QUANTITATIVE REMOTE SENSING APPROACHES FOR MONITORING AND MANAGING AGRICULTURAL RESOURCES

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MISSION

The ultimate goal of this research is to use remote sensing technology to increase our understanding of processes associated with environmental variability and to provide resource managers with information that will assist them in making tactical and strategic management decisions on farms, rangelands, and natural plant communities. Emphasis will be given to approaches that have potential for operational application, and that also have a strong physical foundation based on quantitative measurements.

IMAGE-BASED REMOTE SENSING FOR AGRICULTURAL MANAGEMENT - PERSPECTIVES OF IMAGE PROVIDERS, RESEARCH SCIENTISTS, AND USERS

M.S. Moran, Physical Scientist

PROBLEM: Precision crop management (PCM) is an emerging agricultural management system using information and technology to identify, analyze, and manage site-soil spatial and temporal variability within fields for optimum profitability, sustainability, and protection of the environment. Many experts agree that there is a good match between the information needs of PCM and the offerings of spatially-distributed information about crop and soil conditions provided by image-based remote sensing (RS). The question remains: *"Can current RS technology meet the very stringent information requirements of PCM?"*

APPROACH: To answer better the posed question about remote sensing (RS) technology, I conducted a limited survey of three groups (with number of contacts in parentheses): image providers (5), research scientists (5), and users (13). By my definitions, *image providers* are companies trying to make a profit from selling remote sensing image products for farm management; *research scientists* are people at universities or government research laboratories studying remote sensing science with the goal of providing algorithms and models for farm management; and *users* are people or corporations who have already purchased remote sensing image products for PCM. Representatives from each of the three groups were contacted by telephone and asked a series of questions related to remote sensing for PCM. The results of this limited survey provided an insight into their experiences, attitudes, and expectations and provided the foundation to answer the posed question.

FINDINGS: Measurement Accuracy: Users agreed that an accuracy of 70-75% in the measurement of most crop or soil conditions was sufficient to implement PCM and improve farm profitability. This is in contrast with the goal of many research scientists to provide algorithms and models with 90-95% accuracy. Furthermore, users were in agreement that the accuracy of the image product must be quantified through a series of documented experiments and further testing on their own farm. In all cases, users were willing to provide their own test plots and pay for the image data in return for interpretation and analysis by a scientist working with the image provider. All users in the survey were already testing other new technologies at their own expense.

Product Delivery: The highest priority for all users and image providers was quick turnaround. Unlike measurement accuracy for which users were willing to accept 70% accuracy, the users expected 100% reliability in image delivery. The consensus of all users and image providers was that images must be delivered within 24 hours, preferably within 12 hours.

Location Accuracy: The second highest priority for all users and image providers was highly accurate geo-registration. For PCM, it is necessary to pinpoint the location of the anomalous crop or soil condition for proper precision management and inclusion in a geographic information system (GIS). This was one issue for which users and image providers had largely different expectations. The user accuracy requirements of approximately 2 m contrast with the positional accuracies (20-500 m) offered by some image providers.

Revisit Period: Unlike the very restrictive requirements for turnaround time (12-24 hours with 100% reliability), users had more relaxed expectations for repeat coverage. The requirements ranged from twice per week for irrigation scheduling to biweekly for general damage detection. All users agreed that when the image products are more quantitative (that is, offering an accurate assessment of the cause of the anomaly and suggesting a management activity) then the users would request more frequent repeat coverage. Image providers working with aircraft-based sensors reported that they were stretching their personnel and equipment limits to provide repeat passes on a weekly basis. Image providers working with satellite-based sensors are confined by the orbital constraints and numbers of satellites, and are often limited to repeat passes every two weeks.

Management Unit: Like positional accuracy, the spatial resolution required for PCM depends upon the management operation. There was a user consensus that it was economical to manage crop and soil units with a nominal size of 10 m.

The user requirements for remotely sensed information in PCM based on this limited survey of users, image providers, research scientists, and the literature are summarized in Table 1. The first three user requirements translate directly to sensor and algorithm specifications, where the value-added product accuracy should be on the order of 75%, the turnaround time should be within 24 hours of acquisition, and the geo-registration should be as accurate as possible (within 1 pixel). To translate the latter two user requirements (revisit period and management unit) into sensor specifications, Moran (2000) accounted for basic sensor limitations and site-specific atmospheric conditions.

Table 1. PCM user information requirements translated to RS system specifications.

User Information Requirements		System Specifications	
Measurement Accuracy	70-75%	Algorithm Accuracy	70-75%
Product Delivery	< 24 hours	Turnaround Time	< 24 hours
Location Accuracy	2 m	Geo-registration Accuracy	1 pixel
Revisit Period	1 week	Repeat Cycle	3 days
Management Unit	10-20 m	Pixel Size	2-5 m

Remotely-Sensed Product for PCM: The users contacted in this survey were confident and unanimous in their description of the preferred image product:

(1) Users expected a color map product (hardcopy, or preferably digital) with "quantitative" information that could be used to make decisions, not simply identify anomalies. They wanted to know where the anomaly was located, how large it was, and *what had caused it.*

(2) Users wanted personal help with image interpretation in the form of person-to-person contact, a reliable help line, or user-friendly software. Person-to-person contact was the preferred information delivery method.

(3) Users expected the image provider (or research scientists) to do the product validation first,

before presenting it to the user for purchase. Users were all willing to conduct additional yield tests on their own farm, but they were not interested in high-risk ventures.

(4) Users wanted honest, reasonable marketing of the image product. All users felt that RS products had been oversold, and that users had been promised much more than had ever been delivered. As a result, users described themselves as skeptical, reluctant, and distrustful.

The image providers interviewed were aware of the users' expectations. Four of five image providers were offering "high end" products including maps of weeds, insect infestations, nutrient deficiency, water deficiency and/or yield. The fifth image provider was providing only maps of anomalies; he hoped that buyers, such as crop consultants or chemical dealers, would process the high quality image to sell value-added products to farm managers. All image providers were conducting product validation studies to some extent.

All image providers were struggling to provide help in image interpretation to the users. Some companies were providing face-to-face on-farm interpretation at a great deal of expense, but with good success. Other companies were putting similar expense into providing a useful and simple software interface that could improve users' image interpretation. Finally, one company had a 24-hour help line to allow users to get personal information at any time.

When users were asked what caused them to continue purchasing RS images for a second (or third, fourth, etc.) season, they all responded that it was profitability; that is, the imagery either improved yields or reduced costs. Secondarily, it was because they had a personal interest in the technology, and thought they might benefit economically in the future. The factors cited by users who did not continue to purchase images were lack of profitability, lack of time and labor, and inability to use variable rate technology (VRT) in response to image information. The image providers described the same story from a different perspective. They stated that they lost customers primarily due to weather and the economy, and secondarily due to instrument failures that prevented them from offering further overflights.

Role of Research Scientists: Both users and image providers appreciated the studies of research scientists working at universities and government laboratories. On the other hand, users would like to see more research scientists working hand-in-hand with image providers because they felt it provided more credence to the company's agricultural products. Image providers suggested that research scientists should put more effort into technology transfer to prove that their algorithms and models were robust and operational. The research scientists interviewed for this review were already working with commercial companies. In their view, the role of research scientists in promoting remote sensing for PCM was to "be practical," understand the accuracy requirements in algorithm and model development, and keep in mind that the users and image providers are interested primarily in profitability.

With these issues in mind, the role of research scientists in promoting RS for PCM could be improved through greater interaction with the client (either the user or the image provider), including

- definition of the research program based on client needs (identified by the client) and participation of clients in the program operation;
- ownership of the system by the client (clients need to help assembling information and applying it);

• education of clients on the capabilities of remote sensing, and gradual implementation of the new program (to allow the client to maintain an understanding of the new technology); and
• economic analysis to show clients the economic benefit of using RS over traditional approaches.

Furthermore, research scientists reported that universities and government laboratories were changing to reward research scientists for technology transfer and to encourage them to use a team approach and involve clients in program development.

INTERPRETATION: Nearly 9% of the one-half million farmers growing corn in the U.S. used some aspect of PCM for corn production in 1996 (representing nearly one-fifth of 1996 harvested corn acreage); and, of these PCM users, 54% used tractor-mounted yield monitors to map field variability. These numbers illustrate the large potential market for remotely sensed agricultural information and the capacity of farm managers to adopt new technology. Whether image-based RS technology is included in emerging PCM systems will depend on the ability of commercial image providers, engineers, and research scientists to meet the stringent PCM requirements for quantitative, validated information products. This will mean improvements in product turnaround and image registration, as well as successful launches of upcoming commercial satellite-based sensors with spatial resolutions of 2-5 m and/or further advances in aircraft-based mounts and sensors. A strategy will have to be developed for independent validation of algorithms produced by research scientists and proprietary products produced by for-profit commercial companies to satisfy the requirements of risk-adverse farm managers. The economics of RS for PCM will have to be determined through well-designed experiments comparing profits obtained through conventional and high-technology management systems. Finally, an effort will have to be made to encourage a systematic, triangular education of image providers, research scientists, and users through inclusion of all clients in program development and implementation.

