Use of Airborne Multi-Spectral Imagery in Pest Management Systems

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ABSTRACT

A multi-spectral imaging system for use on agricultural aircraft was developed and tested to provide images of fields and help farmers and crop consultants manage agricultural lands. The results of this research indicate that the airborne MS4100 multi-spectral imaging system has a great potential for use in areawide pest management systems, such as weed control or detection of insect damage. Multi-spectral image processing produces NIR, red, green, NR, NG, NDVI and NDNG indices or images, which can be used to evaluate biomass, crop health, biotypes, and pest infestations in agricultural fields. The classified images identify the ground land cover clusters by differentiating the variation of spectral signatures in the image. The results of the image classification can provide critical input to generate prescription data for precision application of crop production and protection materials.

Keywords: Areawide pest management, MS4100, pest management, airborne remote sensing, multi-spectral imagery, USA

1. INTRODUCTION

Areawide Pest Management (APM) is a concept of preventive suppression of a pest species throughout its geographic distribution, rather than reactive field-by-field control. APM essentially represents coordinated adoption of one or more Integrated Pest Management (IPM) programs, which integrates control tactics to manage one or multiple key pest species in a single field, to a large multi-field area. Scientists and researchers in APM programs have been developing, integrating, and evaluating multiple strategies and technologies into a systems approach for management of field crop insect pests. Remote Sensing along with Global Positioning Systems (GPS), Geographic Information Systems (GIS), and variable rate technology (VRT) are additional technologies that scientists can implement to help farmers maximize the economic and environmental benefits of APM through precision agriculture.

Remote sensing can be conducted through satellites, aircraft, or ground-based platforms. Satellite remote sensing is primarily for large-scale studies (>1 km^2) but sometimes not adequate in applications that require finer spatial resolution. Airborne remote sensing is flexible and able to achieve different spatial resolutions with different flight altitudes. Ground-based platforms, such as handheld spectroradiometers, are typically used for ground truth study.

In pest management, detection of insect damage to crops along with weed infestation and crop disease provides valuable information for management planning and decision-making. Handheld devices have been used in labs or fields to fundamentally study the optical characteristics of crops, weeds, and damages of insects and plant diseases (Hart and Mayer, 1968; Gausman et al., 1981; Sudduth and Hummel, 1993; Riedell and Blackmer, 1999; Smith and Blackshaw, 2002). Airborne remote sensing has been widely used in detection and analysis of pest damages in fields. Weed detection has probably been the most successful application of airborne remote sensing in pest management. In recent years, there has been a shift away from uniform, early season weed control towards using herbicide-ready crops and applying post-emergence herbicide only as needed. This strategy change has generated increased interest in using remote sensing to define the extent of weed patches within fields so they can be targeted with variable rate ground and aerial spray rigs (Pinter, et al., 2003). Richardson et al. (1985) demonstrated that multi-spectral aerial video images could be used to distinguish uniform plots of Johnsongrass and pigweed from sorghum, cotton, and cantaloupe plots. By visual assessment of herbicide injury in cotton with CIR (Color-Infrared) photography, NIR (Near InfraRed) videography, and wideband handheld radiometer, Hickman et al. (1991) concluded that remote sensing and mapping of moderate herbicide damage was possible, and from which the application rate of herbicides could be estimated. Medlin et al. (2000) evaluated the accuracy of classified airborne CIR imagery for detecting weed infestation levels during early-season *Glycine max* production. Ye et al. (2007) used airborne multi-spectral imagery to discriminate and map weed infestations in a citrus orchard. There have been a number of successful applications of airborne remote sensing in detection of insect infestation for pest management. Hart and Myers (1968) used aerial CIR photography to detect the insect infestation on trees in a number of citrus orchards. Aerial CIR film and multispectral videography have been also used to detect citrus blackfly and brown soft scale problems in citrus as well as whitefly infestations in cotton (Hart et al., 1973; Everitt et al., 1991; Everitt et al., 1994; Everitt et al., 1996). Airborne remote sensing technology has been employed for detecting crop disease and assessing its impact on productivity (Heald et al., 1972; Henneberry et al., 1979; Schneider and Safir, 1975; Cook et al., 1999). Satellite remote sensing has been used to detect some pest problems. Fletcher (2005) evaluated QuickBird imagery for detecting citrus orchards affected by sooty mould. Researchers have used Landsat (Nelson, 1983; Vogelmann and Rock, 1989) and SPOT (Buchheim et al., 1984; Ciesla et al., 1989; Frinklin, 1989; Sirois and Ahern, 1989) satellite imagery with coarse spatial resolutions to detect and assess insect damage to forests.

