Spider Mite Damage Mapping and Cotton Canopy Biophysical Characterization Using Spectral Mixture Analysis

Glenn J. Fitzgerald[1]*, Stephen J. Maas[2], Paul J. Pinter, Jr.[1], Douglas J. Hunsaker[1] and Thomas R. Clarke[1]

[1] U.S. Water Conservation Laboratory, USDA-ARS, 4331 East Broadway Road, Phoenix, AZ 85040, U.S.A.

[2] Department of Plant & Soil Science, Texas Tech University, 3810 4th Street, Lubbock, TX 79415, U.S.A.

*Corresponding author (E-mail: gfitzgerald@uswcl.ars.ag.gov)

ABSTRACT

Spectral mixture analysis (SMA) is an analytical tool that can identify and measure the components that make up mixed pixels. Used with hyperspectral remotely-sensed (HRS) imagery, SMA permits mapping of surface components from research plot to landscape scales. These technologies are being used increasingly in agronomic research and have potential for precision agriculture to map spatially and temporally variable crop conditions and stresses. SMA was applied to two data sets collected from different hyperspectral imagers. For both studies, radiometrically-calibrated crop and soil spectra were collected using ground-based spectroradiometers and imagers to provide reference spectra. In one experiment, strawberry spider mite (*Tetranychus turkestani* U.N.) damage in cotton was mapped. This pest causes leaf puckering and reddish discoloration and can reduce boll yield. Analysis showed that pest damage could be successfully identified, the relative abundance mapped in large research plots, and temporal changes in damage were consistent with known ground conditions. One confounding factor was shadows which interfered with proper abundance estimation of mite damage. To understand the effects of shadows on estimating canopy characteristics, a second study was conducted where spectra of sunlit and shadowed leaves and sunlit and shadowed soil were measured in cotton research plots. The intent was to determine whether SMA and HRS could simultaneously measure percent cotton cover, height, and chlorophyll concentration and whether the influence of shadows could be isolated. Results showed that including shadows as reference spectra improved relationships between imagery and ground measurements. Mapping sub-pixel landscape components based on spectral signatures could be useful for crop and ecosystem models, irrigation scheduling, locating water and nitrogen stress, and simultaneous measurement of key plant and crop parameters.

Key words: Spectral mixture analysis, Hyperspectral remote sensing, Precision agriculture, Cotton, Spider mites.

INTRODUCTION

Spectral mixture analysis (SMA) is one

type of advanced image processing technique that has been used to analyze hyperspectral imagery from ecological studies for a number of years, and the procedure is well documented (Adams and Smith, 1986; Roberts, *et al.*, 1998; Okin, *et al.*, 2001). A few manuscripts have addressed the issue of detection or discrimination of field- or canopy-level features in agricultural crops with hyperspectral remote sensing (Palacios-Orueta and Ustin, 1996; Gat *et al.*, 2000; Estep and Davis, 2001; Fitzgerald, *et al.*, 2004a). However, using spectral unmixing for estimating crop biophysical characteristics or arthropod detection is not well established.

Linear spectral unmixing is based on the assumption that each pixel is a physical mixture of distinct components (endmembers), and the spectrum of this mixed pixel is a linear combination of the endmember reflectance spectra (Tompkins, *et al.*, 1997). SMA assumes that a small number of endmember spectra can describe most of the spectral variation in a scene and be used to "unmix" the pixels to determine the fractional abundance of each component within a pixel. A modified SMA, the Multiple Endmember Spectral Mixture Analysis (MESMA) allows each pixel to be modeled by a variable number of endmembers (Roberts, *et al.*, 1998). Either SMA or MESMA could allow discrimination of one plant stress from another through identification of differences in spectral curves and then quantify the amount present in each pixel. Relationships can also be developed between the imagery and canopy parameters, allowing simultaneous estimation of canopy cover, height, chlorophyll concentration, or other traits. Fractional abundance maps produced could indicate both the spatial extent and severity of particular stresses or amount of a particular canopy parameter. Such maps would permit a farm manager to locate a stress precisely in a field, thereby providing guidance for field scouting and precision application of pesticides or fertilizer. They could also be used as inputs to crop, irrigation, carbon cycling or other models to permit spatial modeling.