FUTURE PLANS: Work will focus on addressing the research, development and policy issues identified in the previous section.

COOPERATORS: This work would not have been possible without the honest insights provided by the anonymous image providers, research scientists, and users contacted in this limited survey.

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A NEW CANOPY CHLOROPHYLL CONTENT INDEX FOR COTTON

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PROBLEM: According to a recent meeting between commodity group representatives and members of the remote sensing research community, one of the most important decisions a grower must make is how to manage crop fertilizer inputs in order to assure a good yield while preventing ground water contamination. Variable rate application technology has recently been developed, but the technology for directing applications effectively is less mature. A means of rapidly assessing a crop's fertilizer needs with sufficient frequency and spatial resolution is needed for this aspect of precision agriculture to succeed.

APPROACH: A Canopy Chlorophyll Content Index (CCCI) using reflectances from three wavelengths of light was developed and field tested. Reflectance measurements of a cotton field were made in the summer of 1999 using a linear move irrigation system that had been fitted with a sensor platform and precision water and fertilizer application capabilities developed by The University of Arizona Department of Agricultural and Bioengineering. The sensor platform carried a multi-spectral sensor developed at the U.S. Water Conservation Laboratory (USWCL) (1998 Annual Report) in such a manner that a 1-meter resolution image of the 16 plot, 1-hectare field could be acquired in about 2 ½ hours. Images were acquired several times per week. The initial coarse reflectances were produced using a painted reference panel attached to the central tower of the linear irrigation system, and sampled by the sensor every minute. Half of the plots received 50% of the recommended nitrogen application, which was applied before planting and at three times during the season. The remaining plots received the full 200 lbs./acre recommended nitrogen. Half of the plots also were subjected to periodic water stress, so that four replicates each of four different treatments (full-water, full-nitrogen; full-water, half-nitrogen; low-water, full-nitrogen; and low-water, half-nitrogen) were present.

FINDINGS: Preliminary findings show that the CCCI was able to clearly reveal the low nitrogen plots even when a vegetation index showed no difference, as seen in Figure 1. What is more, the CCCI differences disappeared within a couple days of a fertilizer application.

INTERPRETATION: These data are still in the early stages of analysis, but the coarse results seen so far are very promising. If a good correlation is found between the CCCI and chlorophyll meter and leaf petiole analyses, which were collected but are not yet available, the index could be converted to a fertilizer recommendation. Hand-held sensors, sensors mounted on tractors, or airborne cameras could then be used to provide spatial nutrient deficit information to variable rate applicators.

FUTURE PLANS: The methodology used in the CCCI is currently under review for patentability, and therefore details cannot yet be released. Analysis of the 1999 data must be completed. Specifically, the coarse reflectances will be refined using data from an up-looking sensor which were collected during each measurement run. An image processing program currently under development by The University of Arizona Department of Agricultural and Biosystems Engineering will then be able to produce the 70 partial- and full-field images collected. Petiole analyses and SPAD chlorophyll meter data will be used to test the CCCI sensitivity. We plan to test the index on other crops, specifically vegetables and wheat, as the opportunity arises.

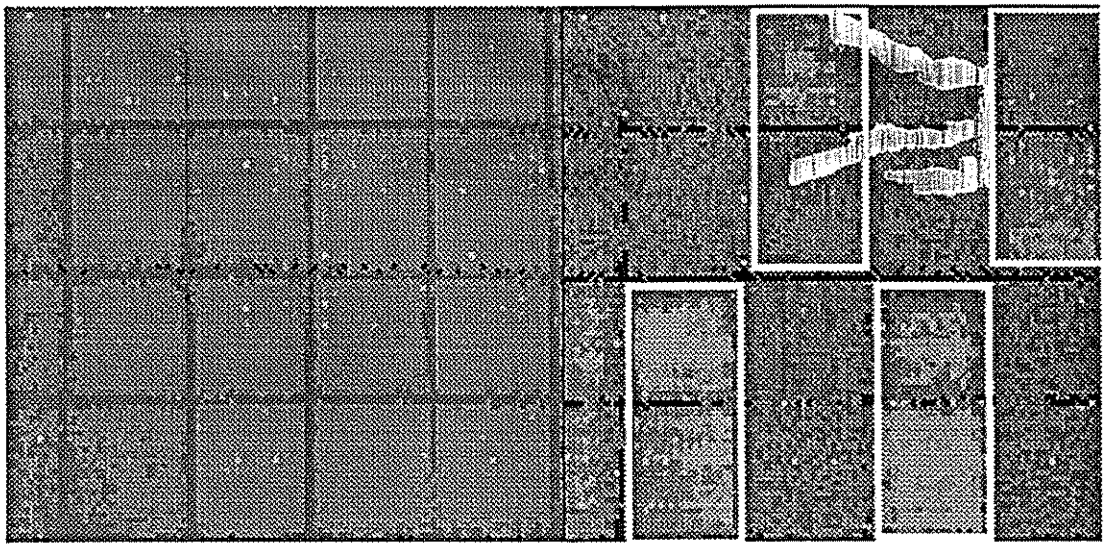

Figure 1. Image of the experimental field acquired August 19th, 1999. The left half is an enhanced Normalized Difference Vegetation Index, showing little variation among treatments. The right half of the figure is the recently developed Canopy Chlorophyll Content Index (CCCI) of the same field, the same day. Low nitrogen plots are outlined in white.

COOPERATORS: Images were collected in cooperation with The University of Arizona Department of Agricultural and Biosystems Engineering, funded through a grant from the Department of Energy's Idaho National Engineering and Environmental Laboratory. Peter Waller and Christopher Choi were assisted by graduate students Paul Colaizzi, Julio Haberland, and Michael Kostrzewski in the design and assembly of the precision application and sensor platform systems. The linear move irrigation system was provided by Valmont. Tom Thompson of The University of Arizona Department of Soil, Water, and Environmental Sciences designed the nitrogen treatment experiment and his graduate student Emily Riley supplied ground truth data on nutrient status. The experimental site, field operations, and management were provided by The University of Arizona Maricopa Agricultural Center, Robert Roth, Director.

MULTISPECTRAL DATA FOR SOIL MAPPING: OPPORTUNITIES AND LIMITATIONS

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PROBLEM: Soil maps derived from random or grid-based sampling schemes are often an important part of precision crop management. Sampling and soil analysis to derive such maps require a large investment of both time and money. Aerial photos have been used as a soil mapping aid for years (e.g., Bushnell, 1932). Studies have shown such an approach can be useful for defining management units in precision farming (e.g., Thompson and Robert,1995), but these studies are often limited to a single field, not an entire farming operation. The objective of this study was to determine if multispectral airborne (green, red, near infrared, and thermal) and satellite (SPOT and Landsat TM) data could be used to derive soil maps for a 770 ha research and demonstration farm in Maricopa, Arizona [Maricopa Agricultural Center (MAC)].

APPROACH: Soil data used in this study were collected by Post et al. (1988) from May 1984 until January 1987. There were 303 sample locations in the fields considered in this analysis. For each of these samples, textural fractions of sand, silt and clay were determined and the location recorded in a UTM coordinate system. Kriging techniques were used spatially to interpolate the data to a 2-m grid. Individual grids were generated for the sand, silt, and clay percentages. These three grids were then used to derive a textural classification map of the farm (i.e., class of sandy loam, sandy clay loam, or clay loam).

Three image data sources were considered in this study:
(1) multi-temporal, aerial-borne digitized video images acquired during the summer of 1994,
(2) a SPOT High Resolution Visible (HRV) image from April 9, 1989, and
(3) a Landsat Thematic Mapper (TM) image taken April 13, 1989.

The images were geometrically registered to the same coordinate system used to identify to the soil sampling locations (UTM projection, NAD 27 datum). The airborne image was composed from portions of 56 individual video frames, forming a single mosaic of the study area. Details on the airborne data set are given by Moran et al. (1996). Both satellite images easily encompassed the entire study area in a single image frame. Image data corresponding to the location of the soil samples were extracted in a tabular format so that correlation coefficents could be calculated between the soil textural percentages (sand, silt, clay) and the spectral bands.

Unsupervised classification was conducted on the images using the Iterative Self-Organizing Data Analysis Technique (ISODATA) (Tou and Gonzalez, 1974). This technique uses iteration to define "clusters" of data in multi-dimensional spectral space. A convolution filter was then applied to the classified images to remove small, spatially discontinuous classes. The classification process was conducted across two different spatial scales: classification using data for the entire farm (farm-level) and classification on a field-by-field basis (field-level). For the farm-level classification, the resulting classes were then assigned to a soil class of sandy loam (SL), sandy clay loam (SCL), or clay loam (CL) based on the spectral classes present in two fields that contained a wide range of soil conditions.

For the field-level classification, soil data within each field were used to assign a spectral class to a soil textural class.

FINDINGS: Correlation coefficients (r) between the Landsat spectral bands and textural percentages are shown in Table 1, using data for the entire study area. Results from the other sensor platforms were very similar. With the exception of the thermal bands, all of the coefficients are significantly different from zero ($p = 0.05$). Also note that r values tend to increase in magnitude with increasing wavelength (excluding thermal data) for all sensor systems. Additionally, sand is positively correlated with reflectance, while sand and clay show a negative correlation.