In order to realize preventive suppression of a pest species throughout its geographic distribution in APM, remote sensing is taking a leading role in developing, integrating, and evaluating multiple strategies and technologies into a systems approach. The objective of this research is to develop and test a multi-spectral imaging system on an agricultural aircraft to provide an airborne multi-spectral remote sensing method for pest management systems. Specifically, the airborne multi-spectral imagery will be processed and evaluated in order to aid in site-specific pest management applications.

2. REMOTE SENSING FOR APM

The concept of APM is based on a set of principles that are somewhat different from those of traditional IPM. Definitions of IPM vary widely. However, many individuals regard IPM as a decision support system for the selection and use of pest control tactics, solely or harmoniously coordinated into a management strategy, based on cost-benefit analyses that take into account the interests of and impacts on producers, society, and the environment (Kogan, 1998). Most growers currently practice IPM by using the best available pest management tactic(s) as needed against a key pest(s) on an individual field or farm. APM has involved as a component of IPM and is currently viewed as an effective method to manage pests of economic importance using an organized and coordinated attack on pest populations over large areas (multi-field or farm). APM is most effective when conducted against a single or small group of pests over large geographical areas that are delineated by biological criteria associated with pest colonization and dispersal potential. Numerous APM programs are currently being conducted throughout the world (Chandler et al., 1999).

Chandler et al. (1999) presented that in the U.S., several cotton pests are managed using area-wide techniques. In 1995, the USDA's Agricultural Research Service (ARS) implemented the first formal APM program against the codling moth in the Pacific Northwest. That multi-state cooperative program was developed to assess, test, and implement an integrated strategy for the management of the pest on fruit orchards using mating disruption to alleviate the impact of chemical insecticides on natural enemies and to open the opportunity for use of more environmentally friendly control tactics against other pests.

As IPM expands to APM type programs, data management and decision needs become more critical. Pest management using remote sensing techniques with GPS and GIS supports to pursue site-specific strategies will become more important over large and distributed geographic management units. Rapid data acquisition, data assessment and precise decision capabilities will be needed by grower/consultants to adequately manage a crop. Chandler et al. (1999) gave an example of use of a GIS for tracking crop development, insect management activities, and land use within the South Dakota corn rootworm areawide management site. In this example it was readily apparent that GIS/GPS technologies could certainly benefit crop managers in tracking changes in insect density over large areas. Furthermore, laborious and time-consuming insect counting over the large area can be replaced by airborne remote sensing of the surface data, which could be rapidly identified, assessed, and presented with GIS/GPS from the aerial multi-spectral imagery at any requested spatial resolution. Airborne remote sensing should be able to provide accurate ground cover data for APM.

3. AIRBORNE MULTI-SPECTRAL IMAGING

An MS4100 multi-spectral camera (Geospatial Systems, Inc., Rochester, NY) was the central component of the airborne multi-spectral imaging system described herein. This

MS4100 camera is a 3-chip, multi-spectral HDTV-format digital camera with more than two million pixels per sensor. Three-chip image capture combined with advanced image processing provided excellent image quality. Each of the three sensors in the camera has a 1920 x 1080 pixel array. The image sensors are charge coupled device (CCD) array sensors with spectral sensitivity from 400-1000 nm. The camera supports three standard models for RGB, CIR and RGB/CIR with blue band in between 437 and 483 nm, green band in between 520 and 560 nm, red band in between 640 and 680 nm, and NIR (Near InfraRed) band in between 767 and 833 nm. Digital image output can be through LVDS (Low-Voltage Differential Signaling), RS-422 and CameraLink frame grabber.

The MS4100 multi-spectral camera was successfully applied for remote sensing, machine vision, flat panel display inspection, reconnaissance, advance surveillance, medical/scientific imaging, robotics, and document archival. The areas of remote sensing applications included: precision agriculture (http://www.gointime.com/), environmental assessment, archeology, geology, and oceanography.

