USING AERIAL IMAGERY TO DETERMINE THE NEED FOR

WITHIN-FIELD MANAGEMENT

by

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(Under the direction of Craig Kvien)

ABSTRACT

Although many agricultural fields vary spatially in soil properties and crop growth patterns, some agricultural fields are not good targets for precision agriculture because they are fairly uniform. The purpose of this project was to determine whether aerial imagery can be used to define areas within peanut fields requiring variable management. We found that the best time to acquire images to detect variability within dryland peanut fields is approximately 7.5 to 11.5 weeks after planting. Fields showing a great deal of variability in the images also varied in soil conditions or crop growth within the field. A variability index which incorporated all of the measured soil parameters accounted for 42% of the variability in reflectance values. Of the measured soil properties, the most important predictors of differences in reflectance and yield for the fields in this study were soil texture, organic matter, CEC, Ca, and Mn.

INDEX WORDS: Precision agriculture, Aerial imagery, Aerial photographs, Remote sensing, Peanut, Within-field variability

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B.S., Auburn University, 2000

A Thesis Submitted to the Graduate Faculty of The University of Georgia in Partial

Fulfillment of the Requirements for the Degree

MASTER OF SCIENCE

ATHENS, GEORGIA

2002

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May 2002

ACKNOWLEDGEMENTS

There are many people to whom I owe a great debt of gratitude for helping me complete this thesis project. First, I would like to thank Craig Kvien, my major professor, for all of the guidance and encouragement he gave to me for this project. His enthusiasm for the topic definitely inspired me to complete the project. In addition, he has been very gracious to me and is a wonderful person for whom to work. I would also like to thank my other committee members, David Kissel, George Vellidis, and Glen Rains for their time, advice, and much needed direction in my project. I owe a debt of gratitude to Stuart Pocknee and Tasha Wells, who both know much more about this topic than I did, and were always willing to help. I would like to say a special thanks to Brad Buchanan, Ali Csinos, and Gene Hart, my coworkers in the lab at NESPAL, for their advice and especially their help with field labor. I could have never gotten all of the work done without them. I would also like to thank Corley Holbrook, and all of his staff, including Betty, Danny, Vickie, Clint, Shannon, and many others, for helping me with the aflatoxin analysis, peanut thrashing, peanut cleaning, and many other tasks. In addition, I also am very grateful for Andrew Thompson and Johnny Enfinger, who provided me with the peanut fields to study. They both offered a lot of advice and were very patient.

Finally, I would like to thank all of my family for their loving support. You were all very supportive during all of my moves from Auburn to Tifton to Athens to Tifton. First, I should thank my husband Aaron, because he is the one who listened to my complaints and encouraged me every step of the way. My Mom and Dad, Carl and Donna Sanders, have supported me emotionally and financially throughout the process. During this time they even helped me plan a wedding from five hours away. My in-laws, Billy and Sue Wells, helped me move all of those times and always gave an encouraging word. In addition, I would like to thank my sisters and sister-in-law, Melissa, Sarah, Lindsey, and Hanna, for always being there, and my little brother Jonathan, for always making me smile.

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CHAPTER 1

INTRODUCTION AND LITERATURE REVIEW

Precision agriculture has recently received much attention from farmers and agricultural researchers as an alternative to conventional farming. Within field management is beneficial in many agricultural fields because they vary in soil properties such as soil moisture, water availability, and fertility levels (Han et al., 1996; Goderya, 1998). In addition, weed populations, pest conditions, irrigation patterns, and other factors may also vary spatially within agricultural fields (van Groenendael, 1988; Ellsbury et al., 1999; Jordan et al., 1999). These factors may cause crop growth and development to vary within fields. In these fields, management zones can allow a farmer to precisely manage individual areas of a field in different ways in regards to the type and variety of crop planted, the amount and timing of fertilizer, pesticide, and irrigation applications, as well as the timing of harvest (Pocknee, 2000). However, all agricultural fields are not good targets for precision agriculture. Some fields are fairly uniform in soil properties and crop growth, and would not benefit from within field management.

Remotely sensed data has often been used to optimize soil and plant sampling strategies and to design variable field management (Panten et al., 1999). Remote sensing techniques have also been used to identify differences in crop development and predict yield (Plant and Munk, 1999; Vellidis et al., 1999). Aerial imagery is one type of remotely sensed data which has the ability to show anomalies within a field. For this reason, aerial images may also be used to determine whether variability exists within a field and predict the need for within field management.

The purpose of this project was to determine whether aerial imagery is a useful tool in defining areas within peanut (*Arachis hypogaea* L.) fields requiring variable management, and if so, to determine the best image acquisition time to distinguish within field variability. In addition, we wanted to determine whether "stressed areas" detected in the aerial images could be related to aflatoxin contamination. To achieve this goal we selected sixteen dryland fields to study during the season in 2001. Aerial photographs were taken of the fields from early in the season until harvest. In each field we selected strong and weak growth areas from the imagery and sampled each area for crop development and quality, soil physical and chemical attributes, and topography. Through the study we learned that every field is a unique case, and no single property could be related to the imagery across all fields. This thesis indicates that aerial images can be used to determine whether differences exist within a field, but that the source of variability within the fields varies among fields.

Causes of within-field variability

Soil properties, irrigation patterns, topography, water availability, weeds, plant populations, and pest conditions often differ within a field. These factors all affect crop growth and development, and cause variability in crop growth within a field.

Soils

Crops depend on the soil for support, nutrition, and water. Soils also differ in their ability to supply roots with air and water, differ in temperature, and differ in the growth of beneficial and destructive organisms (Reid and Cox, 1973). A soil suited for peanuts has been described as a “well-drained, light-colored, loose, friable, sandy loam” that is well supplied with calcium and organic matter (York and Colwell, 1951). These soils are typical of most peanut-producing areas. Sandy soils are usually considered better suited for peanuts than clayey soils because the crop is more easily harvested (i.e., fewer pods are left in the ground).

Soil properties that affect plant growth and development often vary spatially within a field (Uehara et al., 1985). Spatial variability in yield of a given crop grown during a season under the same management conditions is often determined by soil variability (Bresler et al., 1981). Han et al. (1996) studied the spatial variability of soil properties in two center-pivot irrigated fields in Washington state. They found large spatial variability of soil texture and nutrients within the two fields, with clay content being the most variable and pH being the least variable. In a review of the literature, Goderya (1998) combined data relating to field scale variations in soil properties. The coefficient of variation was used to express variability on a relative basis. The coefficients of variation ranged from 3 to 120% for the sand and clay content, less than 15% for pH, 12 to 70% for nitrate-nitrogen, 25 to 46% for organic matter, and 8 to 30% for yield. The coefficient of variation for soil water content varied from 4 to 48%, but it was noted that the high variations in water content were associated with sandy loams. As was earlier noted, sandy loams are typical of peanut-producing soils in the Southeastern United States.

There are several causes of spatial variability of soil properties in a landscape. Some natural causes include differences in parent material, chemical and mineralogical variability of the rock, erosion and deposition of soil materials, climate and topography (mainly temperature and rainfall), physical and chemical processes, and biological activities (Goderya, 1998). Other causes do not result from natural processes. This variability is often caused by human activities such as cultivation, application of fertilizers and wastes, irrigation, plowing, sub-soiling, and leveling (Goderya, 1998). Different cropping patterns and land uses are also often cited as reasons for within field variability.

Because plants depend on the soil for their water supply, soil properties affecting soil water are important to plants. The amount of water available to plants depends on the amount of available water in the soil. In general, only the soil water between the field capacity (-0.01 to -0.03 MPa) and the permanent wilting point (-1.5 MPa) is available to plants (Brady and Weil, 1996). Optimal plant growth usually occurs when the soil moisture content is near field capacity. Because many soil properties often vary spatially, the amount of water available to plants varies spatially within a field.

Crop yield variability is often caused by variation in seasonally available water which is a consequence of irrigation and soil heterogeneity (Warrick and Gardner, 1983). Soil water availability may also influence crop growth and maturation. Consistencies have been found between crop growth and soil water storage patterns (Tomer et al., 1997). In addition, differences in soil moisture content could cause plants to germinate and emerge at different times, therefore maturing at different times. For example, in a cool wet spring corn (*Zea mays*) plants in an Iowa field emerged more rapidly on upper portions of the field than low-lying areas of the field (Karlen et al., 1999). In peanut, early season drought will delay flowering and peg formation and subsequently harvest date (Shorter and Simpson, 1987).

One soil property affecting available water capacity (AWC) of soils is texture (Salter et al., 1966; Brady and Weil, 1996). Soil texture has been defined as “the relative proportions of the various soil separates in a soil material” (Committee on Terminology, 1956). Salter et al. (1966) quantified the effect of the proportion of sand-, silt-, and clay-sized particles on the AWC of soils. The AWC of soils decreased as the percentage of coarse sand increased, and increased as the percentage of silt increased. In general, AWC increases from sands to sandy loams, loams, and silt loams. Because clays have a high wilting coefficient, they may provide less AWC than silt loams. However, they still provide more AWC than sands and sandy loams (Brady and Weil, 1996).

Soil structure may also contribute to the amount of soil water available to plants (Salter et al., 1966; Cambardella et al., 1996). Soil structure has been defined as the “aggregation of individual soil particles into larger units with planes of weakness between them” (Buol et al., 1997). Cambardella et al. (1996) found that aggregate size distribution contributed significantly to yield variability because of direct and indirect effects on AWC. Soil structure combines the effect of soil properties such as soil texture, mineralogy, and organic matter content with percent water space, soil matric potential, and surface-seal formation.

Another soil component that directly affects AWC is soil organic matter content. Soils high in organic matter content have significantly higher AWC than soils of similar texture that contain less organic matter (Hudson, 1994). Increasing organic matter increased the amount of soil water held at field capacity and at the permanent wilting point but the amount of water held at field capacity increased at a faster rate than the amount of water held at the permanent wilting point. This resulted in a net increase in

AWC with increasing organic matter content (Hudson, 1994). Organic matter may also have an indirect effect on the water available to plants through its influence on soil structure and total pore space (Brady and Weil, 1996). Because organic matter helps stabilize soil structure and increase pore size, it will also increase the amount of water a soil can hold due to physical structure.

Environmental Factors

Environmental factors affect crop growth and maturity. Rainfall patterns, which are especially important to non-irrigated crops, vary among years and locations in the Southeastern United States. These differing rainfall patterns apply varying amounts of water to crops and soils, causing differences in crop growth and development. Temperature and daylength also often affect crop development. In peanut, the rate of development towards flowering is controlled mainly by moisture and temperature (Bell et al., 1991a). However, the initiation of pegs and pods and distribution of dry matter to these structures is mainly influenced by daylength (Bell et al., 1991b).

Irrigation Patterns

Water availability within a field may vary because of spatial variability of irrigation patterns. Irrigation systems are usually designed to apply uniform amounts of water to a field. In the case of center pivot irrigation systems, several factors can affect the uniformity of water application. Topography differences within the center pivot radius of a field can affect the pressure distribution along the lateral (Jordan et al., 1999). This can in turn affect the amount of water released by individual sprinkler heads. End gun operation may also affect the performance of a center pivot irrigation system (Jordan et al., 1999). The end gun may cause different pressure distributions along the lateral. If sprinkler heads are not equipped with pressure regulators when the end gun is turned on, significant differences in the discharge rate of individual nozzles occur.

Many agricultural fields are also irregularly shaped. In these cases, a center pivot irrigation system may not irrigate all areas of a field, even though the entire field is cropped. In low rainfall seasons, the non-irrigated areas would have less available water than the irrigated areas. In addition, these areas may be watered with another form of irrigation, such as a cable tow system. The two systems will likely apply different amounts of water to the field, causing more water variability within the field.

Nonuniformity of irrigation patterns within a field may induce variability in AWC. Or and Hanks (1992) irrigated fields nonuniformly to induce variations in water availability. Plant height and crop yield were spatially correlated across ranges similar to the quantities of water applied by the irrigation system. This is another indication that available soil water affects crop growth and yield patterns.