This report describes the real-world application of hyperspectral remote sensing and SMA from two USDA-ARS published studies. In one, the severity and extent of damage to a cotton crop caused by the strawberry spider mite (*Tetranychus turkestani U.N.*) is demonstrated. In a second study, cotton cover, height, and chlorophyll *a* (Chl *a*) concentration were estimated.

MATERIALS AND METHODS

Methods are fully described in Fitzgerald *et al.* (2004a and 2005). A brief description is provided here.

Spider Mite Study

An experiment was established on two, 2.8 ha fields at the USDA-ARS research station in Shafter, CA (35.5° N, 119.3° W., 120 meters above sea level). Each field was planted to cotton (*Gossypium hirsutum* L. variety "Maxxa") on 4 May 1999. Both were managed according to standard cultural practices for cotton in the area except in one (Field 41) spider mites were allowed to prosper by applying a broad acting pesticide, reducing beneficial predators. The other (Field 42) was treated with pesticides to control spider mite infestations following standard local practices.

Spectra of ground components were collected using a liquid-crystal tunable-filter imaging system (Fitzgerald *et al.*, 2004a; Fitzgerald, 2004b). Components included sunlit healthy leaves (H), sunlit mite-damaged leaves (M), tilled sunlit soil (S), tilled shaded soil (Sh), opened cotton boll (CB), and dead leaf (D) (Fig. 1). These were selected based on observation of the principal canopy components. Reference spectra of these components were constructed by selecting representative pixels on leaves and soil. Each image was acquired within one hour of solar noon. Images were corrected to reflectance using a 99% Spectralon calibration panel (Labsphere, North Sutton, NH, USA), which was placed in the field of view before and after image acquisition.

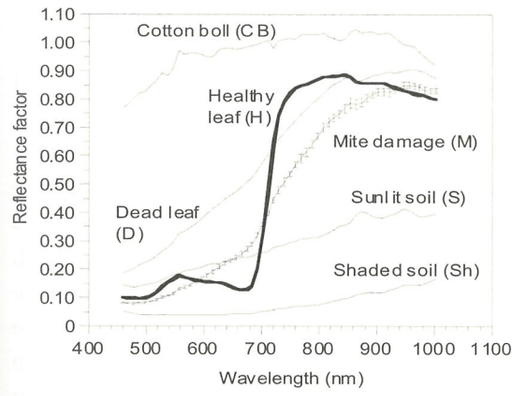


Fig. 1. Six reference spectral signatures for the spider mite study. The error bars on the mite spectrum represent ±1 standard error.

Imagery of the research fields was acquired under clear skies from NASA's Airborne Visible Infrared Imaging Spectrometer (AVIRIS) on four separate dates in 1999. The hyperspectral imagery was composed of 224 images acquired contiguously from 400-2500 nm in 10 nm bands. Those bands matching ground spectra were used in the analysis in the range 459 to 1002 nm. The AVIRIS data sets were atmospherically corrected and converted to reflectance. Ground pixel resolution was 18 m.

Cotton Canopy Components Study

Cotton (*Gossypium hirsutum* L., variety Deltapine 458BR) was planted on raised beds in a 2.5 ha field at the Maricopa Agricultural Center (33.073 N; 111.979 W, 350 m above sea level) in Central Arizona on 7-8 Apr 2003 (DOY 97-98). The beds were spaced 1.02 m (40 in) apart, in a north-south orientation. The cotton germinated beginning on 16 Apr 2003 (DOY 106), was defoliated on 18 Sep (DOY 261), and harvested in mid-October.