Based on the requirements of the research, the body of the MS4100 camera was equipped with a 14 mm Sigma lens with a 58.1 degree field of view and an IMAQ PCI/PXI-1428 camera link frame grabber (National Instruments, Austin, TX) (Figure 1).

Figure 1: MS4100 multi-spectral camera with 14mm Sigma lens

A single-engine airplane, Cessna 206 (Wichita, KS), owned by the USDA-ARS (Figure 2) was assigned to fly over the selected fields to produce CIR and/or RGB images for analytical inference in APM. The assembled imaging system was mounted on the agricultural aircraft for image acquisition (Figure 3).

Figure 2: Cessna 206 aircraft

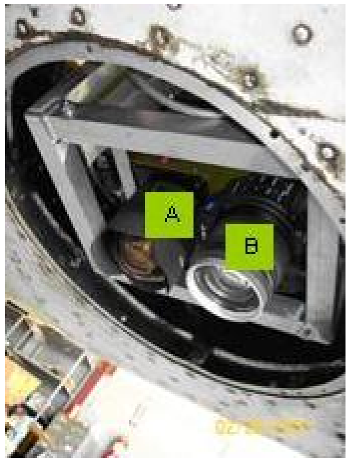


Figure 3: Bottom view of MS4100 multi-spectral camera (A) and regular digital RGB camera (B) on Cessna 206.

The raw data of the acquired images in over-flight were digital numbers (DNs), which typically represent gray scales in each band (0-255 for 8-bit images). Post-processing of the acquired images was critical for producing high quality analysis. In general, remotely sensed image processing involves radiometric correction, image de-noising and enhancement, image registration, geo-referencing and geometric correction, area of interest (AOI) determination, classification, and vegetation indexing.

Image denoising and enhancement is important to assure the quality of the images acquired. Methods and techniques are available in regular image processing for denoising and enhancement of the remote sensing images. Image registration was not necessary for the images acquired by the MS4100 system because the camera has a built-in function to do it. The images generated by this multi-spectral imaging system were composite CIR and/or composite RGB. With each composite image the image could be worked on overall or band by band after decomposition. Image geo-referencing requires the use of geo-referenced ground control points (GCPs) to reorient the image similar to the real geographic orientation at the field. The GCPs are typically selected at the points within an image with a significant feature (i.e. buildings, roads, intersections, and/or trees).

Determination of AOI (Area of Interest) in an image is necessary. The AOI will make later processing and analysis more focused on the area of interest and save computing power as well. Image classification is an important product from image processing. Image classification can be supervised or unsupervised. Supervised classification uses the data from an image to train the image to recognize a number of known signatures. Unsupervised classification works in a self-organizing way to cluster the data in the image with a pre-defined number of centers. Supervised classification typically works fine with an image covering a relatively small piece of land while unsupervised classification works with an image covering a relatively large piece of land. Supervised and unsupervised classifications can work together to get improved results compared with what each of them does individually.

The MS4100 multi-spectral imaging camera produced CIR and/or RGB composite images. The blue, green, red, and NIR bands could be extracted out individually by decomposition of the composite images. With the individual band images, another important product, vegetation indices, from image processing could be generated.

Vegetation indices include band ratios and normalized differences (ND), which are derived from the individual blue, green, red and NIR spectral bands, including:

1. Band ratio indices

NB=NIR/Blue, NG=NIR/Green, NR=NIR/Red

2. Normalized difference indices

NDNB=(NIR-Blue)/(NIR+Blue), NDNG=(NIR-Green)/(NIR+Green), NDVI=(NIR-Red)/(NIR+Red)

where NDNB is the normalized difference ratio of NIR and blue bands; NDNG is the normalized difference ratio of NIR and green bands; and NDVI is the normalized difference ratio of NIR and red bands, i.e. normalized difference vegetation index In this research, only CIR composite containing green, red and NIR bands was sufficient. The CIR image would only give four vegetation indices: NG, NR, NDNG, and NDVI. In the process of remote sensing image processing interacting with GIS functions, it is important to eventually allow the overlay of the image processing results on GIS shape files for further analysis. In this research, ERDAS Imagine (Leica Geosystems Inc., Norcross, GA) was used for aerial multi-spectral image processing. The products of the processing, such as the classification results, were converted from raster to vector (grid or geo-tiff). ArcMap (ESRI, Redlands, CA) took the vector data to reclassify with the Spatial Analyst extension. With the reclassification the ArcMap overlaid and manipulated the classification image over the shape file(s).