Weeds

In cropping systems, weeds interfere with crop harvesting and reduce crop yields and quality (Anderson, 1996). Several authors have noted the spatial variability in the distribution of weeds within a field (Dessaint et al., 1991; Mortensen et al, 1995; Stafford and Miller, 1996). Typically weeds are neither uniformly nor completely randomly distributed, but tend to cluster (Thornton et al., 1990). Several processes cause this spatial pattern of weed populations. Reasons include local dispersal of seeds by the parent plants, local distribution of conditions for successful seed germination (van Groenendael, 1988), and field operations such as tillage and harvesting. Many agronomic variables, including soil fertility and previous field history also have effects on weed distribution (Mortensen et al., 1993). Many of the same factors causing spatial variability of a crop will also cause variability in weed distribution within a field.

Pests and Diseases

Pest populations and severity of diseases often vary spatially within a field because of crop variability, soil factors, or life stages of the pests. Pests and diseases, which affect crop growth and development, also cause spatial differences in crop growth and maturity patterns. For example, spatially variable factors such as soil type, soil moisture, and crop residue affect soil temperature. This, in turn, affects the development of certain insects within a field (Ellsbury et al., 1999). Plant disease severity may also vary over a landscape because of topography and moisture conditions. For example, some diseases are more common on lower slope positions, whereas other diseases are more severe on upper slope positions (Kutcher et al., 1999).

Several pests may vary spatially within peanut fields. For example, Aflatoxin, a toxic substance produced by the fungus *Aspergillus flavus*, has been associated with drought and temperature stress during the end of the growing season. Aflatoxin is a serious economic concern for the U.S. peanut industry. Peanuts that have visible *Aspergillus flavus* growth in loose shelled kernels (LSK) of official grade samples are classified as Segregation three and are diverted from the edible market (Whitaker et al., 1992), greatly reducing the price a farmer receives for a load of peanuts.

The association of high aflatoxin contamination and drought stress was reported as early as 1965 in South Africa (Sellschop, 1965). Several studies have been conducted to define the conditions associated with preharvest contamination of peanuts with aflatoxin. Wilson and Stansell (1983) found significantly more aflatoxin in peanuts when water stress was imposed at least 40 days immediately preceding harvest. However, drought stress alone did not consistently induce aflatoxin contamination. They concluded that these year to year variations in aflatoxin contamination probably resulted from environmental interactions including water, temperature, and biological factors (Wilson and Stansell, 1983).

Blankenship et al. (1984) reported that the mean threshold geocarposphere temperature required for aflatoxin development during the latter part of the peanut growth cycle was between 25.7°C and 27°C. It was later reported that the optimum mean geocarposphere temperature range for aflatoxin production in water stressed soil is 26 to 30.5°C during the last part of the growing season (Cole et al., 1985). High maximum geocarposphere temperatures are usually related to a small canopy cover or an extended interval between rainfalls that results in observed plant stress (Davidson et al., 1991). Sanders et al. (1985) found that a threshold stress period for preharvest contamination of peanuts by *A. flavus* when soil temperatures are in the optimum range for aflatoxin development (28-30.5°C) was more than 20 and possibly less than 30 days before harvest.

Invasion and aflatoxin contamination in peanuts grown under drought conditions usually occur first and to a greater degree in small immature peanuts. Cole et al. (1985) reported that oil stock peanuts contained 2600 ppb aflatoxin after 30 days of stress whereas 40-50 days of stress were required for significant contamination of jumbos. Sanders et al. (1985) found that smaller immature kernels were more easily colonized or were invaded in a shorter period of time than kernels in more mature pods. They concluded that conditions in immature kernels are more conducive to growth of *A. flavus* or that a resistance mechanism breaks down sooner in immature kernels in response to water and temperature stress. For this reason, it is recommended that harvesting be delayed until peanuts reach optimum maturity.

Management zones: a tool to manage within-field variability

There are several possible ways to manage within field variability. Some of these include varying rates of fertilizer, chemicals, and irrigation, planting different cultivars or crops, and differential harvesting. All of these techniques could be accomplished by dividing a field into zones. These zones would have different soil characteristics or other properties that could potentially allow the crop to benefit from different management strategies. Management zones have been defined as “regions of a farm that have been differentiated for the purpose of receiving individual management attention” (Pocknee, 2000).

Management zones may be identified in a number of ways. Farmer-identified management zones based on past production history correlate well with such parameters as soil nutrient levels, soil texture, soil conductivity, and crop yield (Fleming et al., 1999). Analysis of remote sensing data, including aerial photographs, is also an effective tool for delineating soil management units for site-specific farming (McCann et al., 1996). Some other resources used to create management zones include topographic maps, soil surveys, field boundaries, management history, past yield maps, soil test results, and an estimation of the minimum manageable size for zones (Pocknee, 2000).

Remote Sensing

Remote sensing may be defined as the science and art of obtaining information about an object through the analysis of data acquired by a device that is not in contact with the object under investigation (Lillesand and Kiefer, 1994). Sensors are used to collect data to improve our understanding of objects. In the past, remote sensing has had limited applications in agriculture. However, as remotely sensed data becomes more readily available, growers will begin to look towards imagery to enhance their farming operation. When coupled with global positioning systems (GPS) and geographic information systems (GIS), remote sensing offers the potential to improve farm management practices by optimizing soil and plant sampling strategies and aiding in variable field management. Remote sensing observations in agriculture are commonly made from aircraft, satellites, and field equipment.

Types of Remote Sensing

Aerial photographs obtained from low altitude airplanes have the ability to show anomalies within a field. Small planes can produce high resolution data sets over small areas and a free choice of wavelengths. Disadvantages are that the timing for collecting images is dependent on weather conditions and the availability of an airplane and pilot (Panten et al., 1999). However, when a pilot and plane are available, they may offer flexibility in the time of acquisition. Panchromatic color and near infrared film photographs offer a fast and flexible method to collect remotely sensed data. The desired wavelength and ground resolution depends on flight height, film type, and filter type, and thus can be adjusted for individual demands (Panten et al., 1999). One disadvantage of these film photographs is the delay in returning the images to growers because of film processing and slide scanning. This problem may be solved by the latest generation of digital cameras which operate without a film medium. These cameras may offer ground resolution of less than 1 meter and require less processing time (Panten et al., 1999).

Satellite data has been used for many years to predict crop yields on a regional basis. Satellites which orbit the earth are equipped with sensors that have the capability to rapidly gather large volumes of data in a wide range of wavelengths. The timing and frequency of data acquisition from a satellite source depends on its' orbital path. The major disadvantages of satellite imagery are clouds, the restricted ground resolution, delivery time span from acquisition to use, fixed date of recording, and cost (Panten et al., 1999). Some of these problems may be overcome by a new generation of satellites developed by private companies that will offer a higher spatial resolution, reduced repeating time, fast delivery, and lower costs. This would make satellite imagery more suitable for agriculture applications (Pocknee, 1999).

Researchers have devised remote sensing systems that can be mounted to field equipment to measure soil and plant parameters within a field. Various systems have been developed which can rapidly measure soil nitrate levels, pH, texture, and organic matter. The data is recorded in the field and tagged to a geographic location using a GPS receiver. Mapping of spatial distribution can be obtained by coupling these sensors with a GIS (Panten et al., 1999).

Uses of Aerial Imagery and Remote Sensing in Agriculture

Remotely sensed data offer a fast and economical way to help optimize soil and plant sampling strategies and to design variable field management (Panten et al., 1999). Aerial photographs have been used in the past to determine soil survey locations, sampling sites, and map unit boundaries. However, in the past aerial photographs in crop and soil studies were interpreted manually. Computer digitization and spatial registration now allow statistical approaches to easily quantify the variability captured with aerial photographs (Tomer et al., 1997). Coordinates of the images may also be used for fast navigation in the field using a global positioning system (GPS) (Panten et al., 1999).

Literature showing the benefits and uses of aerial imagery in agriculture is plentiful. Aerial photographs of bare soil aid in understanding the soil properties in the field. For example, bare soil images can show variations in soil texture and organic matter, as well as drainage patterns within the field (Pocknee, 1999). Surface reflectance information has been directly related to various soil properties including loess thickness, organic matter, calcium carbonate content, soil nutrients, iron oxide content, and soil texture classes (Moran et al., 1997). Despite these relationships, remotely sensed images are not currently being used to map soil characteristics on a routine basis. This is because the reflectance characteristics of the desired soil properties may be easily confused by variability in soil moisture, surface roughness, cloud cover, climate factors, solar angle, or view angle (Moran et al., 1997). However, bare soil images are still useful to direct samples or interpolate the results of grid soil samples (Barnes et al., 1996).

There are several uses for in-season images of a growing crop. First, vegetation images may highlight changes as the season progresses. Anomalies such as weed patches and watering problems may be identified. Plant and Munk (1999) found that remote sensing using false color infrared aerial photographs can detect differences in crop development due to soil texture differences within the field, and may be of value in irrigation timing. Aerial images may often aid in identification of water and heat stressed areas, regularly flooded zones, and weed controlled zones of a field. Vegetative period images may reveal patterns in the field, but ground truthing is usually necessary to identify the causes of these patterns (Panten et al., 1999).

Secondly, in-season aerial images may be used to easily assess crop damage due to isolated weather conditions such as hail, tornados, or frost damage. This information is critical to farmers and insurance companies when making yield loss assessments (Pocknee, 1999). A third and common use of aerial photographs is yield forecasting. Research at The University of Georgia has shown that early season classified aerial images of cotton fields show striking similarities to spatial patterns generated from a yield monitor at the end of the season (Vellidis et al., 1999).

Reflectance of soil and vegetation

These techniques are possible because of the unique spectral reflectance properties of healthy vegetation and soil. Spectral reflectance curves for growing vegetation typically have a "peak and valley" configuration (figure 1.1). These peaks and valleys are dictated by the pigment in plant leaves. Chlorophyll strongly absorbs energy in the wavebands centered around 0.45 (blue) and 0.67 μm (red). We see vegetation as green because of the very high absorption of blue and red light energy and very high reflection of green energy. A reflectance peak of growing vegetation is seen between the wavebands 0.5 and 0.6 μm (green band). If stress interrupts the normal growth of a plant, it may decrease chlorophyll production. This results in less absorption in the blue and red bands. In the near infrared portion of the spectrum (>0.7 μm) the reflectance of healthy vegetation increases dramatically (Lillesand and Kiefer, 1994).

Spectral reflectance curves for soil show less peak and valley configuration because the factors that influence soil act over less specific spectral bands. Soil reflectance is affected by moisture content, texture, presence of iron oxides, and organic matter content. However, soil reflectance is generally greater than that of vegetation in all wavebands of the visible spectrum (Lillesand and Kiefer, 1994). This can be seen in figure 1.1.

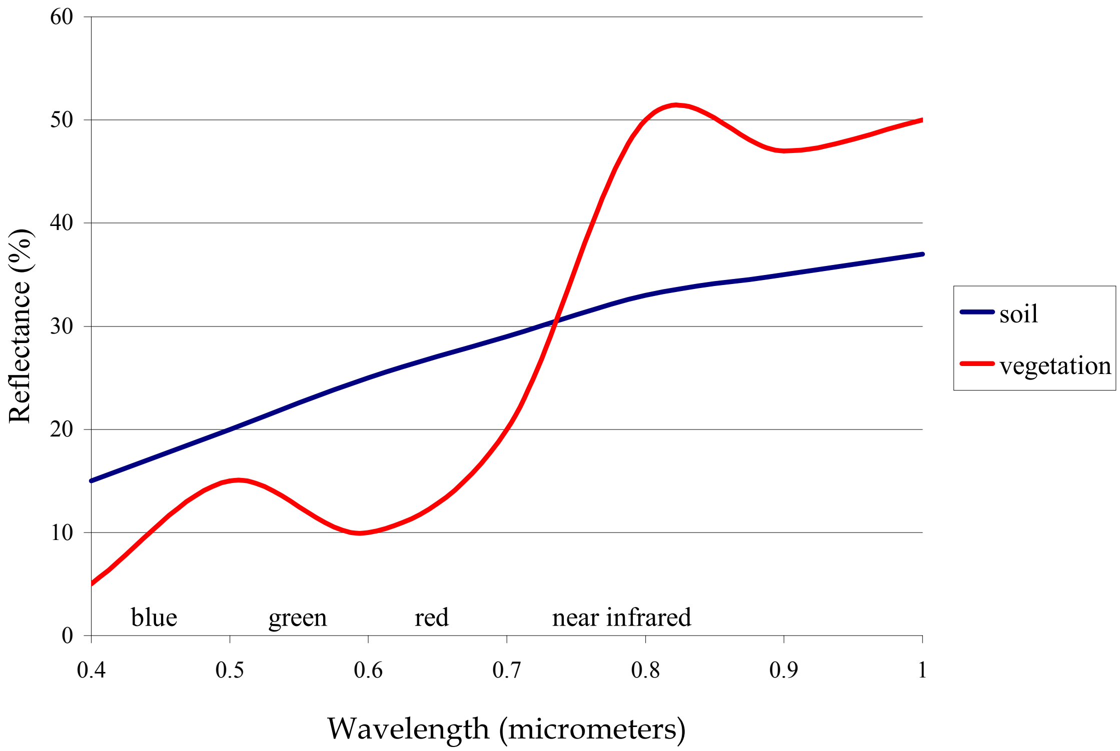

Figure 1.1. Typical spectral reflectance curves for vegetation and soil. (Adapted from Lillesand and Kiefer, 1994).