Table 1. Correlation coefficients between the percent sand, silt, or clay and the Landsat TM bands for the entire area considered in the analysis.

	Spectral Region						
	Blue	Green	Red	NIR	SWIR1	Thermal	SWIR2
r(%Sand,Band)	0.296	0.380	0.462	0.493	0.526	-0.053	0.572
r(%Silt,Band)	-0.268	-0.346	-0.426	-0.466	-0.502	0.001	-0.547
r(%Clay,Band)	-0.309	-0.394	-0.473	-0.494	-0.524	0.094	-0.568

While statistically significant, the correlation coefficients indicate that typically less than 30 percent of the variation in any given band can be attributed to differences in soil texture.

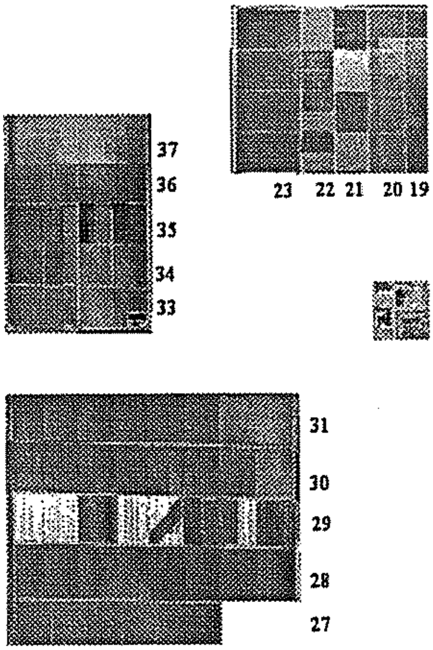


Figure 1. Near infrared image from the airborne sensor of the study area. Note numbers are field identification numbers.

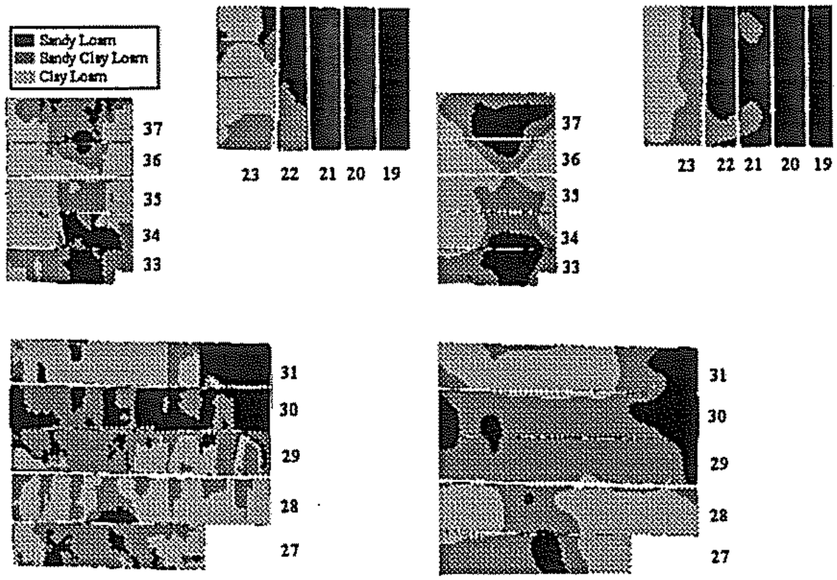
Explanation for the remaining variation can be partially found by viewing the gray scale images in the near infrared (NIR) portion of the spectrum from the airborne sensor in figure 1. The numbers shown on the figure are field identifiers. In this figure there are several differences in reflectance levels that are not related to soil texture. The two dark rectangles in field 35 are due to irrigation in progress. There is also a distinct "corner" in the upper center portion of the field that is an artifact of the individual frames used to create the image (also visible in field 20). Field 37 appears consistantly brighter than field 36 which is an artifact of using different image dates in the mosaic and different tillage conditions in both fields. Similar confounding factors also were found in the SPOT and LandSat scenes; however, there were no moasicing problems in the satellite images as the farm is contained in a single frame. Other interfering factors found during the course of the analysis include row direction (north to south versus east to west), tillage condition (e.g., freshly tilled or rain compacted surface), and seed bed preparation (flat versus raised beds).

All of these factors also impacted the results of the unsupervised classification procedures as evidenced in Table 2, where none of the images were classified with accuracies much higher than 50 percent when the procedures were executed for the entire farm. However, there was a signficant improvement when the classificaiton was conducted on a field-by-field basis (Table 2). The increase

Table 2. Accuracy assesment results from the unsupervised spectral classification procedures.

	Sensor System		
	Airborne	SPOT	Landsat
Classification Level	Percent of points correctly classified.		
Farm	51	50	48
Field	81	88	92

in accuracy can be attributed to the fact that surface conditions are much more consistant within a field as they typically receive the same tillage practices at the same time. The results of the field-by-field classification from the airborne data is shown in figure 2 (similar results were obtained with Landsat and SPOT). For comparison purposes, the soil map based on the kriging procedures is also presented in the figure. Overall there is good agreement in the majority of the spatial patterns between the two methods. Some of the sandy loam areas that appear in field 30 on the map derived from the airborne data that are not in the kriged map and can be attributed to small grain residue in this field. The residue gives the soil a "brighter" appearence, which is also characteristic of soils with higher sand content at this site. It was determined that the area percent classified differently from the kriged map were 30, 23, and 27 for the airborne, SPOT, and Landsat derived maps, respectively. More soil samples are needed to determine if the differences between the image-derived maps and the kriged map are due to errors in the kriged map or in the classified images for cases where there were no known confounding factors. However, it is speculated that patterns derived from the images in fields with uniform soil surfaces are more



a) Airborne data b)Interpolated soil samples

Figure 2. Soil map derived from the airborne data using unsupervised classification on a field-by-field basis (a) and the map derived from the kriging procedures (b).

accurate than those from the interpolated data. Additionally, only 60 soil sample locations were used in generating the image-based maps, while 303 locations were used for the kriged map. The number of points needed for the image-based method could have been substantially reduced if the soil surface had been uniform across the farm.

INTERPRETATION: Many factors can impact a soil's apparent reflectance that are not related to the soil's physical properties (e.g., tillage patterns, residue, row direction). Therefore, the use of multispectral imagery is best suited for large fields that have a uniform soil surface at the time of image acquisition. It is also necessary that the soil property of interest exhibit a spectral response. If such conditions are present, the number of soil samples needed to map soil properties can be significantly decreased when compared to spatial interpolation techniques. In this study, a general trend was that high sand content was associated with higher reflectance levels; however, this result was specific to the study site and it is not implied that such a spectral response will be true of soil at other locations.

FUTURE PLANS: A similar study is planned for 2000 where fallow fields at MAC will be cultivated just prior to image acquistion so the fields will have similar surface conditions. It is hoped that imagery will be available from one of the satellites' recently launched cables of providing 4-m spatial resolution data in the NIR, red, and green spectral regions.

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DEVELOPMENT OF A MODELING AND SENSOR SYSTEM TO PROVIDE INFORMATION FOR PRECISION CROP MANAGEMENT

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T.R. Clarke and M.S. Moran, Physical Scientists;
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PROBLEM: Precision farm management requires timely, georeferenced information on crop and soil conditions. In this management system, the crop is given what it needs based on the current soil and environmental conditions so that economic return (not necessarily yield) is optimized. Cost efficient methods to provide this information are lacking at the present time. The objective of this project is to provide the tools needed economically to manage crop inputs at a very fine scale (potentially as small as 1 m).

APPROACH: To provide real-time management information, a combined sensor- and modeling-based approach has been under development. This project is part of a cooperative study, primarily funded by the Idaho National Environmental and Engineering Laboratory (INEEL). The U.S. Water Conservation Laboratory is providing the expertise on the remote sensing components of the study and assisting in the execution of field experiments to collect the data needed to validate and develop the system. The University of Arizona is working on the hardware design of a carriage for the sensor and developing techniques to provide an interface between the remotely-sensed data and an energy and water balance model called ENWATBAL (Lascano and van Bavel, 1987). Texas A&M University is providing the expertise on ENWATBAL and conducting a concurrent experiment in Texas. The project also is enhanced by the participation of two private companies, Valmont, which is providing a linear move irrigation system for the project, and CDS Ag. Industries, which is providing an injection pump.

The project began in 1998 with cotton and barley field experiments during which agronomic and hand-held radiometer data were collected. These data were used to begin formulation of quantitative relationships between spectral response and crop condition (see Barnes et al., 1998). Concurrent with these experiments, construction proceeded on a system to allow the linear move irrigation system to serve as a remote sensing platform named Agricultural Irrigation Imaging System (AgIIS, i.e., "Ag Eyes"). AgIIS was completed in time for the 1999 cotton season and was able to provide images in the red, green, red-edge, near infrared (NIR), and thermal portions of the spectrum. Various components of the hardware aspects of the system are under consideration for patents by The University of Arizona and so a detailed description is not possible at present. During the growing season, the AgIIS was used to obtain images at a minimum of weekly intervals, with as many as three images per week during the period of rapid crop development.