The field was divided into 32 plots (each 11.2 by 20 m), which were assigned to 12 different experimental treatments including three plant density and two N level (high and low), which provided a range of variation comparable to a grower's field. The plant density sub-treatments consisted of: Sparse (5 plants/m2, single-line planting); Typical (10 plants/m2 in single-line planting); and Dense (20 plants/m2, double-line planting). The two fertilization levels were: High N (split N applications, based on optimum local practices); and Low N (no additional N applied as fertilizer). A set of smaller plots with unplanted wet and dry soil as well as cotton grown under two different levels of chronic water stress were provided as extremes for measurement of soil and canopy variables.

Hyperspectral imagery was acquired under clear sky conditions from either a light aircraft or helicopter on five dates in 2003. The imagery was acquired with the Portable Hyperspectral Tunable Imaging System (PHyTIS), which captures images in discrete wavebands from 400 to 1100 nm (Fitzgerald, 2004b). Ground pixel resolutions ranged

from 0.55 to 1.2 m. Images were corrected for vignetting, co-registered (Erives and Fitzgerald, 2005), and converted to reflectance using four, 8 m X 8 m reference tarps visible in the scene. The wavelength range of the final imagery used for analysis was from 440 nm to 810 nm with 10-nm sampling interval and spectral resolution.

The canopy components, sunlit leaves (LS), shadowed leaves (LSh), sunlit soil (SS), and shadowed soil (SSh) were measured in the field with an ASD Full Range spectrometer (Analytical Spectral Devices, Boulder, CO). The sensor was mounted on a 1.5 m pole held nadir to the component of interest to emulate the view angle of the PHyTIS airborne sensor platform. The radiance data were converted to reflectance using a 99% Spectralon panel.

Cover was measured photographically with a digital camera. Height was measured non-destructively in the field using a meter stick. Chl *a* concentration was determined using the 80% acetone-BHT method according to Lichtenthaler and Wellburn (1983) on the third fully-expanded leaf from 12 plants per plot, one leaf per plant.

Mixture Analysis

For both studies, SMA was performed using the built-in Linear Spectral Unmixing (LSU) tool in the ENVI software (Research Systems, Inc. Boulder CO). Since this does not account for variable endmember numbers per pixel, the abundance fractions from each region were then exported for further analysis using a spreadsheet-based MESMA model.

The simple linear mixture model takes the form (Roberts *et al.*, 1998):

$$P'_{i\lambda} = \sum_{k=1}^{N} f_{ki} * P_{k\lambda} + \varepsilon_{i\lambda} \text{ and } \sum_{k=1}^{N} f_{ki} = 1, \quad (1)$$

Where $P'_{i\lambda}$ is the spectral mixture at location i at a given wavelength λ modeled as the sum of N reference endmembers, $P_{k\lambda}$, with each weighted by the fraction, f_{ki}. The unmodeled portion is the residual term, $\varepsilon_{i\lambda}$ and the endmember fractions are constrained to sum to 1.

Selection criteria of valid two, three or four endmember sets for each region are described in detail in Fitzgerald *et al.* (2005).

RESULTS AND DISCUSSION

Spider Mite Study

There were statistically significant differences between the two fields for mite counts (Field 41 = 4.9 and Field 42 = 3.1 mites/10 leaves) as determined by a t-test at α = 0.05 (p=0.0002). Spectral unmixing showed that Field 41 had intense mite damage while Field 42 was free of mite damage during the season. This matched ground observations. When the mite, plant, and soil fractional abundance images are composited these image components can be mapped (Fig. 2). Mean mite abundance fractions from the 13 Jun image showed no differences between the fields early in the season before mites had entered the fields (gray). The 28 Aug and 1 Sep images show that Field 41 had significant mite damage (dark gray) but Field 42 was mite free, showing only healthy vegetation (light gray). The final 24 Sep image shows that once senescence began in the cotton, the reddish leaves mimicked the signature of mite damage and thus could also be mapped (dark gray). Late season re-growth of cotton in field 41 is apparent by the light gray color at the west edge.