The differential reflectance between plants, soil, and even plant types has excited many in the remote sensing and agricultural communities. The challenge facing us now is to better understand how this tool can best aid the diverse agricultural systems found in any part of our region, nation, or world.

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CHAPTER 2

DETERMINING OPTIMUM TIME TO ACQUIRE AERIAL IMAGES OF PEANUT FIELDS[1]

[1]Wells, J.S., C. Kvien, N. Wells, S. Pocknee, G. Vellidis, D. Kissel, and G. Rains. 2002. To be submitted to Precision Agriculture.

INTRODUCTION

Soil properties such as soil moisture, water availability, and fertility levels often differ within a field (Han et al., 1996; Goderya, 1998). In addition, weed populations, pest conditions, irrigation patterns, and other factors may also vary spatially within agricultural fields (van Groenendael, 1988; Ellsbury et al., 1999; Jordan et al., 1999). As a result, crop growth and development within the field will vary. However, most agricultural fields are managed as though they are uniform. To maximize returns in non-uniform fields some growers are dividing fields into zones of likeness, each of which is managed individually (Pocknee, 2000).

Remotely sensed images may be used to help optimize soil and plant sampling strategies and to design variable field management (Panten et al., 1999). Remote sensing techniques have also been used to identify various forms of plant stresses and predict yield. When coupled with global positioning systems (GPS) and geographic information systems (GIS), remote sensing offers the potential to improve farm management practices. Aerial photographs are one type of remotely sensed data. Aerial images have the ability to show anomalies within a field. They may also be used to determine the need for within field management. Because of limited resources, many growers cannot have images taken of their crops throughout the growing season. For this reason, it would benefit growers to know the optimum time to get the most benefit from the images.

The purpose of this project was to determine the best time to acquire aerial images that could be used to define areas within peanut fields requiring variable management.

MATERIALS AND METHODS

Aerial images

We chose sixteen dryland peanut fields in two Georgia counties in the year 2001 for this study. Dryland peanut fields were chosen because they are more likely to be contaminated with aflatoxin. Eight of the fields were located in Brooks County, Georgia and the other eight were located in Early County, Georgia. The two locations are approximately 160 kilometers apart. We had no prior knowledge of the soil characteristics or variability within the fields. Low altitude (760-1220 meters) aerial photographs were taken of each field 6 times, beginning early in the season (early June) until harvest (late September). These photographs were taken from the belly of a plane using a 35 mm camera loaded with slide film. The film was processed and the slides were digitized using a Polaroid SprintScan 4000 slide scanner. The early season photographs were georeferenced for groundtruthing purposes using ERDAS Imagine® 8.5 imaging software (ERDAS, Inc., Atlanta, GA).

In August, the early season aerial photographs were used to choose areas of poor, medium, and good growth in each of the fields. These areas were chosen based on a simple visual assessment of the images. There was a wide range of variability within the fields selected. Some fields appeared to have large differences in soil and plant growth characteristics, whereas others seemed fairly uniform. It was difficult to choose good, medium, and poor growth areas in the more uniform fields, therefore two of the fields were assigned only good and poor areas. Three of the fields had more than one area of poor growth. These multiple "poor growth" areas appeared to result from different causes. In these fields, two "poor growth" areas were chosen.

After the season, reflectance values were calculated for each of the selected areas within each of the photographs to quantify the visual differences that we had seen. We used ERDAS Imagine® 8.5 imaging software to create an area of interest layer by drawing a circle around each of the selected good, medium, and poor areas in the digitized images. The pixel reflectance values within each of the area of interest layers were exported to a text file which reported the reflectance values in the red, green, and blue wavebands. We took the average of the reflectance values in each of the color bands, and then calculated a grayscale reflectance (GSR) value for each area. Greyscale was calculated using the following equation, which is a common equation used to convert image data from color to greyscale (Hall, 1989).

$$GSR = 0.299(red) + 0.587(green) + 0.114(blue) \quad \textbf{(Equation 2.1)}$$

At the end of this process, we had a "greyscale reflectance" (GSR) value for each area of good, medium, and poor growth in each field for every photograph date.

We wanted to be able to compare reflectance values across all images, however the photographs were acquired on different days and different times within the days resulting in changes in lighting and other conditions. Therefore we created the normalized difference in reflectance (NDR). This value was calculated using the following equation.

$$NDR = |GSR_g - GSR_p| / [(GSR_g + GSR_p)/2] \quad \textbf{(Equation 2.2)}$$

GSR_g is the greyscale reflectance value calculated in the good growth area and GSR_p is the greyscale reflectance value for the poor growth area. This equation helped normalize the data across all images. The NDR values created ranged from 0.004 to 0.765, where 1 represents high variability and 0 represents no variability. The actual NDR values are shown in tables 2.1 and 2.2. For the three fields which had two poor growth areas, two NDR values were calculated. In the analysis comparing the fields, these were treated as three additional fields.

Groundtruthing

Once the different growth areas were chosen in the fields we began weekly groundtruthing of the fields. The goal was to determine the reasons for the differences seen in the images. The georeferenced aerial images were used to determine the geographic coordinates of the selected areas which were then loaded into a DGPS handheld unit (Garmin Etrex Vista) for field navigation. Each week, notes were made about soil characteristics, canopy height and width, presence of weeds and insects, and other anomalies that were visible. Digital photographs of the crop canopy were taken during the visits using a Kodak DC4800 camera and were tagged to a DGPS location. Measurements of soil moisture and temperature were taken in each of the areas. Soil temperature was measured using a digital meat thermometer and volumetric soil moisture was measured using a ThetaProbe (Delta-T Devices Ltd., Cambridge, England).

Weather data and calculation of heat units

Weather data was gathered for each location using the nearest weather station in the Georgia Automated Environmental Monitoring Network (http://www.griffin. peachnet.edu/bae/). The weather station for the Early County fields was located approximately 16 kilometers from the fields (Arlington, Georgia). The weather station for the fields in Brooks County was located approximately 1 to 8 kilometers from the fields (Dixie, Georgia). These stations report daily maximum and minimum soil temperatures (at 10.2 centimeters deep) and rainfall. The maximum and minimum daily soil temperatures were used to calculate heat units for each day after the planting date. Daily heat units were calculated using the following equation

$$HU = [(MaxT_F+MinT_F)/2]-65 \quad \textbf{(Equation 2.3)}$$

$MaxT_F$ is the maximum soil temperature in degrees Fahrenheit and $MinT_F$ is the minimum soil temperature in degrees Fahrenheit. The base temperature for calculating heat units is 65° F (18.33°C) because peanut plants cannot develop below this temperature. The daily heat units from the planting date were summed for each photograph date to get a value of "accumulated heat units". Using this procedure, the images could be compared based on heat units since the crops were at different growth stages on any particular photograph date due to differences in planting date and location.

RESULTS AND DISCUSSION

In order to determine the best time to acquire aerial images of nonirrigated peanut fields, we graphed the normalized difference in reflectance (NDR) calculated for each image against the accumulated heat units for each photograph date. The peaks in NDR on this graph represented optimum photograph dates for detecting within field variability in the fields that we studied (figure 2.1).

Early season/bare soil images

Early season or bare soil photographs are useful for detecting within field soil differences where there are large differences in soil texture and type. Early season photographs (less than 400 heat units) were taken for 8 of the 16 fields. These represent 11 of the 19 fields for our purposes, since three fields had two "poor growth" areas. Of the 11 fields for which we had early photographs, 4 of them showed an early season peak between 250 and 300 heat units, or 17-19 days after planting. These fields were

Crossroads, Butler, Thaggard4, and Thaggard7 (table 2.1). In addition, 2 fields showed an early season peak near 600 heat units or 38-39 days after planting. These fields were Marco5 and GrooverP2 (table 2.1). Because the crop could not yet be seen in the photographs, the variability seen in the photographs represents soil differences and cover crop residue within the fields.

The differences seen in these photographs often resulted from differences in topography and soil texture. For example, in one of the fields (Marco5) showing the early peak, the "poor growth" area was located in an area of lower elevation where water had moved across the surface of the field (figure2.2). In this field, the soil texture analysis showed that the topsoil and subsoil near the washed area had higher percent sand than the other areas of the field. Differences in other soil properties were seen within these fields, but no general conclusions could be drawn over all of the fields. Early season aerial images of a peanut crop (300 to 600 heat units) proved useful for detecting variability due to soil texture and topography variability.

Within season crop images

Aerial images of a growing crop may be used to detect differences in crop growth and maturity and possibly predict yield patterns. Past research has shown that images taken over irrigated fields six to eight weeks after planting are useful to delineate different crop growth and development zones within fields (Kvien et al., 1996). Other research with irrigated fields has shown that spatial patterns in aerial photographs can be correlated with yield maps when aerial photographs are taken within the first ten weeks of crop growth (Vellidis et al., 1999). In this study, we found that the maximum differences in reflectance values within the fields were seen approximately between 700-

1250 heat units (868 heat units, average), which is approximately 7.5 to 11.5 weeks (9 weeks average) after planting (see figure 2.1 and table 2.2).

The past mentioned research had all been conducted on irrigated fields. However, dryland fields commonly receive less water (as rainfall) or inappropriately timed rainfall events, making the crop slower to develop and mature. This could cause the optimum time to detect variability in crop growth to be later in the season. Approximate examples of weekly water use for peanuts have been established based on previous research (Stansell et al., 1976; Pallas et al., 1979; Stansell and Pallas, 1985;). Figure 2.3 indicates whether each field received a surplus or a deficit for each week according to the weekly water use data for peanuts. All of the fields had received excess total amounts of rainfall by the optimum time for image acquisition. However, the rainfall events were not timed properly. During this season, most of the fields received enough rainfall during the first 5 weeks after planting to keep up with the recommended weekly water use of peanuts. However during weeks 6 and 7, all of the fields were deficient in rainfall compared to the recommended weekly water needed. During weeks 8-11, only a few of the fields received their optimum water use requirement. Improper timing of water supplied to the plants as rainfall during weeks 6-11 probably caused the optimum time for acquiring aerial imagery of these dryland fields to be later than in past studies of irrigated fields.

This mid-season peak (700 to 1250 heat units) was seen in 18 of the 19 fields in the study. The peaks for some of the fields were small, indicating little variability in the images taken during this time period (Butler, B-01, B-02, B-04, and B-08). However in most cases, the fields showing small differences (smaller peaks) during this time period also showed small differences throughout the season, meaning the fields were fairly uniform in crop growth. Although one of the fields (Marco5) did not show a strong peak during the period of 7.5 to 11.5 weeks after planting, it did have large differences in reflectance during this time period due to a washed area where no crop grew. The overall best time for image acquisition to detect variability within dryland peanut fields during the season was approximately 7.5 to 11.5 weeks after planting. Cooler or warmer conditions as well as changes in rainfall distribution would change these results.