4. RESULTS

To evaluate the application of the MS4100 multi-spectral imaging system and establish the airborne remote sensing method, a field (Fig. 4) was selected near Mumford, TX, USA (N30°43’45”, W96°50’45”). The major crops in this area were cotton and corn. In order to achieve desired yield, effective pest management is important. In the spring and before planting, this land grew grass and weeds of different heights and was surrounded by fields already planted in cotton and corn.

Figure 4: Google Earth© image of the agricultural area of interest near Mumford, Texas

The CIR images captured by the MS4100 multi-spectral imaging system during the initial flight over the field is shown in Figure 5. This composite image was in initial form without geo-reference. The high NIR reflectance in the image indicated that this land was full of vegetation with variation. A field survey revealed that the surrounding fields were either planted (A) or bare soil (B). The survey with GPS validated the image observations by indicating that the land was full of spatially distributed grass and weed clusters and the grass clusters varied in different heights and the neighboring brown fields grew young corns and the blue fields are bare soil without growing anything yet. The raw images were needed to process further to reveal variations of biomass on the ground.

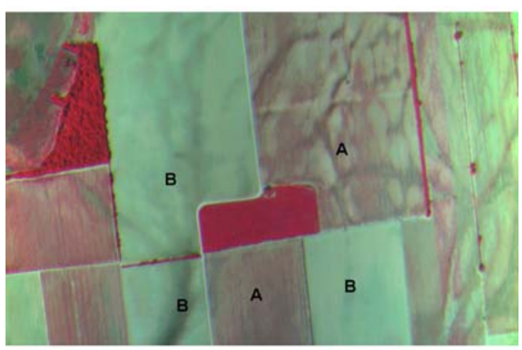


Figure 5: CIR image of the test field near Mumford, Texas, USA.

The geo-referenced image of the test field with AOI cropping is shown in Figure 6. On this image 9 GCPs were overlaid, which were used for geo-reference. Other GPS points shown on this image were collected together with the GCPs in field survey. The raw image was orientated with north at the top of the picture. In ArcGIS, this image was overlaid on the 1-meter resolution DOQQ (Digital Ortho Quarter Quads) aerial photograph provided by TNRIS (Texas Natural Resources Information System, Austin, Texas, http://www.tnris.org/). The image geo-reference was conducted with the polynomial model with a RMSE (Root Mean Squared Error) less than 0.5 m.

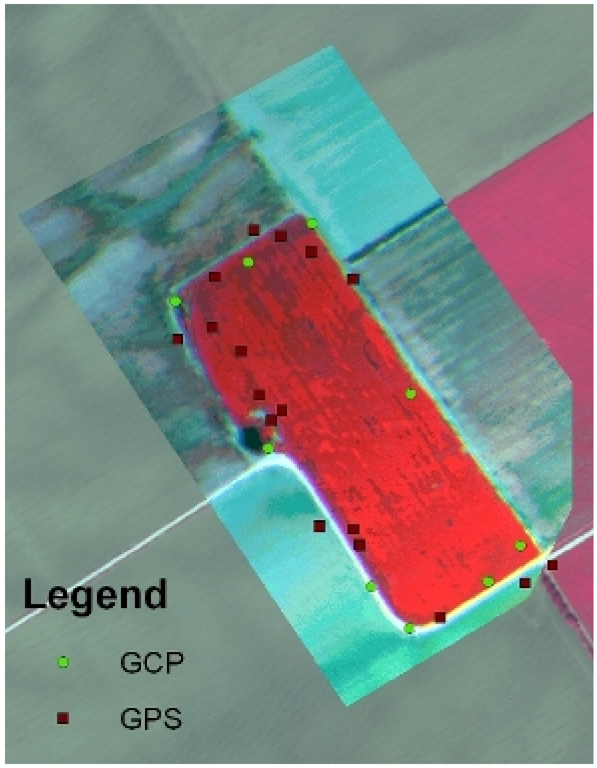


Figure 6: Geo-referenced AOI image of field near Mumford, Texas on DOQQ in GIS.

With the geo-referenced image AOI (Figure 6), the corresponding NR, NG, NDVI and NDNG images were generated and overlaid as GIS layers (Figure 7). The data contained in these four images provided significant indications of the biomass in the field.