A Latin square experimental design was used during the 1999 cotton season with four treatments: (1) control (WN, optimal conditions); (2) low nitrogen (Wn, 50% optimal plant requirements); (3) low water (wN, decreased irrigation frequency, allowing the plants to become water stressed three

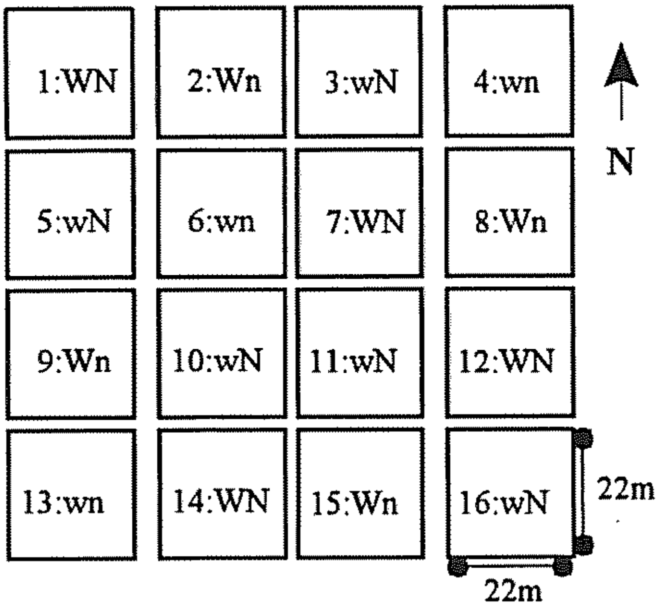

Figure 1. Plot numbers and treatment codes for the 1999 cotton experiment (see text for an explanation of the treatment codes).

times during the season); and (4) low water and low nitrogen (wn). A diagram of the treatment layout is provided in Figure 1.

Soil moisture levels were monitored in every plot using a neutron probe at a minimum of weekly intervals (2 access tubes per plot). Additionally, two plots were heavily instrumented with TDR probes in 4 locations at 4 depths (5, 10, 15 and 20 cm). The probes were used to determine the soil surface moisture content at hourly intervals using an automated data acquisition system. Stem flow gages also were added to these plots to measure the cotton's daily transpiration rate. The plants were sampled weekly for nitrate status, leaf area index (LAI), leaf, stem, and boll dry weights, plant height, and percent canopy cover.

FINDINGS: Analysis of all of the data collected during the experiments is still in process; however, initial results are encouraging. Figure 2 (color appendix) provides a comparison of a true color photograph of the field taken from a helicopter on October 1, 1999, and images from AGIIS acquired four days prior to the flight. The photograph was scanned at an approximate spatial resolution of 10 cm and AgIIS provides 1 m resolution. By this time in the season, most of the low nitrogen and water plots showed some signs of decreased leaf area. In the images, a higher canopy density is evident by intenser shades of green in the photograph (Fig. 2a) and intenser shades of red in the false color composite (Fig. 2b). Note that the spatial patterns in these two images are similar. The other images in Figure 2 provide a sample of the different spectral regions available from AgIIS. The visibile and NIR gray scale images (Fig. 2 c - f) were contrast stretched so that the minimum reflectance corresponded to black and maximum reflectance to white. The thermal band (Fig. 2g) represents the coolest condition as black and warmest as white. The ratio vegetation index (RVI = NIR/Red) has a color map applied so that low values are red and high values are green.

The ability to obtain images of a field is useful only if the images can be related to management information. To demonstrate the potential information from the system, Figure 3 (color appendix) provides two false color composite images from AgIIS on August 19. This day was selected because the low nitrogen treatments were established and the high water plots were irrigated three days earlier, but the low water plots were not. In the standard color infrared image of Figure 2a, most of the color patterns in the image are related to variations in canopy density (brighter red corresponds to a denser canopy); and there are no distinct signs of the experimental treatments. However, many of the color pattens in Figure 2b can be related to the treatments. In this figure, the canopy chlorophyll content index (CCCI) is displayed red (Clarke and Barnes, "A new canopy chlorophyl content index for cotton," this report), which can be related to crop nitrogen status in this experiment. The ratio vegetation index (RVI = NIR/red) is displayed as green, and the crop water stress index

(CWSI) (Idso et al., 1981) displayed as the blue band. Therefore, the control plots (WN) appear green as CCCI and CWSI are low under non-stressed conditions and RVI is higher for high canopy densities. A majority of the low nitrogen plots have a orange tint (higher CCCI values), while the low water plots have a blue tint (higher CWSI values). Plot 13 (lower left corner, wn) has a strong pink tint, as this plot had a low canopy density. The ability to distinguish between canopy density and two crop stresses demonstrates the progress being made in this study to extract more exact information about crop status than has been possible in the past.

INTERPRETATION: The system under development will provide farmers and agricultural consultants with a simple, cost effective data source to map spatial variations in crop water and nitrogen levels. These data will have the potential to serve as an integral part of a decision support system for precision crop management.

FUTURE PLANS: Work will continue to integrate the sensor information with simulation models to provide decision support in water and nitrogen management. Related studies will begin during the 1999-2000 growing season using AgIIS to determine the feasibility of remote sensing and modeling technologies to provide information relevant to quality management in broccoli.

COOPERATORS: Peter Waller, Chris Choi, Mark Riley, Tom Thompson, Paul Colaizzi, Julio Haberland, Mike Kostrzewski, and Emily Riley, University of Arizona, Tucson AZ; Robert Lascano and Hong Li, Texas A&M University, Lubbock TX; Jack Slater, INEEL, Idaho Falls ID; Jim Phene, Valmont Industries, Valley NE; Jim Stubbs, CDS Ag Industries, Chino CA.

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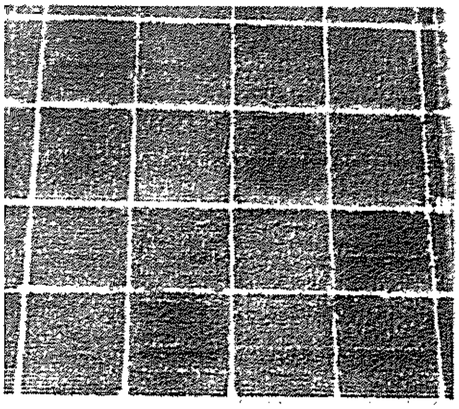
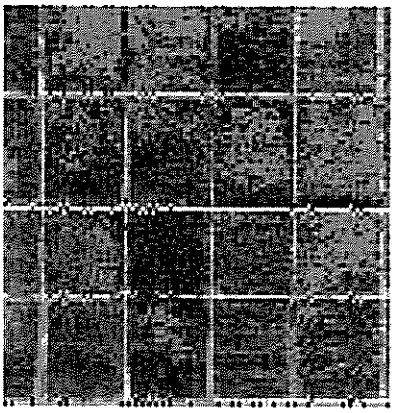
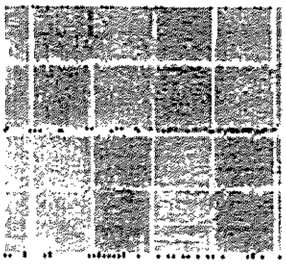


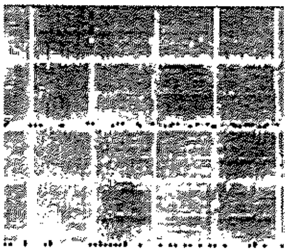
(a) True color photograph



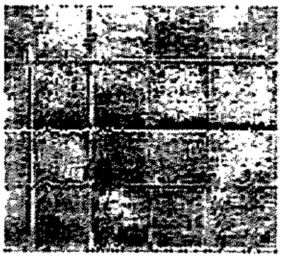
(b) False color composite



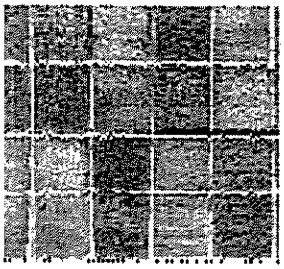
(c) Green band image



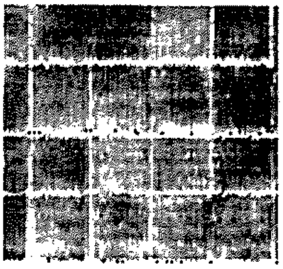
(d) Red band image



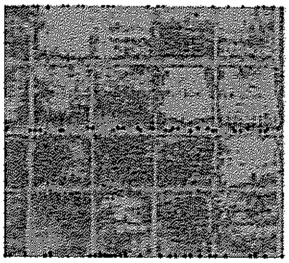
(e) NIR band image



(f) Red-edge image

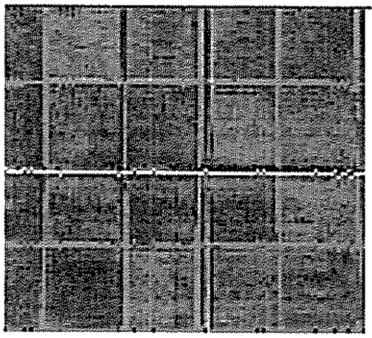


(g) Thermal image

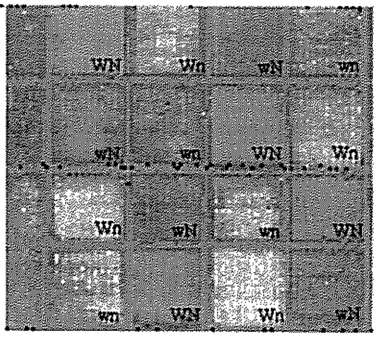


(h) RVI

Figure 2. Comparison of a true color photograph (a) acquired October 1 to images from AgIIS acquired September 27. The false color composite is a display of the NIR image (near infrared, d) as red, the red image (c) as green, and the green image (d) as red. RVI is the ratio of NIR to red.