End of season images

As the end of the season approached, within field differences in reflectance in the images began to decrease. It has been shown in the past that peanuts reach 100% ground cover at 90 to 110 days after planting, which is approximately 13 to 16 weeks after planting (Jaaffar and Gardner, 1988). By approximately 1500 heat units (14-17 weeks after planting) the differences in reflectance (NDR) had declined to almost nothing in most fields (figure 2.1). This is likely because the peanut plants in all parts of the field had achieved full canopy closure. The only fields that continued to show large differences at this point were Marco5 and Thaggard4(P2). These fields showed large differences in reflectance throughout the season because the "poor growth" areas of these fields were located near sandy washed areas where the canopy never closed (figure 2.4).

CONCLUSIONS

Early season aerial images of a peanut crop (0 to 600 heat units) are useful for detecting variability within fields that have differences in soil texture and topography. A bare soil image of the field could also be used for this same purpose. Aerial images of a growing crop may be used to detect differences in a field during the season. We found that the overall best time to acquire images in our dryland fields was 7.5 to 11.5 weeks after planting (700-1250 heat units). However, seasonal differences in rainfall and temperature would change this window.

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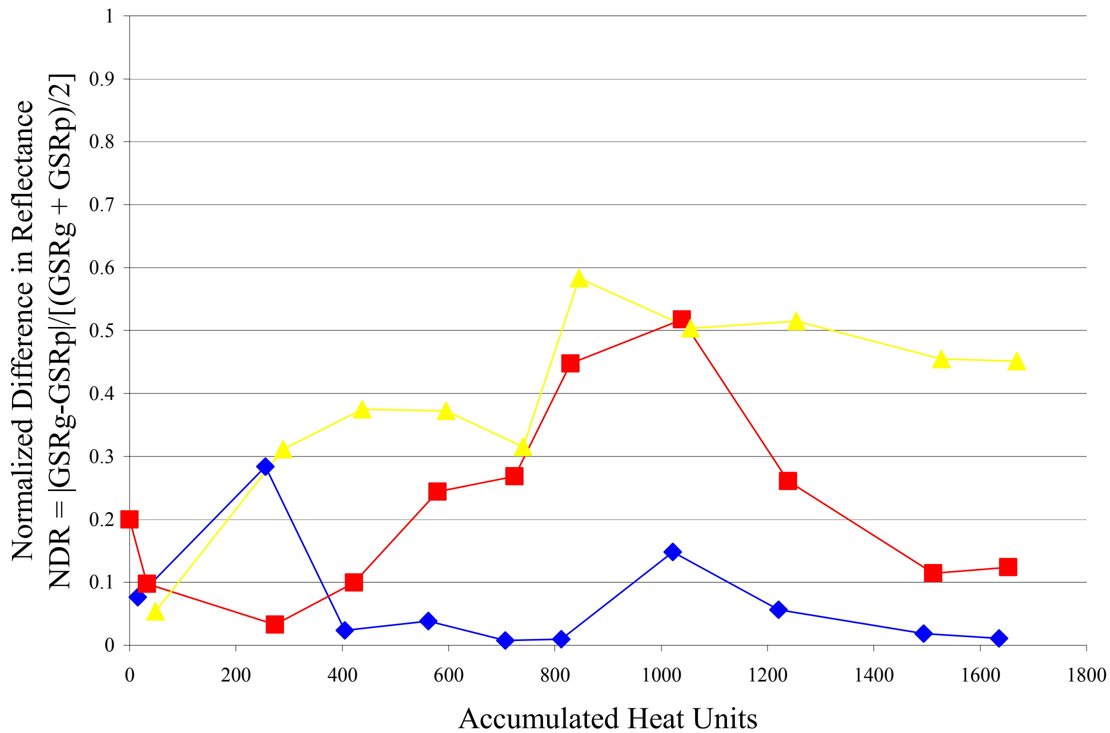

Figure 2.1. Graph showing normalized difference in reflectance (NDR) versus accumulated heat units for three representative fields. The peaks in NDR represent optimum photograph times for detecting within field variability. The blue line represents fields showing an early season peak (~250 heat units) which likely resulted from large differences in soil color and crop residue. The red line represents the mid-season peak found for most fields (~1000 heat units) which was the period of maximum variability in crop canopy development. The yellow line represents a field showing variability throughout the growing season because of a washed sandy area with no crop growth.

Figure 2.2. Aerial image showing the Marco5 field on July 11, 2001. The "poor growth" area, which was located in a sandy washed area of the field, is highlighted.

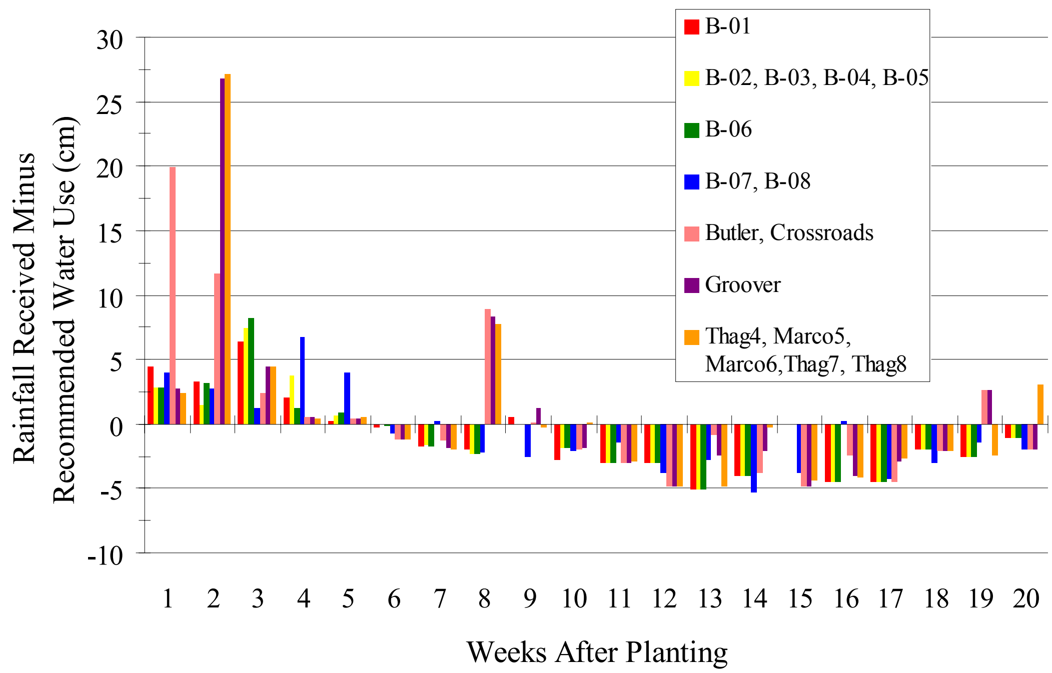

Figure 2.3. Graph showing actual water received minus the recommended water use for peanuts by weeks after planting. Different colors represent different fields which vary because of planting date and location.

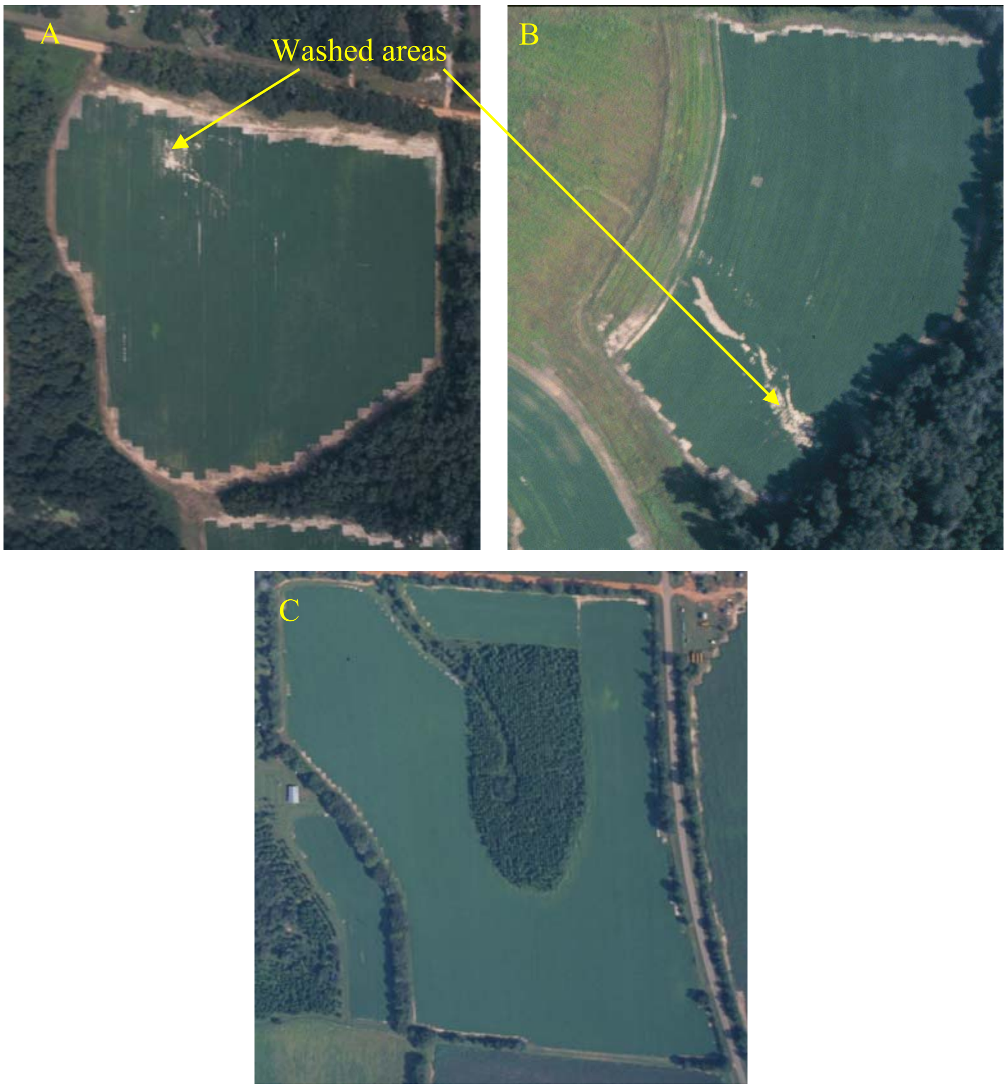

Figure 2.4. A and B show aerial images of two fields that continued to show large differences in reflectance values at the end of the season. In both of these fields, the "poor growth" area was located near a washed area where the canopy never closed. C shows a field whose canopy completely closed by the end of the growing season.

Table 2.1. This table shows the planting date, photograph date, days after planting (DAP), accumulated heat units, and normalized difference in reflectance (NDR) at the time of maximum early season image variability for each field.

Field Name	Planting Date	Peak Photo Date	DAP at Peak	Accumulated Heat Units at Peak	NDR at Peak
Butler	06/04/2001	06/21/2001	17	256	0.284
Crossroads	06/04/2001	06/21/2001	17	256	0.385
Thaggard7	06/02/2001	06/21/2001	19	289	0.361
Thaggard4	06/02/2001	06/21/2001	19	289	0.198
Marco5	06/02/2001	07/11/2001	39	595	0.765
GrooverP2	06/03/2001	07/11/2001	38	579	0.300

Table 2.2. This table shows the planting date, photograph date, days after planting (DAP), accumulated heat units, and normalized difference in reflectance (NDR) at the time of maximum mid-season image variability for each field.

Field	Planting Date	Peak Photo Date	DAP at Peak	Accumulated Heat Units at Peak	NDR at Peak
Butler	06/04/2001	08/10/2001	67	1022	0.149
Crossroads	06/04/2001	07/27/2001	53	812	0.339
Groover	06/03/2001	08/10/2001	68	1040	0.518
Thaggard4	06/02/2001	07/27/2001	55	845	0.312
Marco5	06/02/2001	no peak	no peak	no peak	no peak
Marco6	06/02/2001	08/22/2001	81	1254	0.328
Thaggard7	06/02/2001	07/27/2001	55	845	0.598
Thaggard8	06/02/2001	07/27/2001	55	845	0.542
B-01	05/25/2001	07/27/2001	63	852	0.129
B-02	05/23/2001	07/17/2001	55	710	0.136
B-03	05/23/2001	07/17/2001	55	710	0.527
B-04	05/23/2001	08/10/2001	79	1062	0.117
B-05	05/23/2001	07/27/2001	65	859	0.307
B-06	05/24/2001	07/17/2001	54	707	0.387
B-07	05/15/2001	07/17/2001	63	791	0.228
B-08	05/15/2001	07/17/2001	63	791	0.149
Butler (P2)	06/04/2001	07/27/2001	53	812	0.444
Groover (P2)	06/03/2001	07/27/2001	54	830	0.471
Thaggard4 (P2)	06/02/2001	07/27/2001	55	845	0.583
Average			61	868	
Maximum			81	1254	
Minimum			53	707	

CHAPTER 3

PREDICTING WITHIN-FIELD VARIABILITY IN PEANUT FIELDS USING AERIAL IMAGERY [1]

[1]Wells, J.S., C. Kvien, N. Wells, S. Pocknee, G. Vellidis, D. Kissel, and G. Rains. 2002. To be submitted to Precision Agriculture.