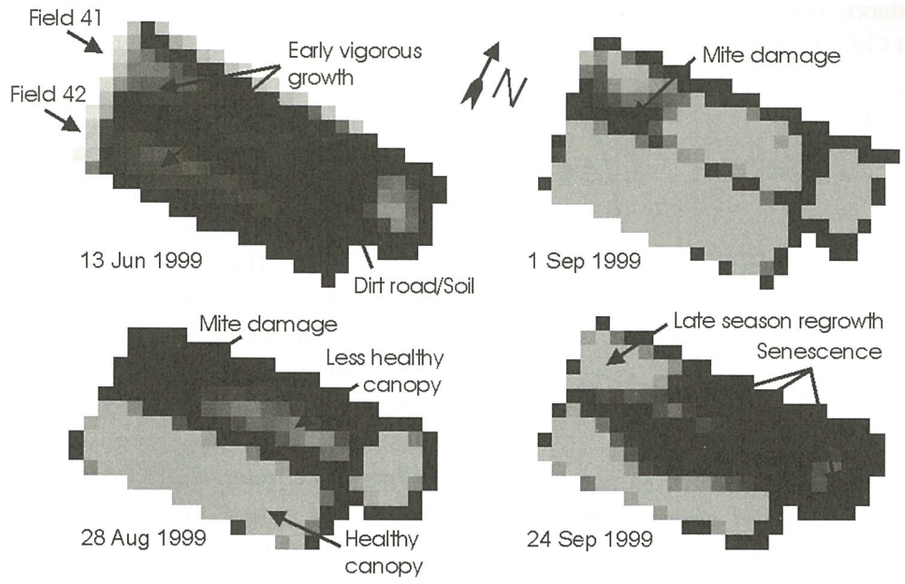


Fig. 2. Composite images normalized for shade of Mite (dark gray), Healthy (light gray), and Soil/Road (black, edges) fractions showing changes across the season. The dark gray areas could direct a farmer to mite damaged areas. The smaller field to the east was managed the same as Field 42.

Shadows were a confounding factor in estimating fractional abundances. Mite fractional values were 0.09 and 0.01, respectively for Field 41 on 28 Aug and 1 Sep. Since these images were acquired only four days apart they would be expected to have similar fractions. Mite fractions were normalized for shadows by dividing by (1-shadow fraction), which tends to remove the influence of shading (Adam *et al.*, 1993). Normalized for shadows, the mite fractions changed to 0.20 and 0.04, respectively, a 5:1 ratio. This only partly corrected for shadows probably because the only shadow fraction incorporated into the analysis was soil shadowing. This was investigated in the following study.

Cotton Canopy Components Study

Since it was shown in the spider mite study that shadows had a confounding effect on the measurement of important canopy components, it was hypothesized that including a self-shadowing reference spectrum would reduce this confusion. The principal spectra in any vegetated canopy are represented by the spectra presented here, LS (Leaves, Sunlit), LSh (Leaves, Shadowed), SS (Soil, Sunlit), and SSh (Soil, Shadowed) [Fig. 3]. The estimations of biophysical and chemical characteristics presented here, canopy cover, canopy height, and Chl *a* concentration, were chosen to represent three distinct canopy features. Cover represents the two-dimensional projection of the crop onto the background. Height is the three-dimensional, structural aspect of crop growth and development. Chl *a* concentration is a leaf-level measure of chemical constituents, which might be measurable because of differences in leaf

transmittance within the canopy caused by different Chl *a* concentrations.

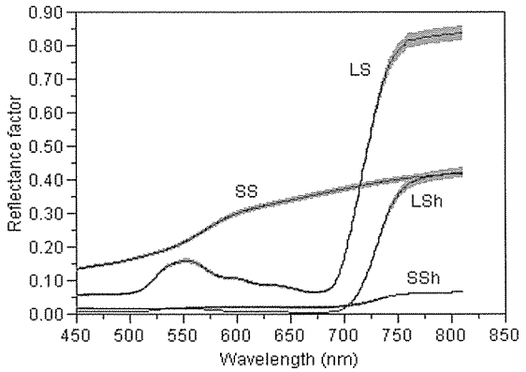


Fig. 3. Spectral references derived from ground spectroradiometer measurements used to unmix the hyperspectral imagery in the cotton component study. The central dark lines represent mean reflectance values and the shaded areas are standard error. Fraction acronoym descriptions: LS–Leaf, Sunlit; LSh–Leaf, Shadowed; SS–Soil, Sunlit (dry); SSh–Soil, Shadowed.

