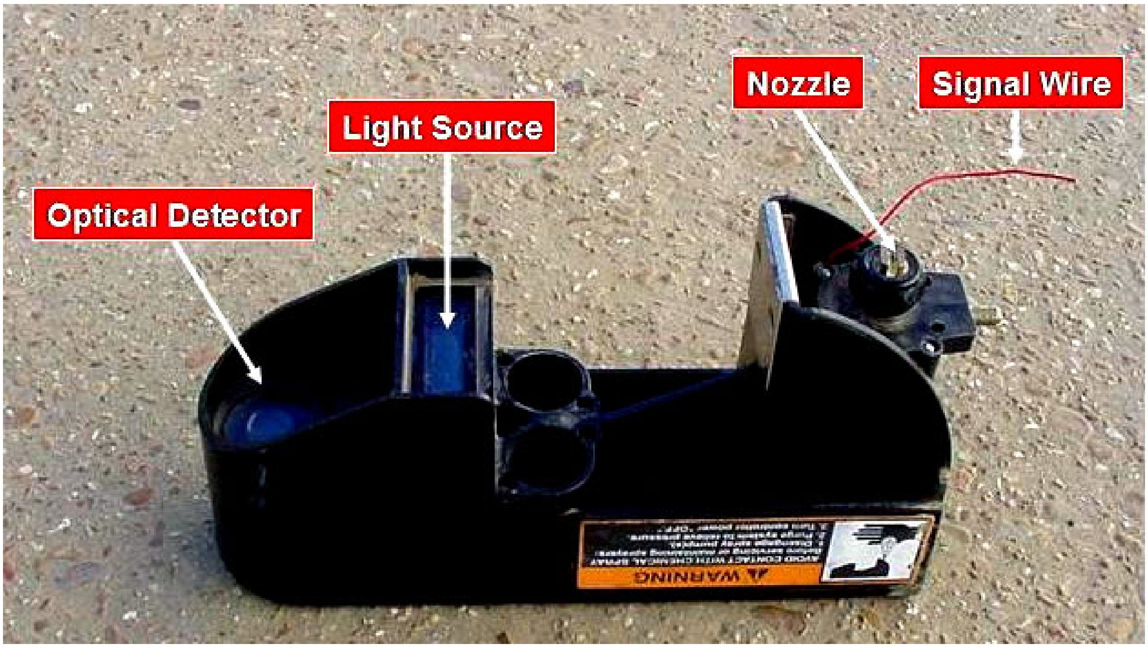

Figure 2. WeedSeeker ® PhD600 optical weed detection sensor. A signal wire was added for collecting output data of the sensor.

Figure 3. Data acquisition system for weed mapping

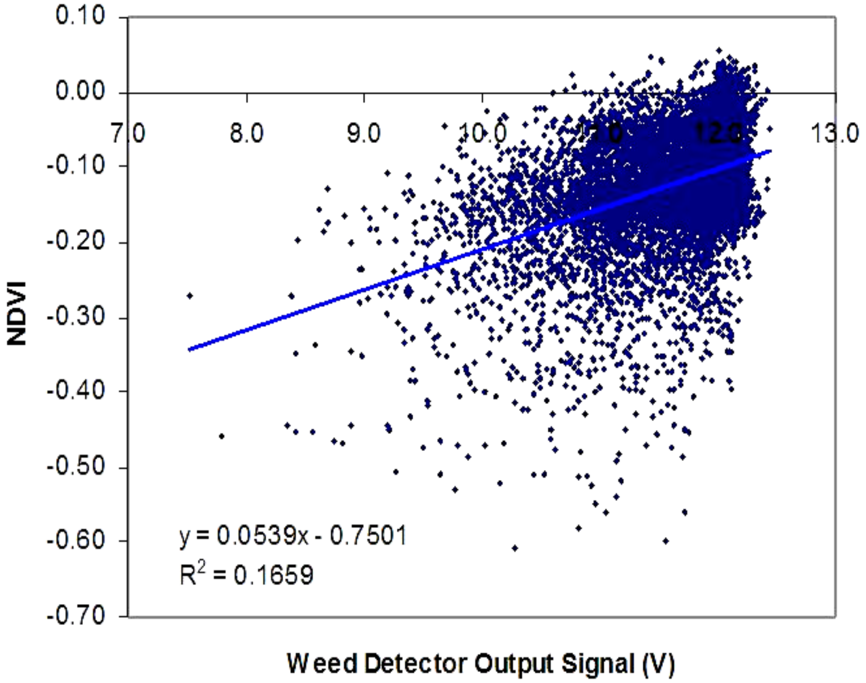

Figure 4. Correlation between weed intensity measured by the weed mapping system on 7/10/02 and NDVI calculated using the remote sensing image taken on 07/02/02.