(a) NIR, Red, Green false color composite



(b) CCCI, RVI, CWSI false color composite

Figure 3. A standard color infrared image (a) similar to fig. 2b and an "indices" false color composite image (b) from AgIIS on August 19. Treatment codes have been overlaid on the indices image. In b, CCCI is displayed as red, RVI as green and CWSI as blue.

DETERMINING CROP WATER STRESS FROM CROP TEMPERATURE VARIABILITY

R.B. Bryant, Physical Science Technician; M.S. Moran and T.R. Clarke, Physical Scientists; and P.J. Pinter Jr., Research Biologist

PROBLEM: Detection of plant water status is of primary importance for efficient and economic irrigation scheduling. Thermal infrared data in the wavelength band 8-13 μm have been found to be particularly well suited for crop water stress detection. Two of the most commonly used thermal indices for irrigation scheduling are the crop water stress index (CWSI) (Jackson et al, 1981) and the thermal kinetic window (TKW) (Burke et al., 1988). These physical indices are based on a comparison of the canopy temperature with the air temperature (in the case of CWSI) or the optimal temperature of a given crop (in the case of TKW). For both indices, it is necessary to convert the digital number (*dn*) recorded by the optical sensor to "true" or kinetic crop temperature (T_K), which is defined as the temperature measured with an accurate *in situ* thermometer in good contact with the crop. This conversion requires that the airborne optical sensor be calibrated (to convert *dn* to at-sensor radiometric temperature T_R'), the atmospheric attenuation of the sensor signal be known (to convert T_R' to surface radiometric temperature T_R), and the surface emissivity be known (to convert T_R to T_K). More often than not, airborne sensors are not calibrated; there is no information on atmospheric scattering and absorption; and there is only a rough estimate of surface emissivity.

APPROACH: The approach proposed here is based on the assumption that a crop with full cover and adequate water should display a normal distribution of thermal *dn*'s. Since the thermal image data of a well-watered crop tends toward a fixed value (the mid-range of its thermal kinetic window), it can be assumed that the data will be normally distributed if there are no other factors affecting the variability of the data (e.g., a bare spot in the field). Presumably, the further a data set of crop temperatures deviates from a normal distribution, the greater will be the plant water stress in the field. This is because, as water conditions for photosynthesis become sub-optimal, soil properties and genetic properties of individual plants will begin to influence the ability of the plant to stay within its thermal kinetic window.

We used this theory to derive an index based on the deviation of the *shape* of a histogram of the image data from the *shape* of a normally distributed histogram generated from the variance and mean of the thermal image data. In order to make the shape of each histogram comparable across different images regardless of standard deviation, the y axis of each histogram (i.e., the frequency for image data histogram and distribution for the generated histogram) was converted to a normalized frequency (f_n) and a distribution ($dist_n$) ranging from 0 to 1, where f_n = (frequency - minimum frequency) / (maximum frequency - minimum frequency), and $dist_n$ = (distribution - minimum distribution) / (maximum distribution - minimum distribution), thus allowing comparison of curve shape rather than *dn* distribution. To compute the Histogram-derived Crop Water Stress Index (HCWSI), we summed

$$HCWSI = \sum_{i=dn_{min}}^{dn_{max}} abs(f_n - dist_n)_i \qquad (1)$$

the absolute difference between f_n and $dist_n$ for each *dn*, where dn_{min} and dn_{max} are the minimum and maximum values of *dn* in the image. Graphically, HCWSI is the area represented by the shaded zones in Figure 1.

According to our theory, a recently irrigated field would have a relatively uniform thermal profile which would result in a histogram that was close to normal. A purely normal curve would have an index of 0.0 so a recently irrigated field would have a low HCWSI number. If the same field were to experience water stress, then the thermal profile would exhibit more heterogeneity and its histogram would deviate more from a mathematically normal curve. Its HCWSI should be higher than the HCWSI calculated from a recently irrigated field.

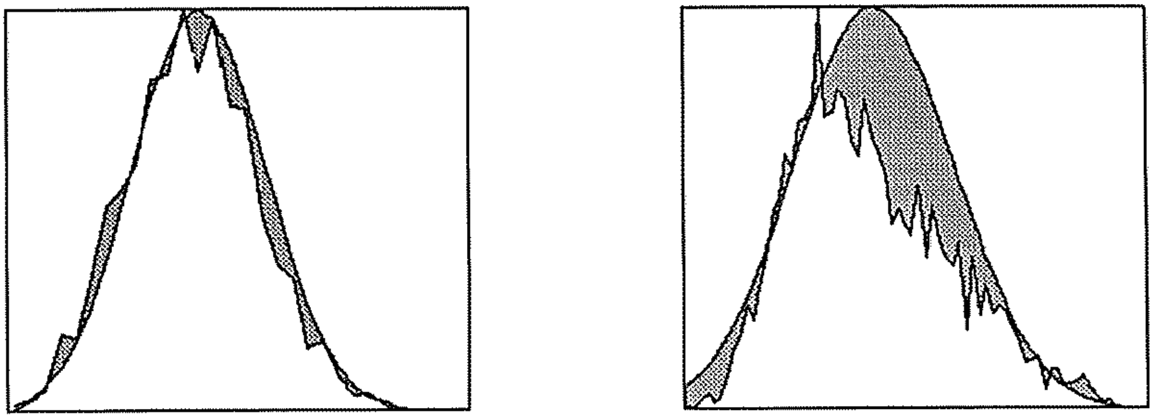


Figure 1. Example of a histogram from a thermal image of a well-watered crop (left) and a water-stressed crop (right), where the x-axis is image *dn* and the y-axis is normalized frequency and distribution. The jagged line is actual data and the smooth line is a mathematically normal histogram generated from the variance and mean of actual data. The integration of the gray area is the HCWSI.

FINDINGS: The images used in this analysis were from overflights of The University of Arizona's Maricopa Agriculture Research Center during the summer of 1994 as part of the Multi Spectral Airborne Demonstration at Maricopa Agricultural Center (MADMAC) (Moran et al., 1996). We chose three production cotton fields with 100% vegetation cover for demonstration of HCWSI. Field 31 was Upland Cotton (Gossypium hirsutum L.) and Fields 33 and 34 were planted with Pima Cotton (Gossypium barbadense). The soil at the east end of Field 33 (Border 2) was substantially more sandy than that of all other field borders. We extracted data for three irrigation borders in three fields from the thermal images with a size of 75x75 pixels which corresponded to ground dimensions of 150 x 150 meters. A histogram of each border was generated on each date using the *dn* range number (dn_{max}-dn_{min}) for the number of bins and f_n values 0-1 along the y-axis. Next, the variance and mean of each extracted data set were used to generate a histogram with a mathematically normal distribution. Using eq. (1), the HCWSI was generated for each temporally different image of each border resulting in a seasonal time series of HCWSI for each field border (Fig. 2).

Since the fields we analyzed were production crops which were regularly irrigated, the plants should not have been subjected to severe or prolonged water stress during the season. Field notes taken during the time of overflight indicated wilted plants in Fields 33 (Borders 3 ,4) and 34 (Border 2) only on one of the six dates analyzed, DOY 193. The HCWSI on that day for Fields 33 and 34 tended to be higher than the other dates for analyzed.

Irrigation occurred on DOY 199; and, according to the HCWSI, all borders in Field 34 recovered by the time of the next overflight on DOY 202. Plants in Field 33 apparently recovered more slowly. In fact, Border 2 retained a higher HCWSI for the rest of the season. This border was considerably more sandy than Borders 3 and 4, so there was a possibility that even when it was well irrigated the plants were still stressed and the thermal profile was still not normally shaped. This hypothesis was supported by the fact that Border 2 on DOY 235 still had a relatively high HCWSI (4.1) only two days after irrigation. It also had the highest HCWSI of all the borders on DOY 193 (10.6) so there is a possibility that permanent damage to the crop had occurred.

The HCWSI of Border 3 in Field 33 was highest on DOY 193 when leaf wilting was recorded in the field notes. According to subsequent HCWSI values, it took several weeks for the plants to recover completely from the severe wilting on DOY 193. That is, HCWSI values were still somewhat high (3.7 and 3.9 on DOYs 202 and 214), and finally reached a low HCWSI value of 1.2 on DOY 235.