INTRODUCTION

Precision agriculture has recently received much attention from farmers and agricultural researchers as an alternative to conventional farming. Within field management can be beneficial in many agricultural fields because of manageable differences in soil properties, water availability, pest conditions, weed populations, and crop growth and development (Han et al., 1996; Goderya, 1998; van Groenendael, 1988; Ellsbury et al., 1999; Jordan et al., 1999). In these fields, management zones can allow a farmer to differentially manage individual areas of a field with regards to type and variety of crop planted, amount and timing of fertilizer, pesticide, and irrigation applications, as well as timing of harvest (Pocknee, 2000). However, all agricultural fields are not good targets for precision agriculture. Some fields are fairly uniform in soil properties and crop growth, and would not benefit from within field management or perhaps the variability occurs on such a small scale that we do not have the ability to manage it.

Remotely sensed data has often been used to optimize soil and plant sampling strategies and to design variable field management (Panten et al., 1999). Remote sensing techniques have also been used to identify differences in crop development and predict yield (Plant and Munk, 1999; Vellidis et al., 1999). Aerial imagery is one type of remotely sensed data which has the ability to show anomalies within a field. For this reason, aerial images may also be useful for assessing the need for within field management.

The purpose of this project was to determine whether aerial imagery can be used to define areas within peanut fields that would benefit from variable management. In addition, we wanted to know whether a common cause of the within field variability could be established from the images. We also wanted to determine whether the stressed areas detected in the images could be related to aflatoxin contamination.

MATERIALS AND METHODS

Aerial images

Sixteen dryland peanut fields in two Georgia counties were selected in the year 2001 for this study. Dryland peanut fields were chosen because they are more likely to be contaminated with aflatoxin. Eight of the fields were located in Brooks County, Georgia and the other eight were located in Early County, Georgia. The two locations are approximately 160 kilometers apart. We had no prior knowledge of the soil characteristics and variability within the fields. Low altitude (760-1220 meters) aerial photographs were taken of the fields 6 times, beginning early in the season (early June) until harvest (late September). These photographs were taken from the belly of a plane (Cessna 206) using 35 mm color slide film. The film was processed and the slides were digitized using a Polaroid SprintScan 4000 slide scanner. The early season photographs were georeferenced for groundtruthing purposes using ERDAS Imagine® 8.5 imaging software (ERDAS, Inc., Atlanta, GA).

In August, the early season aerial photographs were used to choose areas of poor, medium, and good growth in each of the fields. These areas were chosen based on a simple visual assessment of the images. Some of the fields appeared to have large differences in soil and plant growth characteristics, whereas others seemed fairly uniform. It was difficult to choose good, medium, and poor growth areas in the more visually uniform fields, therefore two of the fields were assigned only good and poor areas. Three of the fields had more than one area of poor growth, which appeared to be caused by different reasons. In these fields, two "poor growth" areas were chosen.

After the season, reflectance values were calculated for each of the selected areas within each of the photographs to quantify the visual differences that we had seen. We used ERDAS Imagine® 8.5 imaging software to create an area of interest layer by drawing a circle around each of the selected good, medium, and poor areas in the digitized images. The pixel reflectance values (ranging from 0-256) within each of the area of interest layers were exported to a text file which reported the reflectance values in the red, green, and blue wavebands. We took the average of the reflectance values in each of the color bands, and then calculated a grayscale reflectance (GSR) value for each area. Grayscale was calculated using the following equation, which is a common formula for converting images from color to grayscale (Hall, 1989).

$$GSR = 0.299(red) + 0.587(green) + 0.114(blue) \quad \textbf{(Equation 3.1)}$$

At the end of this process, we had a GSR value for each area of good, medium, and poor growth in each field for every photograph date.

We wanted to be able to compare reflectance values across all images, however the photographs were acquired on different days and different times within the days resulting in nonconformity of lighting and other conditions. Therefore we created the normalized difference in reflectance (NDR). This value was calculated using the following equation.

$$NDR = |GSR_g - GSR_p| / [(GSR_g + GSR_p)/2] \quad \textbf{(Equation 3.2)}$$

GSR_g is the grayscale reflectance value calculated in the good growth area and GSR_p is the grayscale reflectance value for the poor growth area. This equation helped normalize the data across all images. The NDR values created ranged from 0.004 to 0.765, where 1 represents high variability and 0 represents no variability. For the three fields which had two poor growth areas, two NDR values were calculated. In the analysis comparing the fields, these were treated as three additional fields.

In the first paper of this thesis, we chose the "optimal" in season photograph date for detecting variability in each field. These "optimal" images were taken at approximately 7.5 to 11.5 weeks after planting. The NDR values for the "best" photograph of each field were compared to normalized differences in the various soil and crop parameters measured to try to determine the causes of within field variability.

Groundtruthing

Once the different growth areas were chosen in the fields we began to weekly groundtruth the fields. The goal was to determine the reasons for the differences seen in the images. The georeferenced aerial images were used to determine the geographic coordinates of the selected areas which were then loaded into a Garmin Etrex Vista handheld DGPS unit (Garmin Ltd., Olathe, Kansas) for field navigation. Each week, notes were made about soil characteristics, canopy height and width, presence of weeds and insects, and other anomalies that were visible. Digital photographs of the crop canopy were taken during the visits using a Kodak DC4800 camera and were tagged with a DGPS location. Measurements of soil moisture and temperature were taken in each of the areas. Soil temperature was measured using a digital meat thermometer and volumetric soil moisture was measured using a ThetaProbe (Delta-T Devices Ltd., Cambridge, England).

Peanut maturity test

As harvest time approached, peanut samples were taken from each selected area of the fields to measure maturity differences within the fields. Crop maturity was measured on two to three different dates in each field. These dates were August 27, September 11, and September 25 for the Early County fields and September 6 and September 19 for the Brooks County fields. Two samples were taken in each area to equal approximately one meter of row. The hull-scrape method was used to determine peanut maturity in each area, which is represented as recommended days until digging (Williams and Drexler, 1981). The number of pods in each color category was recorded.

Samples for yield and aflatoxin testing

Once the farmers had dug and inverted the peanuts, two six meter samples were taken from each selected area of the field. These samples were picked using a small plot peanut thrasher. The peanut samples were dried, hand cleaned and weighed. The moisture content of each sample was measured using DICKEY-John grain testing equipment (DICKEY-john, Auburn, IL). Yield was calculated for all of the samples by adjusting the weight of the peanut samples to 10% moisture and converting the weights from grams per six meter plot to kilograms per hectare. Loose shelled kernels were removed from each sample, and a 500 gram subsample of each was shelled and graded using the commercial grading screens for runner peanuts. The kernels were sorted into categories of sound mature kernels (SMK), sound splits (SS), damaged kernels (DAM), and other kernels (OK). The peanut grades were calculated by adding the percent SMK and percent SS. This is the standard grading system used by the Federal State Inspection Service.

Aflatoxin analysis

The peanuts from the grade categories SS, DAM, and OK were used for the aflatoxin analysis, because these categories are more likely to be contaminated. It was our intent to test the SMK if aflatoxin was found in any of the samples. The peanuts were tested for aflatoxin using an immunoassay (Trucksees et al., 1991).

Soil sampling and testing

After the peanut harvest, two deep core soil samples were taken in each of the previously selected areas of good, medium, and poor growth for each field. These samples were taken as deep as possible, usually ranging from 38-99 centimeters deep. Photographs were taken of the soil profiles in the clear plastic tubes. Each of the soil profile samples was divided into at least two horizons (A and B) and the samples were sent to the University of Georgia's Soil Plant Water laboratory for routine soil testing, organic matter determination, and texture analysis.

Extractable P, K, Ca, Mg, Mn, and Zn were determined by the Mehlich-1 extraction method (Mehlich, 1953; Nelson et al., 1953; Perkins, 1970). The amount of P, K, Ca, Mg, Mn, and Zn was determined simultaneously on an inductively coupled plasma spectrograph (ICP) (Isaac and Johnson, 1983; Munter and Grande, 1981; Soltanpour and Workman, 1981). The amount of each element determined was expressed as pounds per acre of element on the basis of 2 million pounds of soil per acre. The pH was determined with a pH meter in a 1:1 soil-water suspension. Soil organic matter content was determined for all of the surface horizon samples using the loss on ignition method (Cuniff, 1995). Finally, soil texture was determined using the Buoyoucos method (Bouyoucos, 1936; Day, 1965).

The cation exchange capacity (CEC) was calculated for each surface horizon using the soil test values for extractable non-acid cations (Ca, Mg, and K) as an estimate of the effective CEC at the soil's measured pH. Then the CEC at a specified pH of 7 was calculated by adding the pH dependant CEC to the effective CEC. An estimate of the CEC from the pH dependant charge that results from raising the pH was calculated using the following equation.

$$CEC_{pHdep} = [1/b(7\text{-}pH_{measured})]/1120 \quad \textbf{(Equation 3.3)}$$

The value of b represents the buffering capacity of the soil. This value was estimated from the soil organic carbon and clay content using an equation developed by Autumn Weaver, a graduate student at The University of Georgia. Her work showed that the value of b can be estimated using the following equation.

$$b = [0.00014 - (0.00002)(\%clay)] + (0.0014 / \%\ organic\ carbon) \quad \textbf{(Equation 3.4)}$$

Organic matter values were converted to organic carbon values by assuming that the organic matter contained 40% organic carbon. Finally the CEC at the specified pH of 7 was calculated for each surface soil using equation 3.5.

$$CEC_{pH7} = CEC_{pHdep} + \text{effective CEC} \quad \textbf{(Equation 3.5)}$$

Variability Index

Because no individual measured soil or crop parameter could be directly related to the differences in reflectance values, we created a variability index which incorporated all measured parameters. These parameters included organic matter and calculated CEC in the surface horizon, % sand, % clay, pH, Ca, K, Mg, Mn, and P in the surface and subsoil, as well as crop yield, grade, and maturity. For each parameter, the fields were ranked (1-19) according to the normalized difference within the field for that parameter. The normalized difference was calculated using equation 3.6.

$$|\text{good-poor}|/[(\text{good} + \text{poor})/2] \quad \textbf{(Equation 3.6)}$$

For example, for each field we took the absolute value of the difference in CEC in the good and poor growth areas, and divided by the average CEC in the areas. For peanut maturity, we used the difference in predicted "days until digging" from the hullscrape data for September 19 in the Brooks county fields and September 25 in the Early county fields. For each parameter, the field with the least variability was assigned the number 1 and the field with the most variability received the number 19. The total variability for each field was calculated as the sum of the rank received for each parameter. This number ranged from 123 to 307. The fields with the higher variability index values were assumed to have the most overall variability.

Measuring topography

Topographic maps were created for four of the 16 fields (Butler, Crossroads, Thaggard4, and Thaggard8). Real time kinematic GPS using a base station was used to acquire centimeter accuracy for creating topographic maps. While driving the entire area of the field, FarmWorks Farm Site Mate 7.1 software (CTN Data Service, Inc., Hamilton, IN) was used to drop points at approximately 15 meter intervals. The software recorded the latitude and longitude coordinates as well as elevation at each point. The files were exported as shapefiles and the Spatial Analyst extension in ArcView 3.2 GIS software (Environmental Systems Research Institute, Redlands, CA) was used to create surface and contour maps for the four fields.