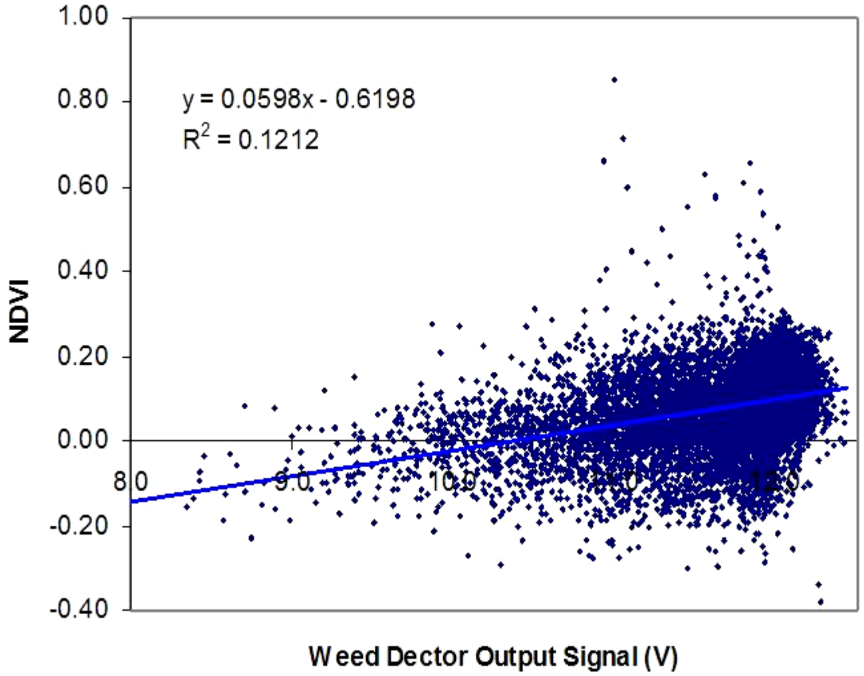

Figure 5. Correlation between weed intensity measured by the weed mapping system on 7/10/02 and NDVI calculated using the remote sensing image taken on 07/17/02.