Results indicate that it is necessary to include the shadowed reference spectra in order to properly quantify cover, height, and Chl *a* in a canopy. Cover was well estimated by summing the LS and LSh fractions (Fig. 4a), although the Normalized Difference Vegetation Index (NDVI) performed equally well (Fitzgerald *et al.*, 2005). It was shown that height up to canopy closure could only be estimated when the LSh reference spectrum was included in the analysis (Figs. 4b, c). The Chl *a* constituent was shown to be estimated best by the LS reference alone and had a negative slope (Fig. 4d). This was due to the reference spectrum being low in chlorophyll and, thus, those spectra that matched the reference most closely (highest abundance) had the lowest Chl *a* concentrations. This was the only reference spectra combination for Chl *a* that modeled the water stressed plots well (Fitzgerald *et al.*, 2005).

CONCLUSIONS

Shadows contribute to mixed pixels and can be separated from plant and soil signals using SMA. There are two main shadow types, shadowed soils and leaves that must be included for proper unmixing. Physical components, such as cover and height were modeled well by this procedure. Chl *a* was modeled less well but choosing the appropriate reference spectrum for green leaf led to successfully including water-stressed canopy. Spider mite damage was modeled due to changes in leaf color. Future work needs to address the issues of appropriate reference (endmember) spectra to represent green plants and shadows, the minimum number of wavebands needed to define an endmember, determine endmembers stability across seasons, and the type and number of factors that can be simultaneously measured.

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Mention of specific suppliers of hardware and software is for informative purposes only and does not imply endorsement by the United States Department of Agriculture.