RESULTS AND DISCUSSION

Using aerial images to detect within field variability

The early season aerial images were used to choose the good, medium, and poor growth areas within each field. Some of the fields appeared fairly uniform while others showed a great deal of variability in soil properties and crop growth. It was difficult to choose varying areas of crop growth in the fields that appeared uniform. However, areas in these fields were selected to determine whether soil and crop differences existed that could not be seen in the photographs. We observed that when fields showed a great deal of variability in the images the soil conditions or crop growth also varied within the field. In addition, the fields that had uniform reflectance values between the sample sites in the images also tended to be more uniform in soil properties, crop growth, and yield. However, we could not relate the within field differences of any single measured parameter across all fields to the differences in measured reflectance values.

The normalized difference in reflectance (NDR) values at the "best" photograph date for each field was used to determine the relative within-field differences between fields. This value allowed us to determine which fields had the most variability in reflectance and to rank the fields according to their amount of variability. Ranking the fields using NDR was successful in predicting whether fields had visual differences in crop growth and soil conditions. Figure 3.1 shows the ranking of all the fields in terms of their NDR values. Generally the fields to the right of the graph have the most within field variability and the fields to the left side have the least within field variability in the images. Marco5 had the highest NDR value and B-04 had the lowest value. This is logical because the poor growth area in Marco5 was located near a sandy wash that was apparent throughout the growing season. In addition, fields B-04, B-02, Butler, B-07, and B-08 were some of the fields for which it was difficult to distinguish within-field differences and choose areas of good, medium, and poor growth. Figure 3.2 shows examples of the images of two fields, one which is uniform and the other showing large variability.

Typically when differences in crop growth were seen in the aerial imagery, differences in crop growth were also apparent during groundtruthing. Figure 3.3 shows two fields, one with large within field differences and one with little visual differences. In field B-04 few differences are seen in the aerial image and the same is true for the groundtruthing photographs. However the Groover field is highly variable in the aerial image and the variability in crop growth is also obvious from the groundtruthing photographs.

Determining the cause of variability using variability index

We wanted to determine if the variability seen in the images could be related to one or more biological, chemical, or physical properties. Therefore, we measured several soil and crop parameters during and after the season. However, little correlation was found when differences in within field reflectance were compared to single measured attributes. The coefficients of determination (R^2) for the linear regression of normalized difference in each parameter versus the normalized difference in reflectance are shown in table 3.1.

Due to the limited correlation between individual parameters, we created the variability index to determine whether the overall within field variability could be related to variability in the images. The resulting ranking of the fields according to variability in measured parameters is shown in figure 3.4. In addition, the components of the variability index are shown in figure 3.5. The variability index does show similarities to the ranking of the fields regarding image variability (figure 3.1), however the correlation is not perfect. Figure 3.6 shows the linear regression of the NDR values vs. the variability index values. The coefficient of determination (R^2) is 0.42, so 42% of the variability in reflectance can be explained by the variability index. We recognize that the variability in reflectance could have been better explained if some other key crop and soil parameters had been measured. For example, we did not have a direct measure of seasonal water availability for each location. This may have improved the correlation because water is often the most limiting factor in crop growth.

Determining the cause of variability using stepwise regression

The measured parameters did account for a portion of the variability in the images. To determine the relative importance of each measured factor within the fields we used a stepwise regression to predict the normalized difference in reflectance for these 16 South Georgia fields. We also used stepwise regression to determine the relative importance of the measured soil parameters in predicting differences in yield. The purpose of the second stepwise regression procedure was to determine whether the same soil parameters that influenced differences in reflectance had also influenced differences in yield. We thought that this was likely because difference in yield was one of the parameters that was most correlated with differences in reflectance in the linear regression (R^2=0.378). Table 3.2 shows the best models with 1, 2, 3, 4, and 5 variables for each stepwise procedure and the corresponding coefficients of determination (R^2).

The best 5 variable model for predicting differences in reflectance used the variables % sand in surface, % clay in subsoil, organic matter in surface, calcium in subsoil, and manganese in the surface (R^2=0.73). The best five variable model for predicting differences in yield used the variables % sand in subsoil, % clay in subsoil, calcium in subsoil, manganese in surface, and CEC in surface (R^2=0.72). Both models used several of the same parameters. The subsoil properties are important in the model because of their affect on crop growth which influences reflectance.

It seemed logical that differences in soil texture, organic matter, and cation exchange capacity were important predictors for differences in reflectance data because the large differences in reflectance in several fields resulted from extremely sandy (washed) areas, wet areas, or high organic matter areas. In addition, these parameters all affect the water holding capacity of the soil. Because water is one of the most limiting factors for crop production, it makes sense that these factors were important in predicting differences in the images as well as differences in crop yield. In most fields (11-14 of the 19 fields) the % clay in both horizons as well as the organic matter content and CEC in horizon 1 was higher in the selected “good growth” area than in the “poor growth” area of the field. In addition, the % sand in both horizons was typically highest in the “poor growth” areas.

Differences in calcium and manganese in the soil were also important predictors of differences in reflectance values as well as differences in yield. The reasons that these variables were important are less obvious than that of texture, organic matter, and CEC. However, closer examination of these two soil parameters revealed that calcium and manganese may reflect other soil properties.

A peanut crop is very sensitive to soil calcium levels (especially under drought conditions) because after the peanut peg has entered the soil, Ca must be absorbed directly from the soil solution. This may be one reason that calcium is such an important factor in predicting yield. In addition, soil pH is one of the factors of greatest importance in determining the availability of calcium (Tisdale et al., 1985). Generally, the Ca level for a given soil is a direct function of pH, with Ca levels being higher in higher pH soils. In eleven of the nineteen observations, the area of the field with the highest pH also had the highest Ca level. Lower cation exchange capacities in the high pH area of six of the remaining fields would explain the areas of higher pH but lower Ca. Calcium was generally found to be higher in the "good growth" areas of the fields (11 fields).

Generally Mn (used by plants as Mn^{+2}) in the soil solution is greatly increased under acid, low redox conditions because the transformation of Mn^{+4} to Mn^{+2} occurs (Tisdale et al., 1985). Mn may even be toxic to plants if the pH falls below 5.5. In 5 of the fields studied, the area of the field with the lowest pH also had the highest level of Mn within that field. In addition, high Mn levels may be associated with temporary water-logged conditions. Poor aeration and high microbial activity consumes oxygen and promotes the transformation of manganese oxide into soluble manganese (Mn^{+2}). We noticed low-lying wet areas in three of the fields studied. The "wet" areas in all three of the fields had the highest Mn level within that field (Thaggard7, Thaggard8, and B-06). Therefore the importance of the differences in Mn levels may reflect and emphasize the importance of pH as well as topography and drainage patterns in predicting differences in yield and image reflectance. Higher Mn levels were generally found in the "good growth" areas of the fields.

Because topography usually affects many soil properties within a field, we predicted that topography would be an important factor in predicting differences in the reflectance data. Therefore, we sampled four fields for differences in topography. Normalized differences in elevation were measured between the good and poor areas of the fields. This variable (topography) was used along with the other soil variables to perform the stepwise procedure to predict the differences in reflectance for these four fields. The best 1,2,3,4, and 5 variable models did not include topography as an important variable. However, perhaps if topographic data had been collected over all fields, this variable would have been more important in the models. In addition, there may have been a better way to represent the topographic differences than simply the normalized differences in elevation, such as by using the % slope and drainage patterns.

Yield prediction from the aerial imagery

Previous research conduced at the University of Georgia has shown that early season classified aerial images of cotton fields show striking similarities to spatial patterns generated from a yield monitor at the end of the season (Vellidis et al., 1999). We predicted that the good, medium, and poor growth areas of the fields showing variability could be used to predict areas of high, medium, and low yield. This would further validate our theory that the aerial images can be used to detect within field variability and determine the need for precision agriculture. Generally the poor growth areas had lower yields than the predicted medium and good growth areas (figure 3.7). In addition, the fields which showed more variability in the imagery tended to have larger differences in yield than the fields that appeared uniform in the images. For example, the Groover field showed large variability in the imagery (figure 3.3) and also showed large differences in yield at the end of the season.

Relating aerial images to aflatoxin contamination

The “high risk” areas in several of the fields had poor plant growth compared to the “medium” and “low” risk areas. When soil temperature and moisture measurements were first taken, some of the high risk areas appeared to have higher soil temperatures and lower soil moisture values. However, little difference could be seen in soil temperature and moisture towards the end of the growing season because of sufficient rainfall. Peanut samples taken from each area were analyzed for aflatoxin contamination. We used the grade categories of loose shelled kernels (LSK), OK, SS, and DAM to test the peanut samples for aflatoxin contamination. These grade categories are more likely to be contaminated with aflatoxin. We found less than 10 ppb aflatoxin in all but one of the sixteen fields. When the sound mature kernels were tested from this field, no aflatoxin contamination was found. Sufficient rainfall at the end of the peanut growing season is uncommon in Georgia. Therefore, it is possible that aflatoxin contamination would have occurred in the stressed areas of the fields in a more common year.

CONCLUSION

Aerial images of peanut fields were shown to be indicators of within field variability. However, the cause of this variability could not be traced to any single measured crop or soil property across all fields. A variability index of all of the measured parameters accounted for 42% of the variability in reflectance values. If other crop and soil parameters had been measured, particularly a season long measure of crop available water, this correlation may have been better. Of the measured soil properties, the most important predictors of differences in reflectance and yield for the fields in this study were soil texture, organic matter, CEC, Ca, and Mn. The images were helpful in delineating areas of good and poor crop growth and were generally successful in predicting high and low yielding areas. In-season aerial images of peanut fields can be used to delineate areas of crop and soil variability. The presence or absence of variability in the images could be used to determine whether a field is a good candidate for differential management.

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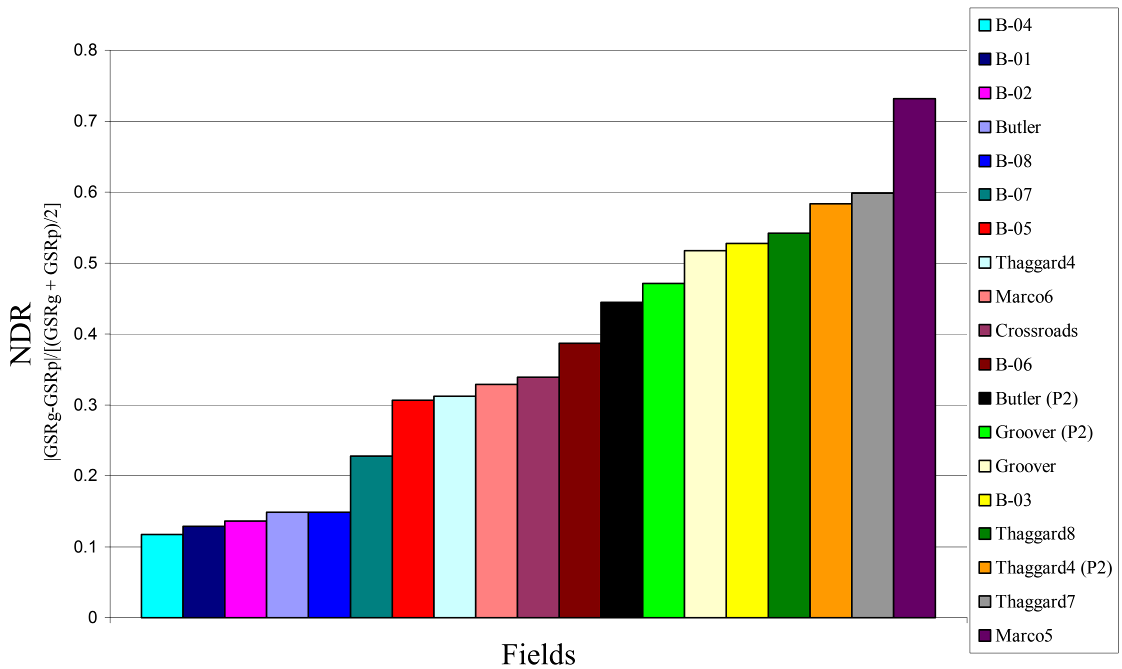


Figure 3.1. This graph shows the ranking of all the fields in terms of their normalized difference in grayscale reflectance (NDR) values. NDR is calculated as NDR = $|GSR_g-GSR_p|/[(GSR_g + GSR_p)/2]$, where GSR_g is the grayscale reflectance value calculated in the good growth area and GSR_p is the grayscale reflectance value for the poor growth area. Generally the fields to the right of the graph have the most within field variability and the fields to the left side have the least within field variability in the images.