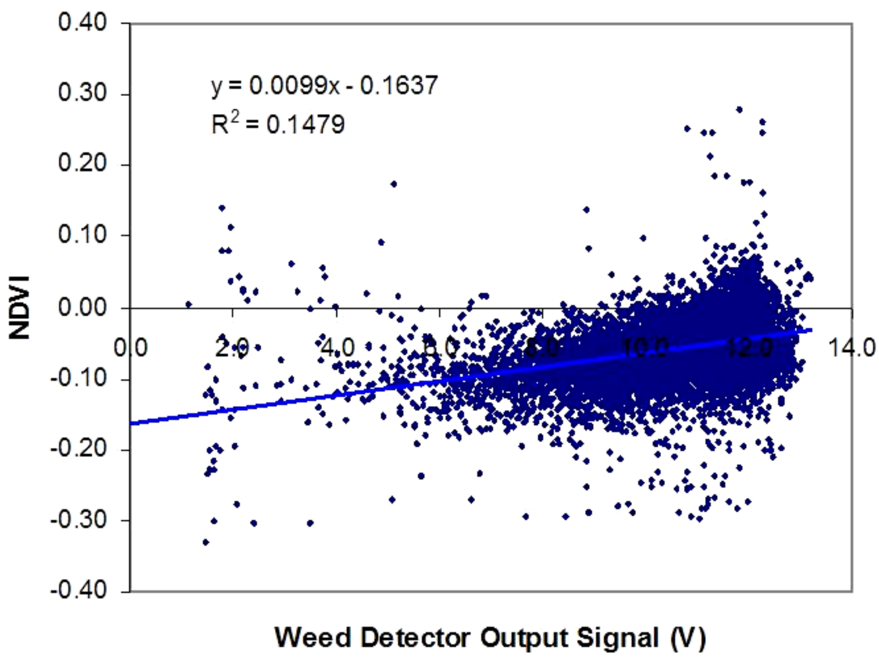

Figure 6. Relationship between the weed intensity measured on 6/24/03 versus NDVI calculated using 06/21/03 image.

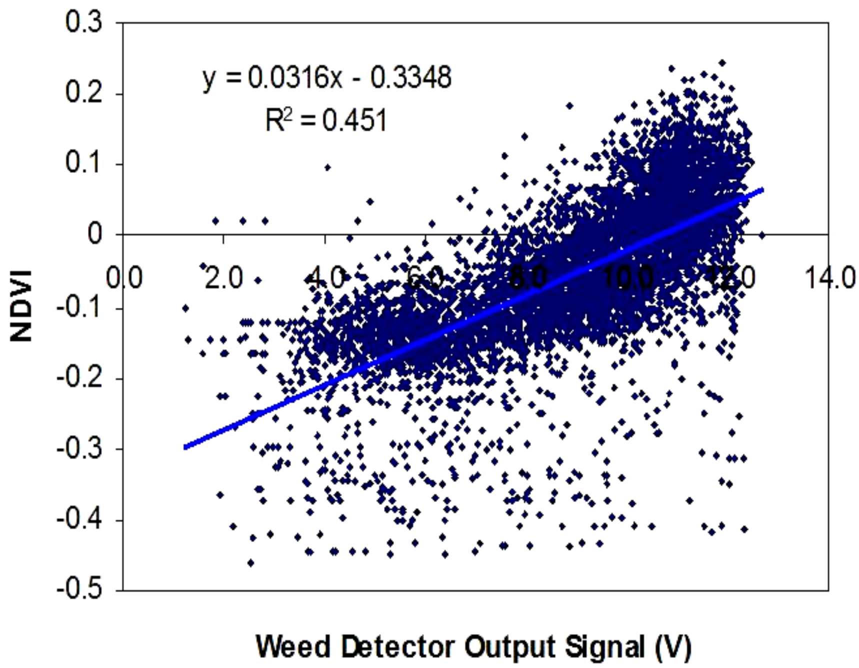

Figure 7. Relationship between the weed intensity measured on 7/14/03 versus NDVI calculated using 07/14/03 image.

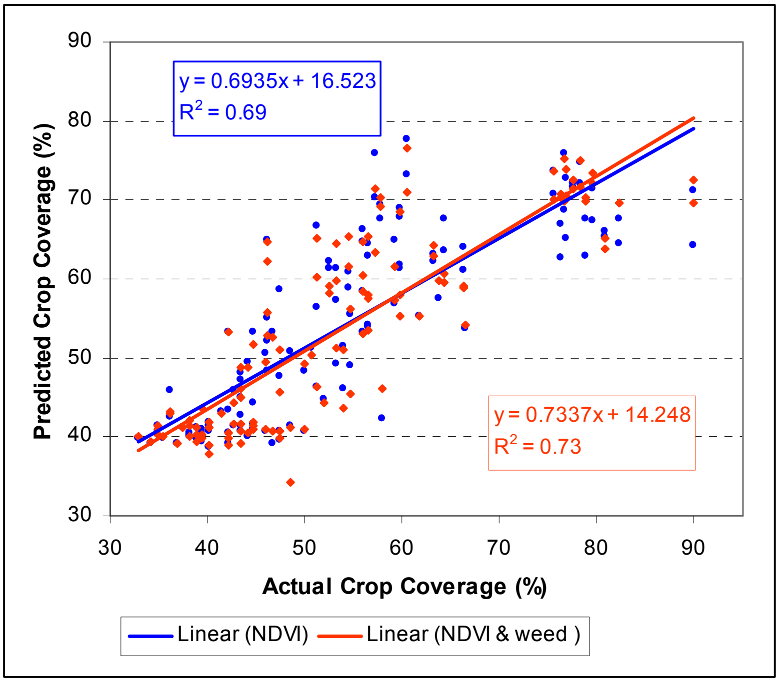

Figure 8. Predicted crop canopy coverage versus actual crop canopy coverage.