Plants in Field 31 exhibited very little stress according to the HCWSI. Borders 3 and 4 on DOY 193 showed elevated numbers of HCWSI=3.2. We inspected the images and found that these borders had a north/south line of elevated *dn* probably due to irrigation problems. The only other border with a noticeably increased index was Border 2 on DOY 214. This also may have been due to irrigation problems.

INTERPRETATION: The HCWSI is a crop stress index based on within-field thermal variability that circumvents the need for ancillary meteorological data, complex atmospheric measurements, and knowledge of surface emissivity. Preliminary results from this study indicate that the HCWSI was sensitive to both early and chronic crop stress, and to irrigation non uniformity (e.g., skipped or partially irrigated fields).

FUTURE PLANS: This study was constrained by the fact that we had only qualitative field notes and no direct information on the water needs of the crop at the time of the overflights. Irrigation schedules and weather conditions were known, but this was not enough information to estimate the water needs of each border. Also, this study considered only fields with full-cover cotton canopy. It is not known if other crops and other field conditions, such as partial canopy closure, high winds, and nitrogen stress, affect the HWCSI to make it less effective as a general index for crop water stress. Another study should be conducted in which quantitative information on crop water stress is obtained at the same time as the acquisition of the thermal images.

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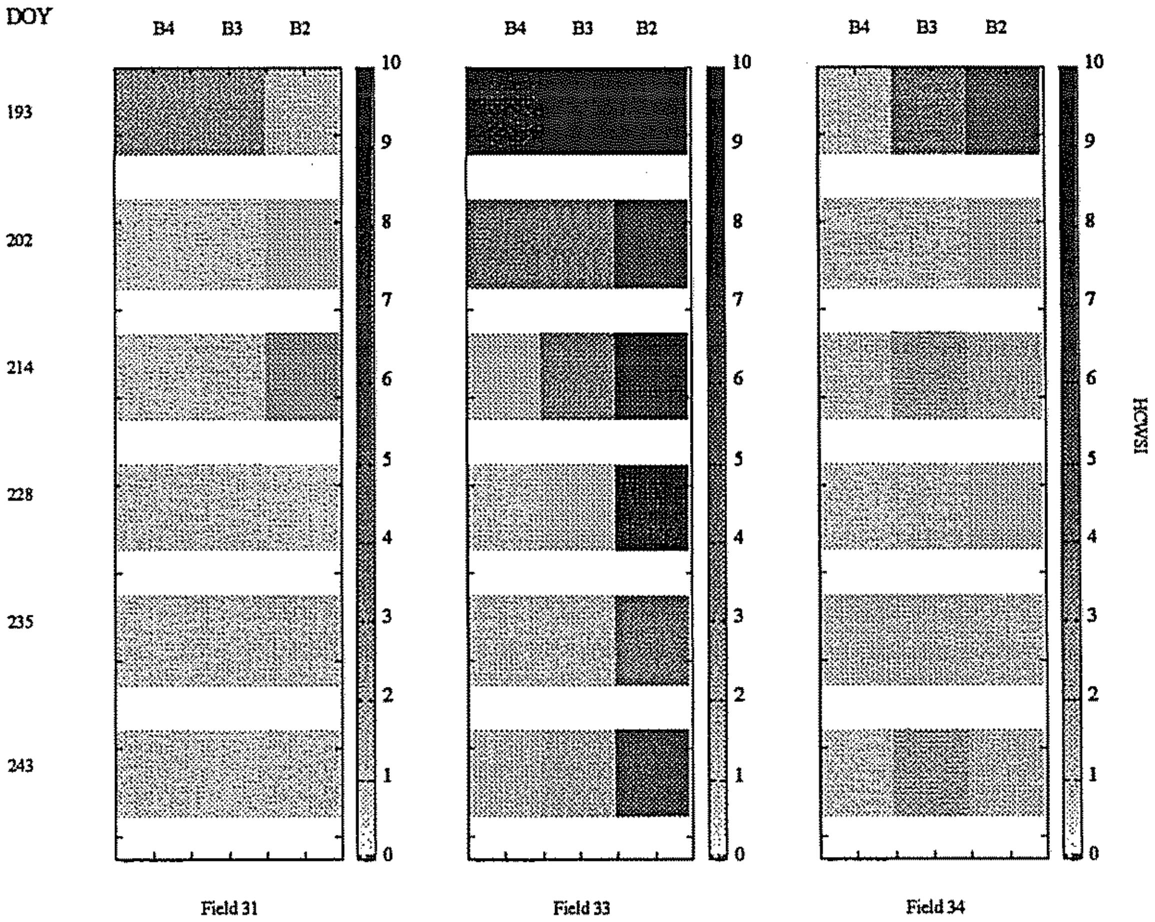

Figure 2. HCWSI values for each border of each field. B4, B3, and B2 refer to Borders 4, 3, and 2, respectively.

COMBINING SATELLITE IMAGERY WITH PLANT GROWTH AND SOIL WATER MODELLING FOR MULTI-YEAR SIMULATION OF GRASSLAND CARBON AND WATER BUDGET

Y.P. Nouvellon, Research Associate; M.S. Moran, Physical Scientist;
and R.B. Bryant and W. Ni, Biological Science Technicians

PROBLEM: Vegetation and soil functioning models have the ability to describe meaningful management processes and variables such as plant growth, crop yield, and soil water budget. Operational applications, however, have been hampered by our inability to provide a spatial distribution of the complete set of required model input parameters. This explains the growing interest in developing methodologies to incorporate remote sensing information in vegetation functioning models. In this work, we refined a Soil-Vegetation-Atmosphere-Transfer (SVAT) model to work on a spatially-distributed basis, continuously over multi-year periods, over a semi-arid grassland watershed, the Walnut-Gulch Experimental Watershed (WGEW) in Southeast Arizona.

APPROACH: The SVAT model used in this study (Nouvellon et al., 1999a, and Fig. 1) is driven by standard daily meteorological data and simulates the biomass dynamics of green shoots, dead shoots, and living roots on a daily basis (plant growth submodel). Plant transpiration, soil evaporation and soil water fluxes also are simulated in a water budget submodel.

The main processes simulated in the plant growth submodel are photosynthesis, photosynthate partitioning between aerial and below-ground compartments, translocation of carbohydrates from roots to shoots at the regrowth period, respiration, and senescence. The water balance submodel uses a simplified two-layer canopy evapotranspiration model where the soil profile is divided into three layers. The main processes simulated are the water infiltration and percolation in the soil profile, the evaporation from the soil and from the sparse grass canopy (using the Penman-Monteith equation), the canopy stomatal control, and the root water uptake in each soil layer.

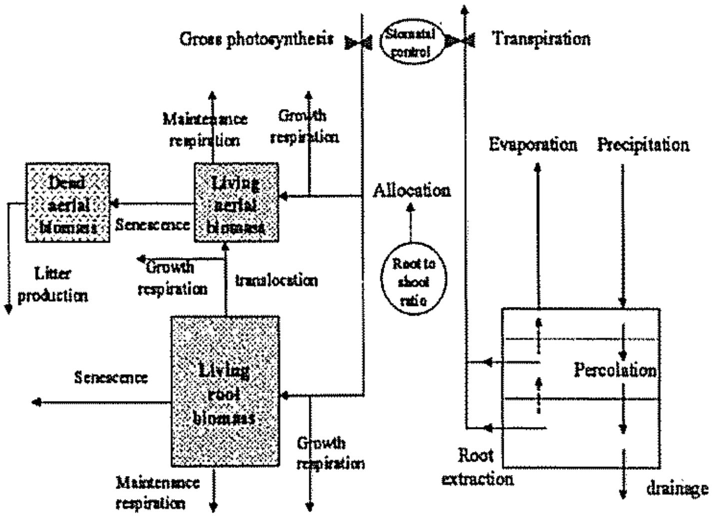

Figure 1: Schematic representation of the plant growth and water budget models.

The SVAT model was combined with a physically-based Radiative Transfer Model RTM [the Markov Chain of Canopy Reflectance (MCCR) model (Kuusk, 1995)] through the green Plant Area Index (PAI) simulated by the plant growth model. The MCCR model accounts for the non-random pattern of leaf distribution through the incorporation of a Markov model for gap fractions computation. The parameters of the Markov model and those used to describe the Leaf and Stem angle distribution (LSAD) were derived from extensive measurements of canopy structure and gap fraction on various sites in Northern Mexico and Southeast Arizona (Nouvellon et al., 1999b).

Landsat Thematic Mapper (TM) images obtained during the summer growing seasons of ten consecutive years (1990-1999) were used to calibrate the SVAT model. The SVAT model was applied over the grassland areas of the WGEW (selected using a digital vegetation map), using soil texture parameters provided by a digital soil map and daily meteorological data measured at the Kendall site from June 1990 through August 1999 (Fig. 2). At each satellite overpass, NDVI were simulated by the combined SVAT-RTM (in the same sun/view zenith angles configuration as the corresponding measurements) and compared to NDVI calculated from reflectances measured by TM sensor and corrected for atmospheric effects. Spatially unknown initial conditions and parameters were estimated using an iterative procedure based on the simplex method that minimizes the difference between simulated and measured NDVI. Parameters and initial conditions chosen to be re-parameterized / re-initialized were such that (1) the model is highly sensitive to them, (2) they are spatially variable, and (3) they are difficult to obtain by direct measurement at the regional scale. Following a sensitivity analysis and taking into account the above criteria, initial living root biomass (BR_{ini}) and maximum light use efficiency (ε_{gmax}) were selected to be initialized and parameterized respectively.