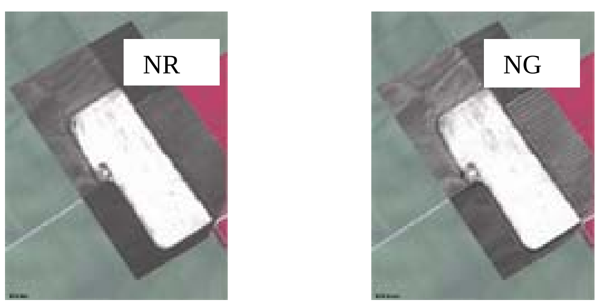


Figure 7: NR, NG, NDVI and NDNG AOI images of Mumford, Texas on DOQQ in GIS

In image classification the unsupervised classification was initialized with 30 classes. The initial classes were labeled with the help of the ground truth data in the GPSed points from field survey. Ninety eight percent of pixels of the image in this area were divided into two major parts: the grassland and the crop field (the rest 2% were for dirt road and a tropical plant along a center pivot irrigation structure). In the grassland areas, the pixels were classified into four main groups: grass, weeds, tree, and flowers. The group of grass was further divided into: grass (not differentiable), high grass, short grass, high and short mixed grass, side grass (i.e. the grass on the surrounding sides of the field), dry grass, and grass compacted by trucks. The classification was done by assigning known classes to corresponding pixels, which were determined in field observations with GPS, and associating the remaining pixels with similar spectral signatures for the given classes. Figure 8 is the classified image layer overlaid on GIS.

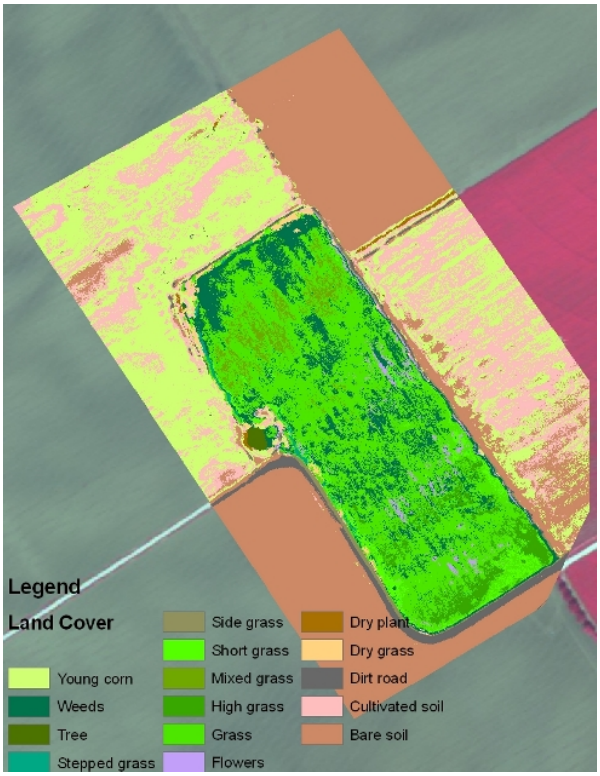
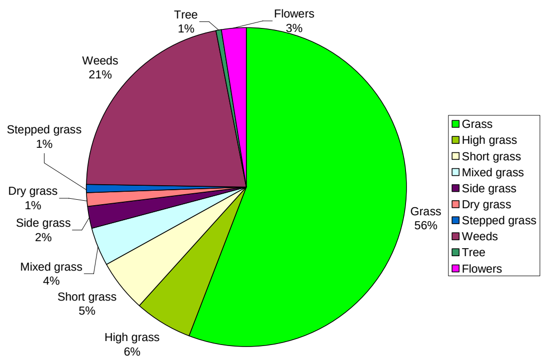
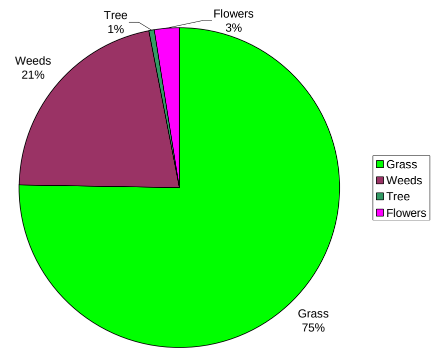


Figure 8: Classified AOI image of Mumford, Texas on DOQQ in GIS.