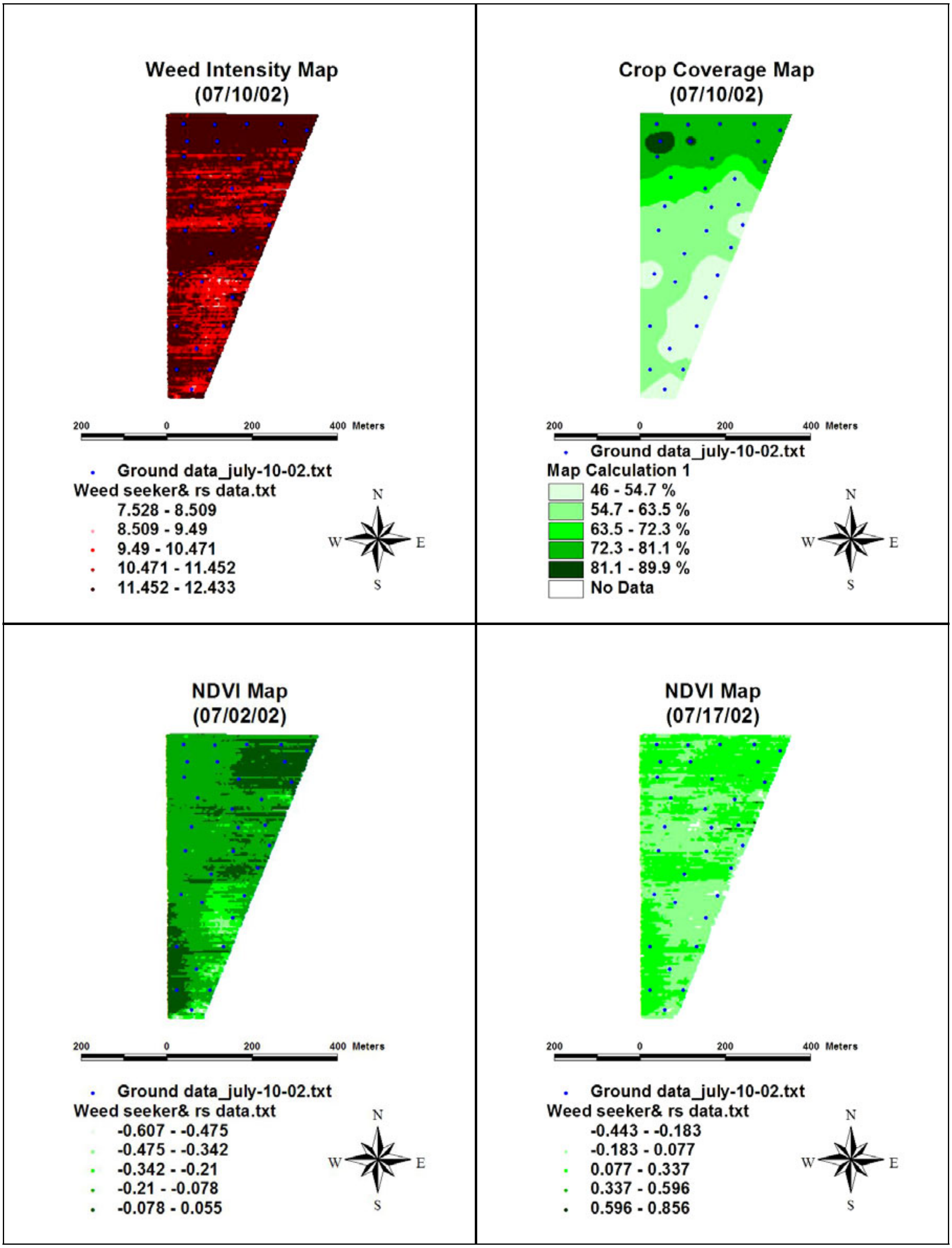

Figure 9. Comparison of weed intensity map on 07/10/02 with crop canopy coverage map on 07/10/02 and NDVI maps on 07/02/02 and 07/17/02. The blue dots shown on the maps were the canopy coverage sampling points.