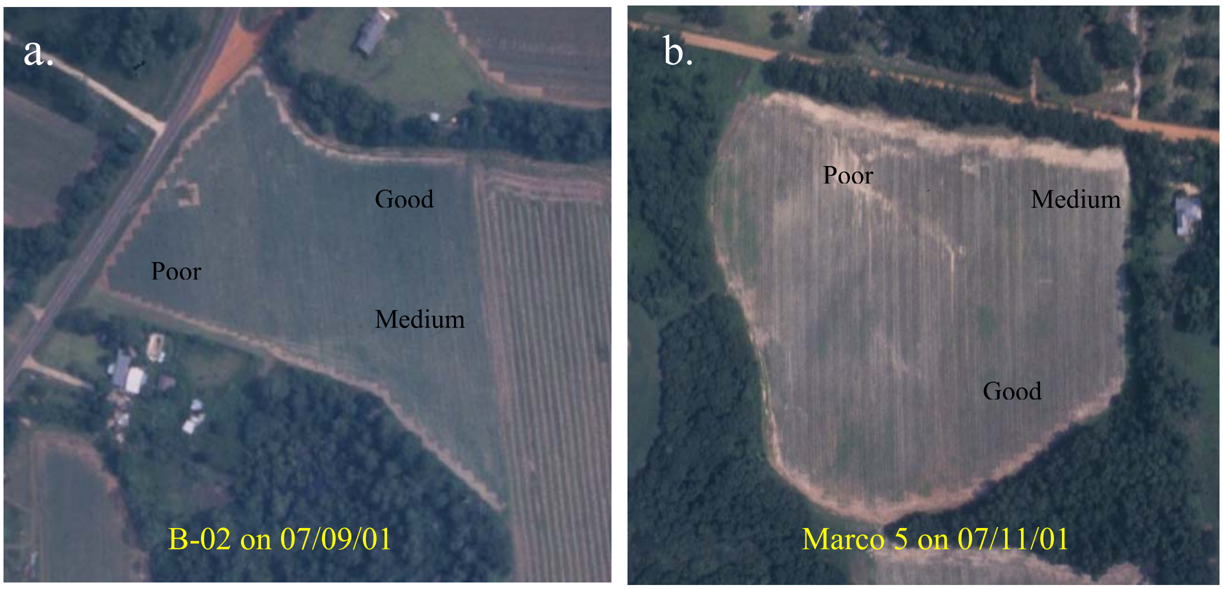


Figure 3.2. Images showing (a) field B-02 at 589 heat units, one of the more uniform fields and (b) field Marco5 at 595 heat units, one of the more variable fields.

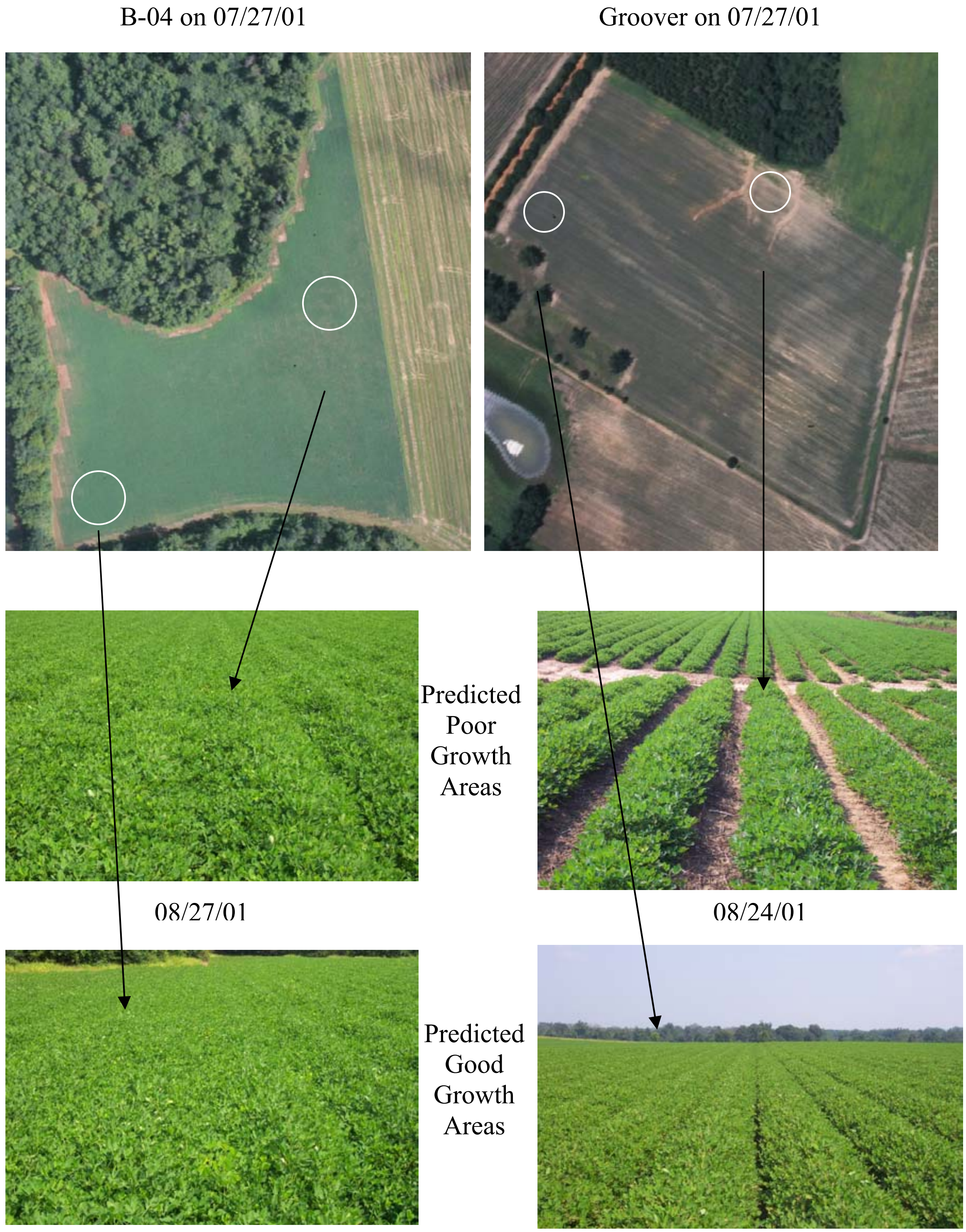


Figure 3.3. Field B-04 represents a more uniform field. The aerial image was acquired on 07/27/01 at 859 heat units. Groover represents a more variable field. The aerial image was acquired on 07/27/01 at 830 heat units. Groundtruthing photographs are shown of the crop growth in each field.

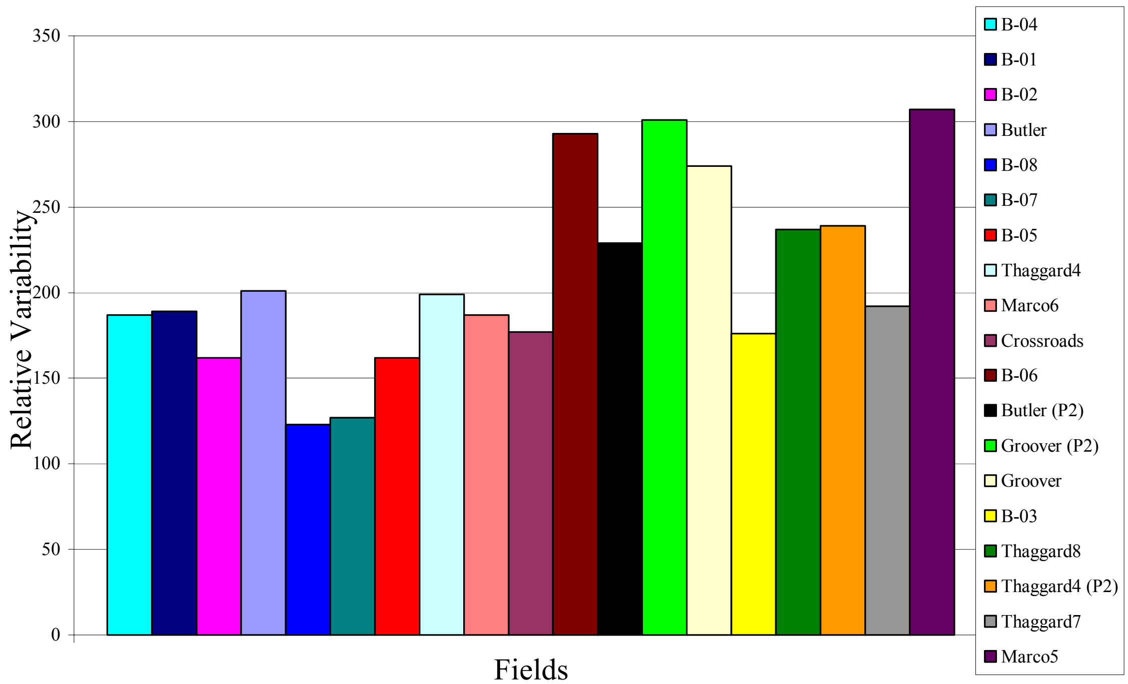


Figure 3.4. This figure shows the variability index, which is the result of ranking the fields according to variability in measured crop parameters and soil chemical and physical properties. The fields are shown in the same order as in figure 3.1, where they are ranked according to variability in NDR. Fields B-04, B-01, B-02, Butler, Crossroads, Groover(P2), and Groover, in particular, were more variable in the variability index than in the imagery.

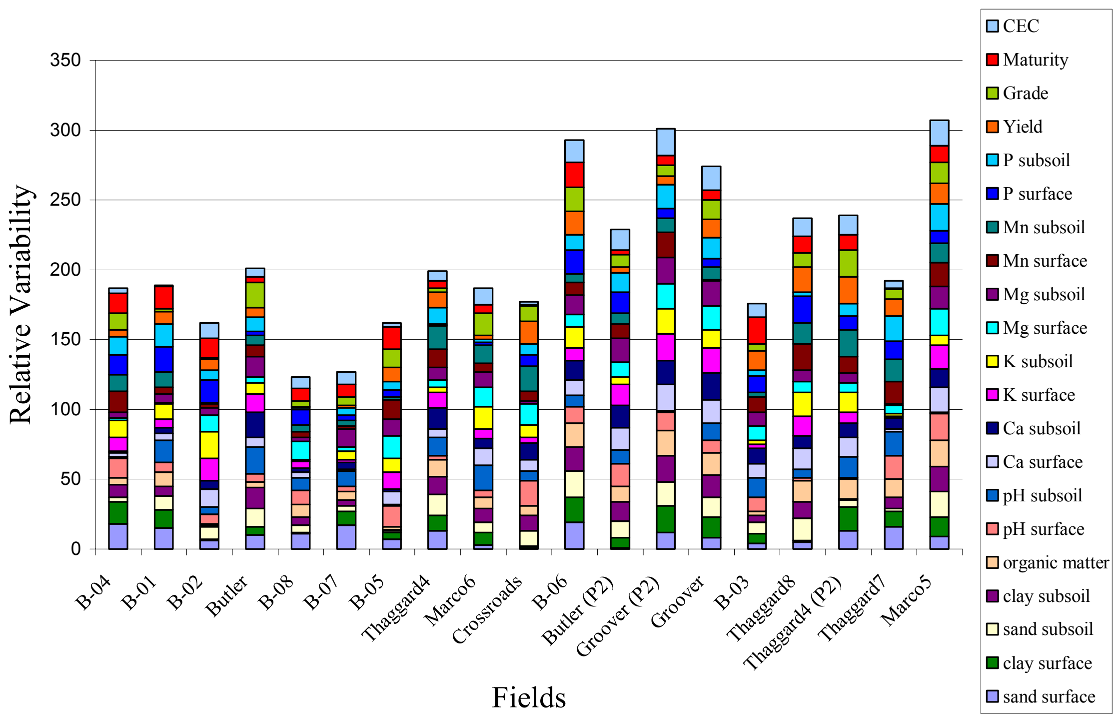


Figure 3.5. This figure shows the components of the variability index. The individual components are the rankings of the relative differences between fields in measured crop and soil parameters.