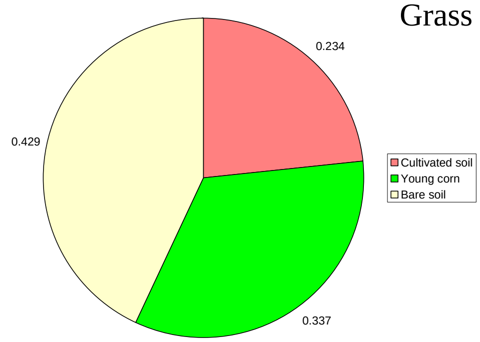
Based on the image classification, the spatial and statistical distributions of the variations in the grass land and the crop fields were revealed. Figure 9 presents the statistically distributed variation over the selected area.



Grass land classes



Grass land group of classes



Crop field classes

Figure 9: Statistical distributions of land cover on the concerned area in Mumford, Texas

In order to generate the prescription for pest management, the classes of the grass land were regrouped into a number of categories: grass, weeds, and tree etc. The group of grass consisted of grass (not differentiable), high grass, short grass, high and short mixed grass, and dry grass etc. as described above. The regrouping produced informative pixel data to generate prescription data for site-specific pest management. Figure 10 shows the classified image with the regrouping of classes.

Figure 10: Classified AOI image with class regrouping of the test field of Mumford, Texas.

5. CONCLUSIONS

The results of this research indicate that the airborne MS4100 multi-spectral imaging system has a great potential for use in pest management systems, such as weed control or possibly, detection of insect damage. The multi-spectral image processing produces NIR, red, green, NR, NG, NDVI and NDNG indices or images, which can be used to evaluate biomass and biotypes in agricultural fields. The classified images identify the ground land cover clusters by differentiating the variation of spectral signatures in the image. The results of the image classification can provide critical input to generate prescription data for application of crop production and protection materials.

In this research image processing provided the quantification of vegetation variation over the crop and grass lands. The results could be converted to prescription data to direct site-specific chemical application over the field. With the developed imaging system the images of the areas can be generated with the geographic distribution of pest infestation, which will produce the spatial data for areawide pest management analysis. MS 4100 camera is a standard multispectral camera in the market. However, how to develop it for a specific research and application in agriculture in a cost-effective way is still an issue.

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6. REFERENCES

Buchheim, M.P., A.L. Maciean, and T.M. Lillesand. 1984. Forest cover type mapping and spruce budworm defoliation using simulated SPOT imagery, SPOT simulation applications handbook. Proceeding of the 1984 SPOT Symposium, Scottsdale, Arizona, 20–23 May 1984 (Falls Church: American Society of Photogrammetry and Remote Sensing). pp. 259–266.

Ciesla, W.M., C.W. Dull, and R.E.Acciavatti. 1989. Interpretation of SPOT-1 colour composites for mapping defoliation of hardwood forests by gypsy moth. Photogrammetric Engineering and Remote Sensing. 55: 1465–1470.

Chandler, L.D., M.M. Ellsbury, and W.D. Woodson. 1999. Area-wide management zones for insects. http://www.ppi-ppic.org/ppiweb/ppibase.nsf/b369c6dbe705dd13852568e3000de93d/ece40a59e3a9a05a852569660061f19c/$FILE/SSMG%2019.pdf

Cook, C.G., D.E. Escobar, J.H. Everitt, I. Cavazos, A.F. Robinson, and M.R. Davis. 1999. Utilizing airborne video imagery in kenaf management and production. *Industrial Crops and Products.* 9: 205–210.

Everitt, J.H., D.E. Escobar, R. Villarreal, J.R. Noriega, and M.R. Davis. 1991. Airborne video systems for agricultural assessment. *Remote Sensing of Environment.* 35(2–3): 231–242, color plate p. 230.

Everitt, J.H., D.E. Escobar, K.R. Summy, and M.R. Davis, 1994. Using airborne video, global positioning system, and geographical information-system technologies for detecting and mapping citrus blackfly infestations. *Southwestern Entomologist.* 19(2): 129–138.