Figure 10. Color-infrared images taken on 07/02/02 and 07/17/02.

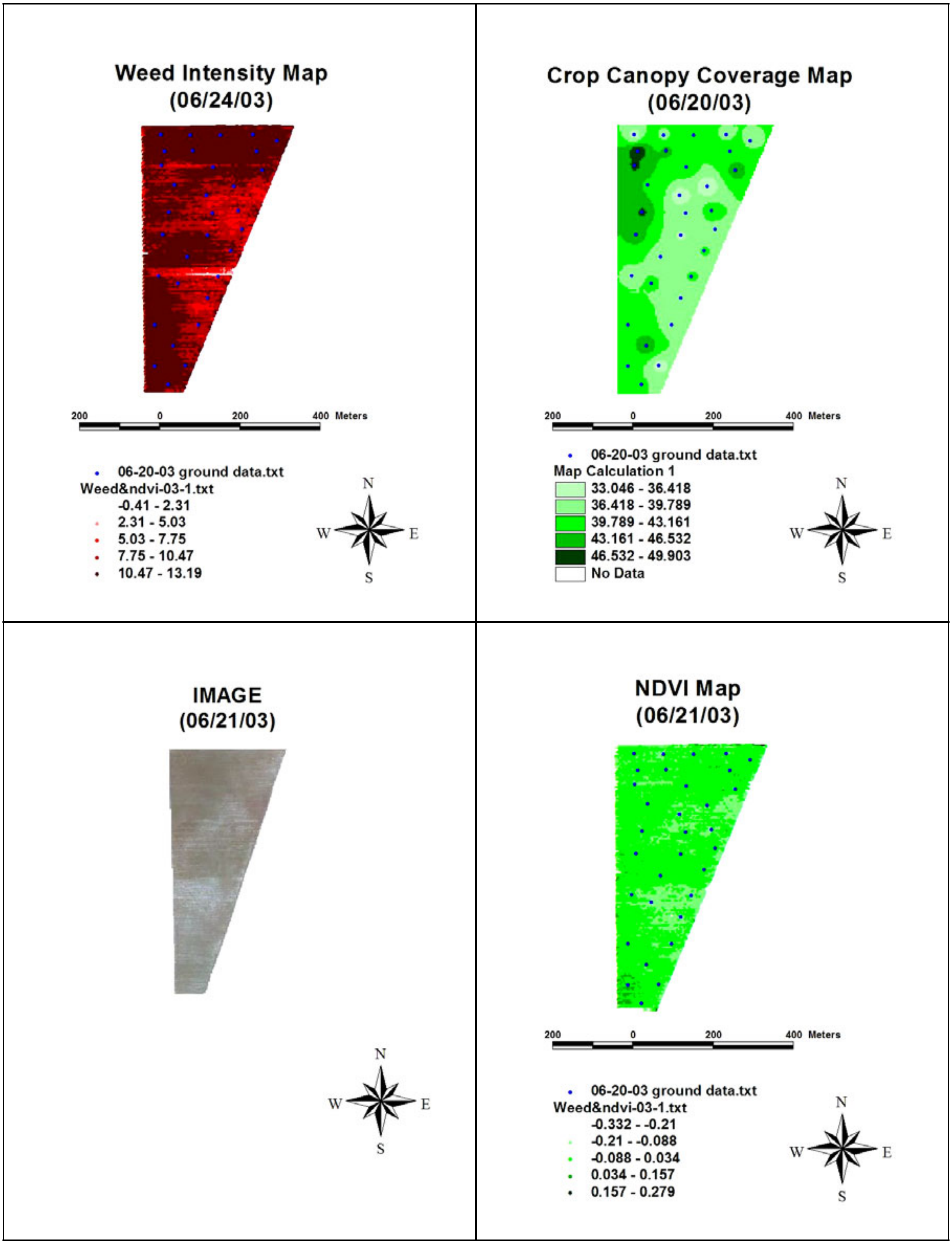

Figure 11. Showing weed intensity map, crop canopy coverage map, the color-infrared image, and NDVI map at late June of 2003.