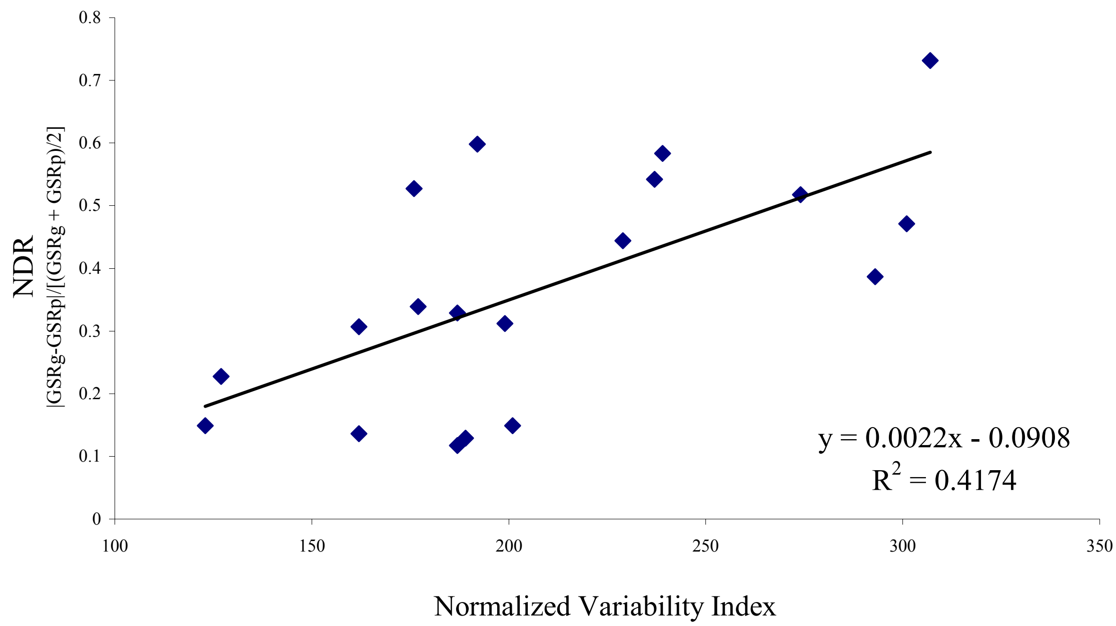
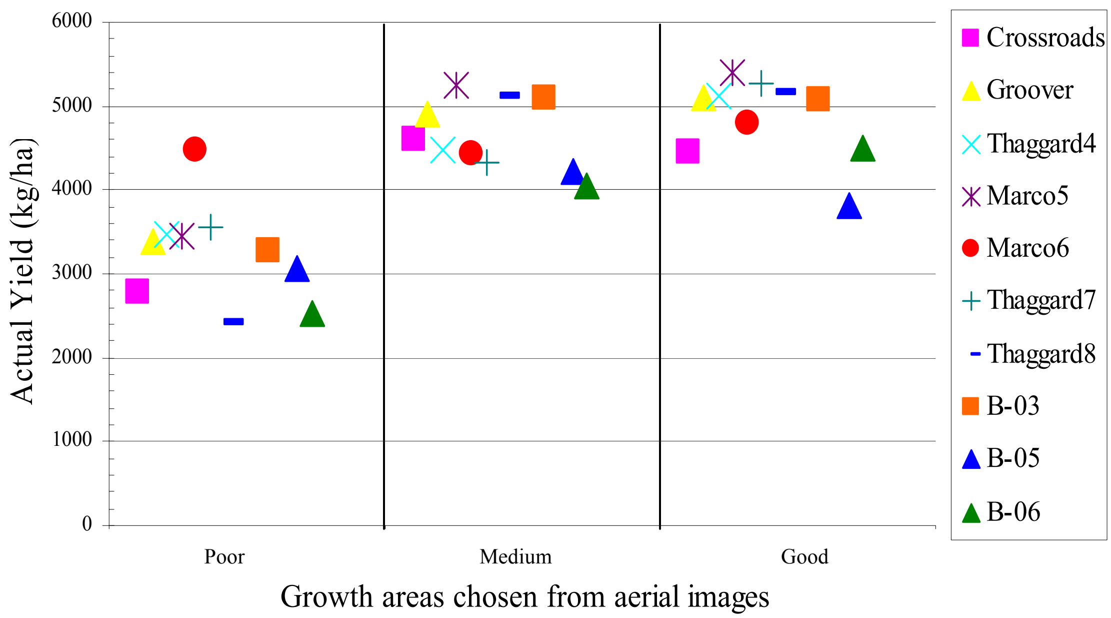


Figure 3.6. This figure shows the linear regression of the normalized difference in reflectance (NDR) values vs. the variability index values.

a.



b.

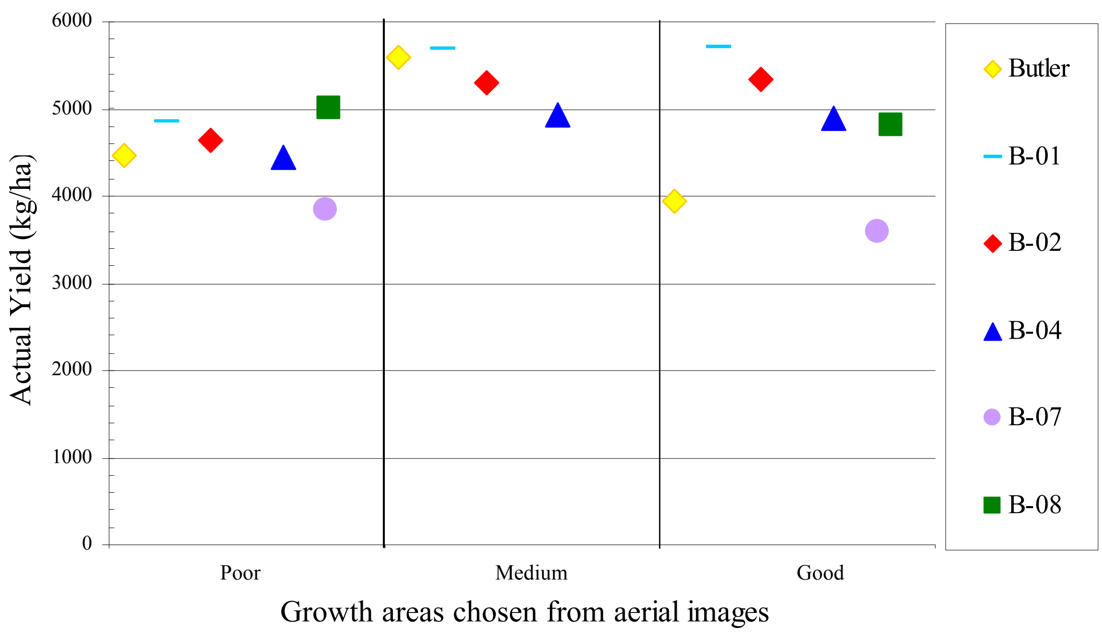


Figure 3.7. (a) Graph showing actual yield in the poor, medium, and good growth areas chosen from the aerial images. Only the fields with NDR > 0.3 are shown, because those with NDR < 0.3 appeared more uniform in the images. **(b)** Graph showing actual yield in the poor, medium, and good growth areas chosen from the images of uniform fields (NDR < 0.3). Yield is not easily predicted in the more uniform fields.

Table 3.1. Coefficients of determination (R^2) for the linear regression of normalized difference in each parameter versus the normalized difference in reflectance at the "optimum" photograph date.

Soil Physical Properties	**R^2**
sand, horizon 1	0.026
sand, horizon 2	0.195
clay, horizon 1	0.101
clay, horizon 2	0.160
org. matter, horizon 1	0.408
Soil Chemical Properties	**R^2**
pH, horizon 1	0.067
pH, horizon 2	0.004
Ca, horizon 1	0.332
Ca, horizon 2	0.110
K, horizon 1	0.046
K, horizon 2	0.005
Mg, horizon 1	0.237
Mg, horizon 2	0.153
Mn, horizon 1	0.264
Mn, horizon 2	0.163
P, horizon 1	0.000
P, horizon 2	0.219
CEC, horizon 1	0.354
Crop Parameters	**R^2**
Yield	0.378
Grade	0.100
Maturity	0.014

Table 3.2. The best 1, 2, 3, 4, and 5 variable models for each stepwise regression procedure using differences in soil parameters to predict differences in reflectance and yield. The corresponding coefficients of determination (R^2) are also given.

	Normalized Difference in Reflectance (NDR)	**R^2**
1 variable	NDR = 0.20012 + 0.43884(orgmatter)	0.41
2 variable	NDR = 0.24915 - 1.27380(sand_sur) + 0.52352(orgmatter)	0.55
3 variable	NDR = 0.33577 - 1.83730(sand_sur) + 0.65072(orgmatter) - 0.17095(K_sur)	0.62
4 variable	NDR = 0.18007 - 1.42755(sand_sur) - 0.17376(clay_sub) + 0.70652(orgmatter) + 0.23262(Mn_sur)	0.68
5 variable	NDR = 0.08721 - 1.16339(sand_sur) - 0.34351(clay_sub) + 0.73750(orgmatter) + 0.19741(Ca_sub) + 0.34748(Mn_sur)	0.73

	Normalized Difference in Yield (NDY)	**R^2**
1 variable	NDY = 0.12486 + 0.17506(Mn_sub)	0.21
2 variable	NDY = 0.23619 - 1.87482(pH_sur) + 0.18659(Mn_sub)	0.27
3 variable	NDY = 0.08311 + 0.53718(orgmatter) + 0.17200(Mn_sub) - 0.30238(P_sub)	0.38
4 variable	NDY = 0.08755 - 0.29250(clay_sub) + 0.95289(orgmatter) + 0.13787(Mn_sub) - 0.27565(P_sub)	0.48
5 variable	NDY = -0.32292 + 3.39925(sand_sub) - 1.78942(clay_sub) + 0.96010(Ca_sub) + 0.90811(Mn_sur) + 0.44590(CEC)	0.72

CONCLUSION

Many agricultural fields vary spatially in soil properties and crop growth patterns. For this reason, precision agriculture techniques have recently received much attention. Remote sensing is also becoming a popular tool for making observations about agricultural fields. However, many farmers are reluctant to implement these techniques because of economical limitations. In addition, some fields are fairly uniform and are not good targets for precision agriculture. Aerial images of agricultural fields are a relatively inexpensive form of remote sensing. These images may be used to assist farmers in determining whether variability exists within fields and selecting fields that may be candidates for within field management.

Early season aerial images of a peanut crop (300 to 600 heat units) and bare soil images are useful for detecting variability within peanut fields that have differences in soil texture and topography. Aerial images of a growing crop may be used to detect physical, chemical, and biological differences in a field during the season. We found that the overall best time to acquire images during the 2001 season in South Georgia dryland peanut fields was approximately 7.5 to 11.5 weeks after planting (700-1250 heat units). The end of season aerial images were only useful for finding differences in fields with large differences in crop growth and soil type, such as extremely sandy or washed areas where the crop canopy never closes.

Generally we observed that when fields showed a great deal of variability in the images, soil conditions and crop growth also varied within the field. In addition, the fields that had uniform reflectance values between the sample sites in the images also tended to be more uniform in soil properties, crop growth, and yield. However, it was difficult to relate the within field differences of any single measured parameter to the differences in measured reflectance values. A variability index which incorporated all of the measured soil parameters accounted for 42% of the variability in reflectance values. If other crop and soil parameters had been measured, this correlation may have been better. Of the measured soil properties, the most important predictors of differences in reflectance and yield for the fields in this study were soil texture, organic matter, CEC, Ca, and Mn.

Aerial images provide farmers with a simple, inexpensive tool to gather information about crop growth and development within their fields and to determine whether their fields are good targets for precision agriculture. Aerial images can help growers make better decisions as to where to spend their limited resources.