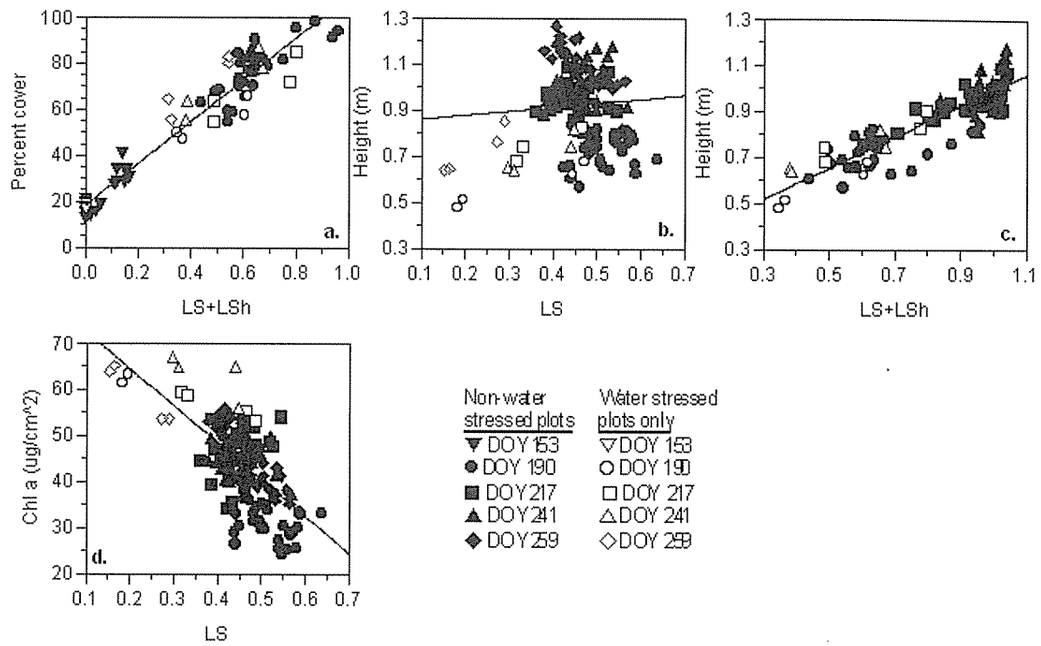


Fig. 4. Cotton canopy constituents at 5 dates in 2003 (day of year – DOY), percent cover (a), height (b, c), and chlorophyll *a* [Chl *a*] (d). Cover was modeled using sunlit (LS) and shadowed (LSh) leaf spectral components (r^2 = 0.95, RMSE = 6.6%). Height was modeled poorly by LS only but well with the shadow fraction (r^2 = 0.79, RMSE = 0.07 m). Chl *a* concentration was modeled by the LS fraction alone (r^2 = 0.46, RMSE = 7.0 µg/cm²). Open circles show water-stressed plots. All were statistically significant at α = 0.05 ($p < 0.0001$).

REFERENCES

Adams, J.B. and M.O. Smith. 1986. Spectral mixture modeling: A new analysis of rock and soil types at the Viking Lander 1 Site. Journal Geophysical Research 91:8098-8112.

Erives, H. and G.J. Fitzgerald. 2005. Automated registration of hyperspectral images for precision agriculture. Computers and Electronics in Agriculture 47:103-119.

Estep, L. and B. Davis. 2001. Nutrient Stress Detection in Corn Using Neural Networks and AVIRIS Hyperspectral Imagery. p. 119-124. *In*: Summaries of the 10th JPL Airborne Earth Science Workshop, R.O. Green, ed. Jet Propulsion Laboratory, Pasadena, CA, USA.

Fitzgerald, G.J., S.J. Maas and W.R. DeTar. 2004a. Spider mite detection and canopy component mapping in cotton using hyperspectral imagery and spectral mixture analysis. Precision Agriculture 5:275-289.

Fitzgerald, G.J. 2004b. Portable hyperspectral tunable imaging system (PHyTIS) for precision agriculture. Agronomy Journal 96:311-315.

Fitzgerald, G.J., S.J. Maas, P.J. Pinter, Jr. and T.R. Clarke. 2005. Shadow Fraction in

Spectral Mixture Analysis of a Cotton Canopy. Remote Sensing of Environment (in press).

Gat, N., H. Erives, G.J. Fitzgerald, S.R. Kaffka and S.J. Maas. 2000. Estimating sugar beet yield using AVIRIS-derived indices. Unpaginated CD. *In* Summaries of the 9th JPL Airborne Earth Science Workshop, R.O. Green, ed. Jet Propulsion Laboratory, Pasadena, CA, USA.

Lichtenthaler, H.K. and A.R. Wellburn. 1983. Determination of total carotenoids and chlorophylls a and b of leaf extracts in different solvents. Biochem. Soc. Trans 11: 591-592.

Roberts, D.A., M. Gardner, R. Church, S. Ustin, G. Scheer and R.O. Green. 1998. Mapping Chaparral in the Santa Monica mountains using multiple endmember spectral mixture models. Remote Sensing of Environment 65:267-279.

Okin, G.S., D.A. Roberts, B. Murray and W.J. Okin. 2001. Practical limits on hyperspectral vegetation discrimination in arid and semiarid environments. Remote Sensing of Environment 77:212-225.

Palacios-Orueta, A. and S. Ustin. 1996. Multivariate Statistical Classification of Soil Spectra. Remote Sensing of Environment 57:108-118.

Smith, M.O., S.L. Ustin, J.B. Adams and A.R. Gillespie. 1990. Vegetation in deserts: I. A regional measure of abundance from multispectral images. Remote Sensing of Environment 31:1-26.

Tompkins, S., J.F. Mustard, C.M. Pieters and D.W. Forsyth. 1997. Optimization of endmembers for spectral mixture analysis. Remote Sensing of Environment 59:472-489.