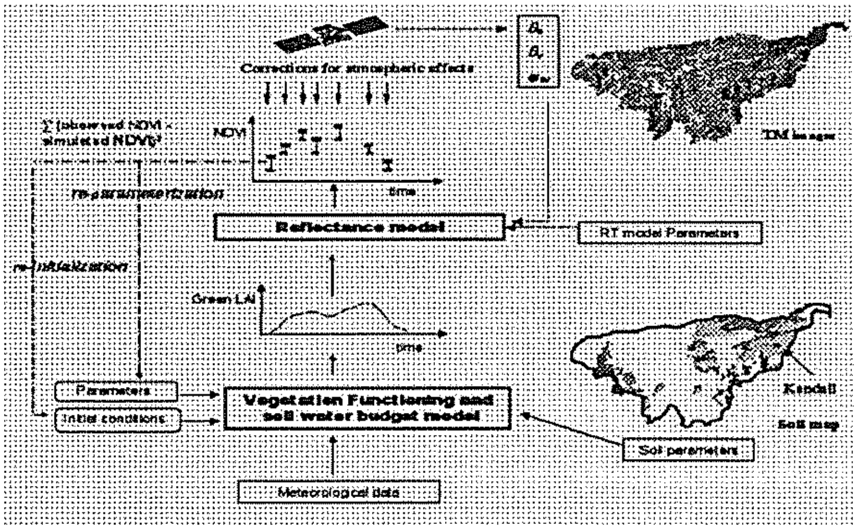

Figure 2: Synoptic view of the approach used to refine the plant growth/ soil water budget model to work on a spatially distributed basis using time series of Landsat TM images.

FINDINGS: Biomass measurements obtained at the Kendall site from 1990 to 1992 were used to evaluate model results obtained without calibration and with calibration using TM images. Daily simulations of biomass obtained for the Kendall site for the ten-year period using two a-priori sets of possible values of ε_{gmax} and BR_{ini} were compared to aboveground biomass measured from 1990 to 1992 (Fig 3). Reflectances and NDVI simulated by the combined SVAT-RTM for these two a-priori parameter sets also were compared to TM-derived red and NIR reflectances and NDVI (mean values of reflectance and NDVI of the pixels that includes the Kendall site). The first set of a-priori values of ε_{gmax} and BR_{ini} resulted in overestimation of measured aboveground biomass (RMSE of 20.0 g m^{-2}) and NDVI (RMSE of 0.065). Underestimation of biomass and NDVI resulted from the second set (RMSE of 18.8 g m^{-2} and 0.068, respectively). These results show that SVAT errors due to uncertain values of ε_{gmax} and BR_{ini} strongly propagate in the RTM resulting in a high sensitivity of NDVI to model errors.

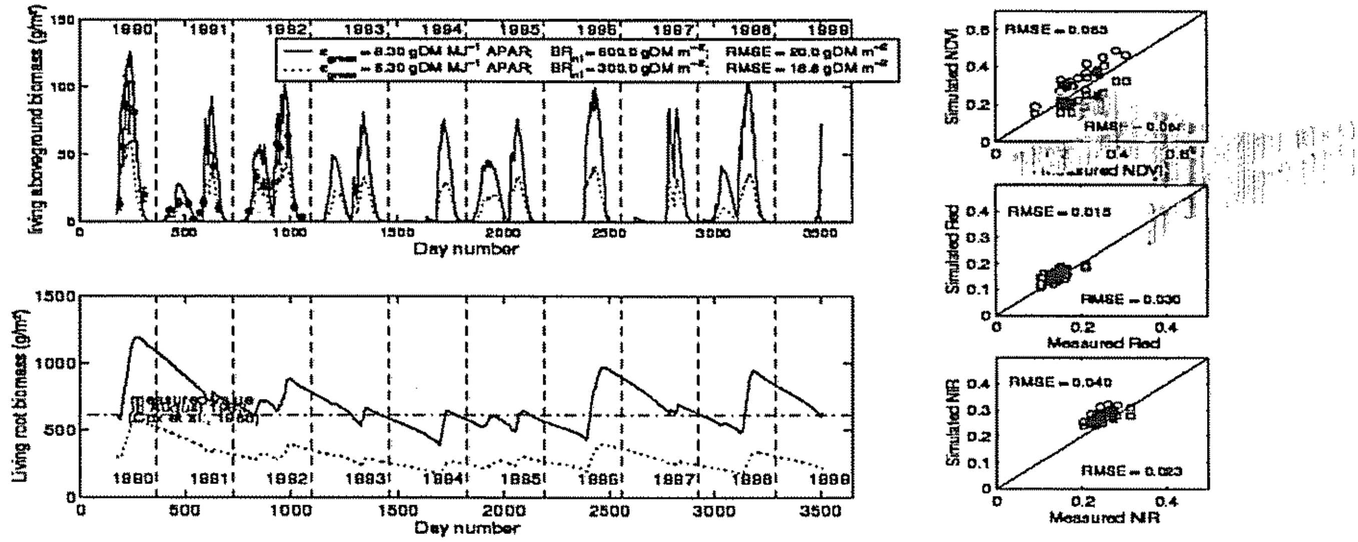

Figure 3: Simulation results obtained using two a-priori sets of reasonable values of ε_{gmax} and BR_{ini}. In the top-left graph, solid circles with error bars show aboveground biomass measurements. In the bottom-left graph, the horizontal broken line show the value of root biomass measured by Cox et al. (1986) in August 1983. The RMSE associated to each set of parameters are indicated on the graphs.

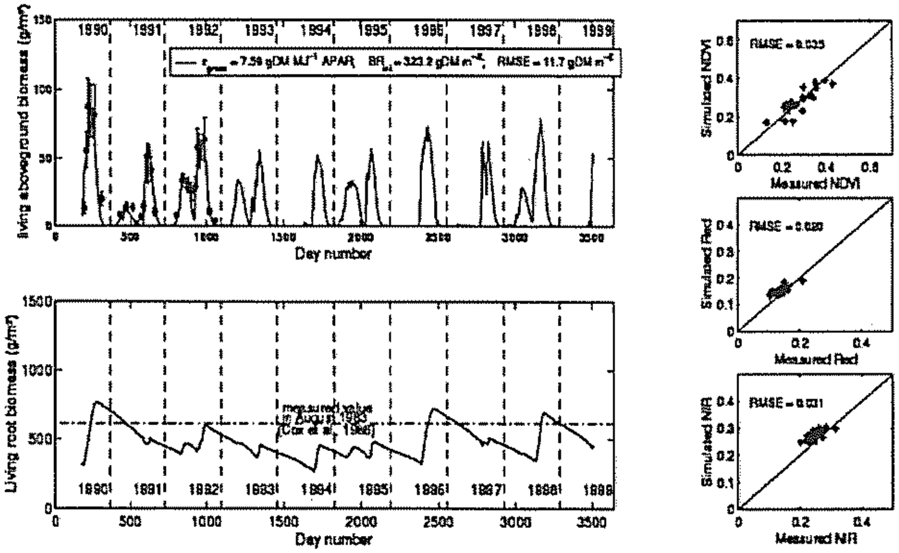

Figure 4: Simulation results obtained on the Kendall site after model calibration using TM images. The retrieved values of ε_{gmax} and BR_{ini} are indicated on the figure. In the top-left graph, solid circles with error bars show aboveground biomass measurements. In the bottom-left graph, the horizontal broken line shows the value of root biomass measured by Cox et al. (1986).

Figure 4 presents the simulation results obtained after model calibration. The results show that, after calibration, simulated aboveground biomass was in good agreement with measurements and with an RMSE of only 11.7 gm^{-2}.

INTERPRETATION: In this study, a coupled SVAT-RTM was run on a spatially distributed basis with assimilation of a ten-year time series of Landsat TM data. It was shown that satellite derived NDVI could be used to control the simulation of the coupled model through a calibration procedure which gives the estimation of two spatially variable initial conditions and model parameters. The results obtained suggest that the approach using both modeling and remote sensing may prove more useful in grassland management than either of them used alone. It also can provide spatially-distributed information about vegetation [e.g., maps of biomass obtained at a daily time step (Fig. 5)] and soil conditions for day-to-day grassland management.

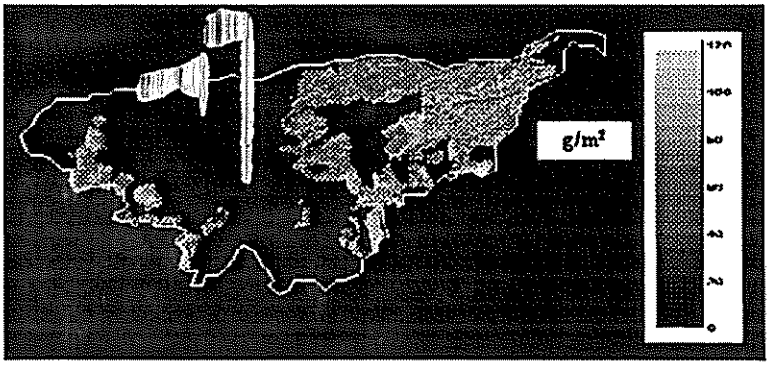

Figure 5: Map of simulated above-ground biomass (DOY 249, year 1992) on grassland areas of the WGEW.