Everitt, J.H., D.E. Escobar, K.R. Summy, M.A. Alaniz, and M.R. Davis. 1996. Using spatial information technologies for detecting and mapping whitefly and harvester ant infestations in south Texas. *Southwestern Entomologist.* 21(4): 421–432.

Fletcher, R.S. 2005. Evaluating high spatial resolution imagery for detecting citrus orchards affected by sooty mould. *International Journal of Remote Sensing.* 26(3): 495-502.

Franklin, S.E. 1989. Classification of hemlock looper defoliation using SPOT HRV imagery. *Canadian Journal of Remote Sensing.* 15: 178–182.

Gausman, H.W., R.M. Menges. A.J. Richardson, H. Walter, R.R. Rodriguez, and S. Tamez, 1981. Optical-parameters of leaves of 7 weed species. *Weed Science.* 29(1): 24–26.

Hart, W.G., and V. I. Myers. 1968. Infrared aerial color photography for detection of populations of brown soft scale in citrus groves. *Journal of Economic Entomology.* 61(3): 617–624.

Hart, W.G., S.J. Ingle, M.R. Davis, and C. Mangum. 1973. Aerial photography with infrared color film as a method of surveying for citrus blackfly. *Journal of Economic Entomology*. 66(1): 190–194.

Heald, C.M., W.J. Thames, and C.L. Wiegand. 1972. Detection of *Rotylenchulus reniformis* infestations by aerial infrared photography. *Journal of Nematology*. 4:299–300.

Henneberry, T.J., W.G. Hart, L.A. Bariola, D.L. Kittock, H.F. Arle, M.R. Davis, and S.J. Ingle. 1979. Parameters of cotton cultivation from infrared aerial photography. *Photogrammetric Engineering & Remote Sensing.* 45(8): 1129–1133.

Hickman, M.V., J.H. Everitt, D.E. Escobar, and A.J. Richardson. 1991. Aerial-photography and videography for detecting and mapping Dicamba injury patterns. *Weed Technology*. 5(4): 700–706.

Kogan, M. 1998. Integrated pest management: historical perspectives and contemporary developments. *Annu. Rev. Entomol.* 43:243-270.

Medlin, C.R., D.R. Shaw, P.D. Gerard, and F.E. LaMastus. 2000. Using remote sensing to detect weed infestation in Glycine max. *Weed Science.* 48: 393-398.

Nelson, R.F. 1983. Detecting forest canopy change due to insect activity using Landsat MSS. *Photogrammetric Engineering and Remote Sensing.* 49: 1303–1314.

Pinter, P.J., Jr. J.L. Hatfield, J. S. Schepers, E.M. Barnes, M.S. Moran, C.S.T. Daughtry, and D. R. Upchurch. 2003. Remote sensing for crop management. *Photogrammetric Engineering & Remote Sensing.* 69(6): 647-664.

Richardson, A.J., R.M. Menges, and P.R. Nixon. 1985. Distinguishing weed from crop plants using video remote-sensing. *Photogrammetric Engineering & Remote Sensing.* 51(11): 1785-1790.

Riedell, W.E., and T.M. Blackmer. 1999. Leaf reflectance spectra of cereal aphid-damaged wheat. *Crop Science.* 39(6): 1835–1840.

Schneider, C.L., and G.R. Safir. 1975. Infrared aerial photography estimation of yield potential in sugarbeets exposed to blackroot disease. *Plant Disease Reporter.* 59(8): 627–631.

Sirois, J. and F.J. Ahern. 1989. An investigation of SPOT HRV for detecting recent mountain pine beetle mortality. *Canadian Journal of Remote Sensing.* 14: 104–110.

Smith, A.M., and R.E. Blackshaw. 2002. Crop/weed discrimination using remote sensing. *IEEE International Geoscience and Remote Sensing Symposium.* 4: 1962-1964.

Sudduth, K.A., and J.W. Hummel. 1993. Portable, near-infrared spectrophotometer for rapid soil analysis. *Transactions of the ASAE.* 36(1): 185–193.

Vogelmann, J.E. and B.N. Rock. 1989. Use of TM data for the detection of forest damage caused by the pear thrips. *Remote Sensing of the Environment.* 30: 217–225.

Ye, X., K. Sakai, S. Asada, and A. Sasao. 2007. Use of airborne multispectral imagery to discriminate and map weed infestations in a citrus orchard. *Weed Biology and Management.* 7: 23-30.