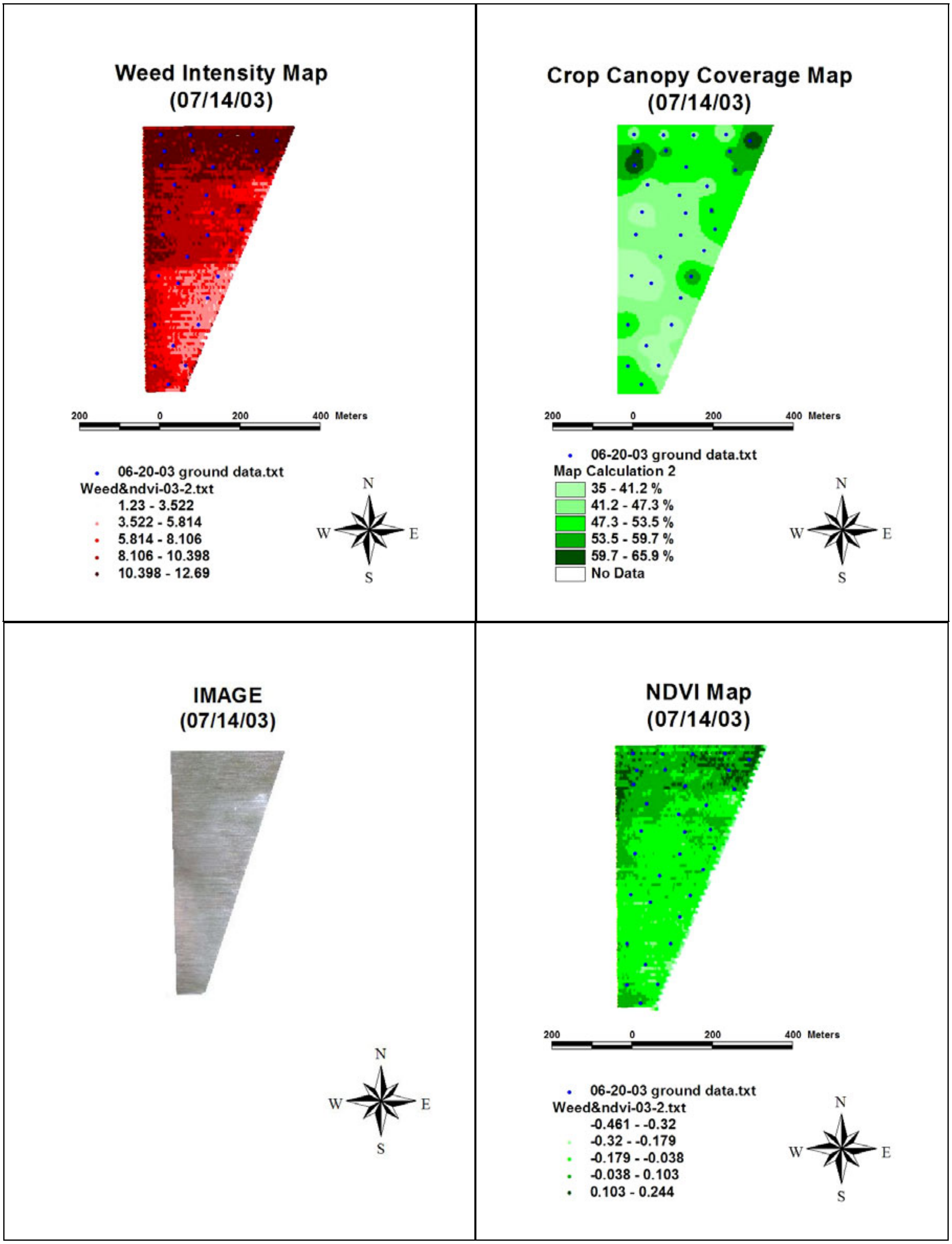

Figure 12. Showing weed intensity map, crop canopy coverage map, the color-infrared image, and NDVI map on July 14, 2003.