FUTURE PLANS: We are currently initiating several works in order (1) to incorporate a runoff model in the grassland model; (2) to test more robust and faster calibration procedures; (3) to use both optical thermal and microwave remote sensing data; and (4) to address the problem of how meteorological data obtained at discrete locations can be used on a spatially distributed basis.

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SPECTRAL REFLECTANCE PROPERTIES OF INSECT TRAPS

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C.C. Chu, Research Entomologist; and T.J. Henneberry, Research Biologist

PROBLEM: A passive insect trap was recently developed for monitoring populations of silverleaf whiteflies (*Bemesia argentifolii* Bellows and Perring) and other insects in cotton and other field crops (Chu et al. 1998). Called the CC Trap after the initials of its inventor, C. C. Chu, the design of this new trap was based on insect behavior, primarily the attraction of insects to certain colors. No sticky materials, pheromones, or baits are used in its operation. From 1996 through 1999, scientists tested the trap efficiency in catching insects in the United States, India, and the People's Republic of China. The purpose of the U.S. Water Conservation Laboratory's involvement was to characterize the spectral properties of variously colored trap bases and relate the findings to trap performance.

APPROACH: The CC insect trap consists of a clear plastic trap top to admit light for insect orientation into the trap, a deflector plate to reduce escape of trapped insects, and a colored trap base that has an opening for insect entrance (Fig. 1). Nine different trap base colors were studied. These are described in the Monsanto Plastic (1993) color chart as white, rum, red, yellow, lime green, spring green, woodland green (dark green), true blue, and black.

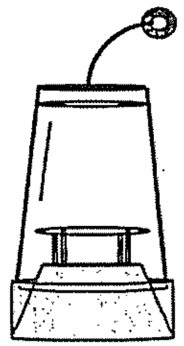

Figure 1. The CC insect trap.

A Personal Spectrometer II (PSII, Analytical Spectral Devices, Inc., Boulder, Colorado) was used to obtain spectral data from trap bases that were illuminated by midday, direct beam sunlight and diffuse sky irradiance. The spectroradiometer has a nominal 350 to 1050 nm spectral response, 1.4 nm sampling interval and approximately 3 nm spectral resolution. Fiber optics on the PSII were equipped with 10° field-of-view foreoptics. Measurements were made with the optics oriented normal (perpendicular) to the outside surface of the trap base. Reflectance factors were computed as the ratio of directional radiances of the trap base to irradiances estimated from frequent measurements over a calibrated $BaSO_4$ reference panel. Reflectance of the abaxial (under) surface of field-grown cotton leaves was used as a reference for comparison with colored trap bases.

FINDINGS: The differently colored plastic traps had spectral reflectance characteristics which varied considerably across the visible (400 to 700 nm) and near-infrared (700 to 1050 nm) portions of the spectrum. The different spectral shapes could be roughly associated with trap efficacy. We observed, for example, that the three most attractive trap colors for whiteflies and leafhoppers (lime green, spring green, and yellow in Fig. 2) had reflectances that were relatively low in the blue (400 to 460 nm) and higher in the green, yellow, and orange spectral regions (490 to 600 nm). It is relevant to note that the abaxial surfaces of green cotton leaves (also shown in Fig. 2) have a small peak at 550 nm that was spectrally similar to the prominent peaks measured on the lime green and spring green trap bases. Green cotton leaves also had low blue and red reflectances as well as high NIR reflectances. Thus the lime green and spring green trap bases seemed to mimic green leaves in an abstract sense. The lime green and spring green colored traps differed considerably from the yellow colored plastic trap and the commercially available, yellow cardboard sticky trap (not shown in figures) by having relatively low reflectances in both the red (600 to 700 nm) and red to NIR transition (700 to 740 nm) spectral regions. The yellow trap base had low blue reflectance, and, although lacking a peak in the green region (500-550 nm), displayed overall high reflectances beginning at 580 nm and continuing upwards into the NIR region. We found that the least attractive trap colors for whiteflies and leafhoppers (Fig. 3) had either very low reflectance at all wavelengths (e.g.., black and dark green) or had moderately high reflectance in the blue (400 to 480 nm; e.g., true blue trap) or red regions of the spectrum (600 to 700 nm, eg. red trap).

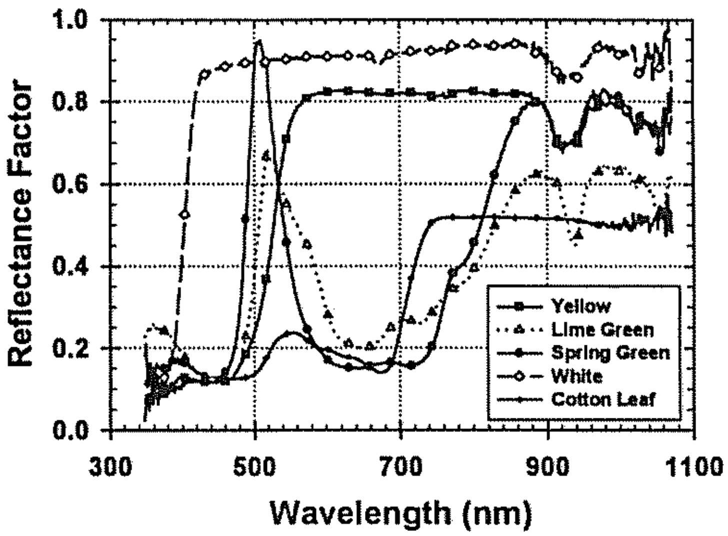

Figure 2. Spectral properties of CC trap base colors yellow, lime green, spring green, and white in reference to the abaxial surface of a cotton leaf.

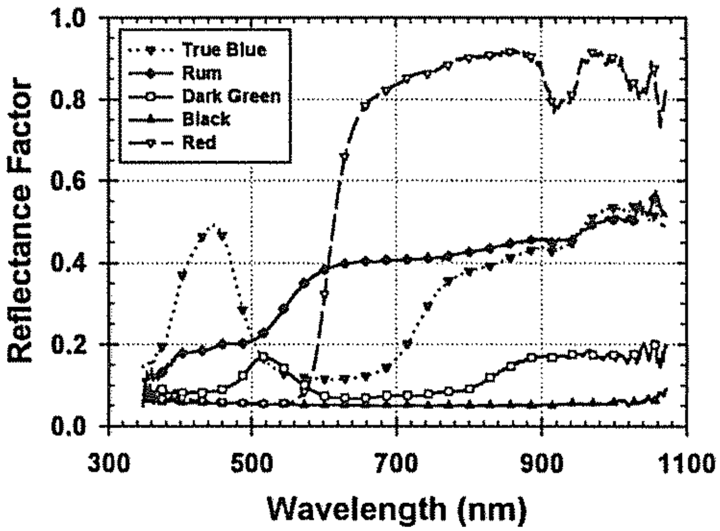

Figure 3. Spectral reflectance of CC trap base colors true blue, rum, dark green, black, and red.

INTERPRETATION: The reflectance factors that we measured from the most attractive trap base colors (lime green, spring green, and yellow) for the silverleaf whitefly and leafhoppers were somewhat similar to the spectral properties of healthy green cotton leaves (i.e., low reflectance in the blue, high NIR reflectance). Spectral properties of leaves and canopies vary with age and environmental conditions, and this may alter the time course of plant attractiveness to insects that use color clues in selecting host plants. We have observed, for example, that as cotton becomes nutrient stressed the green/yellow-green peak tends to become amplified slightly compared with the red (data not shown) although it never becomes as exaggerated as that observed in the lime and spring green traps.

In a previous, unpublished study (Pinter, 1994), we examined the high resolution spectral properties of cotton leaves coated with honeydew produced by actively feeding silverleaf whiteflies. We found that the honeydew caused higher reflectance in both the visible and NIR wavelengths. However, the increases were much greater in the blue and red regions than in either the green or NIR. The honeydew varnish also acted like a spectrally selective mirror so that this effect was accentuated when the leaves were viewed in the forward scattering direction (i.e., so that some sun glint could be seen on the leaf surface). Such changes in leaf spectral properties caused by honeydew may "signal" the presence of high larval densities to migrating adult whiteflies enabling them to avoid areas where resources are already being exploited. Further examination of links between trap performance and spectral deterrents or attractants could lead to improved traps having different construction materials or colors and could improve our basic understanding of insect migration and colonization behavior. Additional research also may provide insight on why some insects are attracted to plants experiencing water or nutrient stress and why some crop cultivars seem more attractive to certain insects.

FUTURE PLANS: A manuscript on the spectral properties and efficacy of the CC Trap has been prepared and submitted (Chu et al.).

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