ABSTRACT

ISAEV, DAVRON. Assessment of GreenSeeker® in Peanut Disease Detection. (Under direction of Dr. Gary T. Roberson).

Crop diseases often occur in non-uniform patterns throughout the field. The patchy distribution of soil-born diseases creates the possibility for growers to use precision agriculture tools to manage disease dispersion. In most instances pesticides are applied uniformly irrespective of the distribution of disease; thus increasing production cost and increasing negative risk to the environment. Consequently, having a device that can distinguish between healthy and stressed crop canopy and further make a disease map of the field would be beneficial to farmers.

The active optical sensor, GreenSeeker®, was used to assess disease incidence during 2011 in peanut (Arachis hypogaea L.) starting in mid-August through harvest in October. Reflectance of the peanut canopy was used to calculate the normalized difference vegetation index (NDVI) which was subsequently correlated with visual disease estimates and yield of peanut. Negative correlation between NDVI and visual disease assessment of peanut was observed. The correlation results between yield and NDVI ratio were positive indicating plots with higher yields have higher NDVI ratio. Results from all statistical analyses demonstrate that GreenSeeker® can be applicable for disease detection in peanut.

Assessment of GreenSeeker® in Peanut Disease Detection

by
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DEDICATION

I want to dedicate this thesis to my loving and supportive parents, Khursheda Isaeva and Azam Isaev, they always have been encouraging me to pursue my goals and dreams.

BIOGRAPHY

Isaev Davron was born in Dushanbe, Tajikistan. He received his bachelor degree in Mechanical Engineering at the Tajik Agrarian University in 2009. After receiving the bachelor degree he was employed at Tethys Petroleum as a service engineer.

After working as a service engineer for almost one year, Davron received a Fulbright scholarship to do his MS degree in one of the universities in the United States. In fall, 2010 he was accepted to the Department of Biological and Agricultural Engineering of North Carolina State University. Throughout his graduate school career he was working under the supervision of Dr. Gary T. Roberson and Dr. Michael D. Boyette.

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CHAPTER 1

1.1 Introduction

In today's crop production system, crop producers are exposed to increasing pressure from environmental concerns to reduce pesticide application to agricultural fields. Application of some pesticides to the field can negatively affect the surrounding environment and can reduce crop yield in cases where inputs are applied where they are not needed. It has been documented that a field with any kind of crop has many variables such as disease distribution, crop yield and density and soil type. Currently most farmers apply inputs uniformly across the field because of difficulty in dealing with the above mentioned variables (West et al., 2003). Although effective, it can be costly considering that fungicides and nematicides are 40 percent of peanut production cost in North Carolina (Roberson, 2007). There are a few pieces of precision agriculture equipment such as the Greenseeker® optical sensor and variable rate applicators (VRA) available in today's market that have the potential to solve the above mentioned issue. Despite the variety of precision agriculture tools, an optical sensor devoted specifically to detect crop diseases has not yet been developed.

However, there are researchers who successfully used available instruments like the spectrograph to detect disease in wheat from its canopy reflectance (Bravo et al., 2003). Different tobacco (*Nicotiana Tabacum*) diseases were successfully identified with the Optic USB2000 spectrometer (Krezhova et al., 2009). Bell et al. (2009) conducted turfgrass quality assessment with an optical sensor, Greenseeker®, that is commonly used to determine the amount of nitrogen required for application to the plant canopy. Nutter (1989) was successful in detecting late leaf spot in peanuts by using a hand-held multispectral radiometer.

1.2 Study objectives

Encouraging results from these studies shows that optical sensors could be implemented in disease detection of particular crops. In the current research study, a Greenseeker® sensor, (NTech, Ukiah, CA) was assessed in disease detection of a peanut field based on normalized difference vegetation index (NDVI) of the peanut leaves. In order to validate collected data, it will be correlated first with the yield of the scanned plots and second with visual disease severity ratings of the scanned plots.

1.3 Previous studies on assessment of remote sensing devices in disease detection, yield and injury estimation.

Current crop producers typically maintain uniform application of inputs across the field, which are targeted against different types of diseases. Crops in some areas of the field, which are not infected, may not need any kind of input. Moreover, diseases in crops occur mainly in patchy distribution rather than uniform distribution (West et al., 2003), thus when farmers spray inputs uniformly, they lose significant amounts of pesticides and money; plus excessive chemicals negatively impact the environment (West et al., 2003). Therefore, engineers should be motivated to develop a device that can detect and map disease locations of specific crops so that only stressed areas of the field can be treated with inputs. Peanut extension specialist, Barbara Shew, states that: “Soilborne pathogens have limited mobility, so mapping the location and intensity of the diseases they cause is a useful tool for deciding where certain cultural practices and/or chemical treatments should be applied the next time peanuts are grown” (Shew, 2004).

A range of technologies, such as GPS, optical sensors, and variable rate applicators (VRA) are available today to make variable rate application possible, the only concern is to be able to detect diseased crops in the field.

There are several authors who conducted research in disease detection of different crops using remote sensing devices that can detect, at a specific wavelength of light, the change in spectral reflectance of stressed plants. Bravo et al. (2003) observed in his experiment that diseased plants had higher spectral reflectance as opposed to healthy plants. Cibula et al., (1992) used a scanning spectrometer to detect the *mycorrhizae*, a common type of symbiosis occurring in slash pine. The authors wanted to determine the wavelength to which the sensor should be tuned so that a stressed plant's disease could be detected. Based on conducted experiments the authors came to the conclusion that non-inoculated plants had higher reflectance than inoculated plants at a wavelength close to 700 nm. Bravo et al. (2003) worked on developing an optical sensor which could be applied for detecting yellow rust, a commonly observed disease in wheat fields. In order to compare the reflectance there were six plots that were inoculated with yellow rust and a similar number of plots with healthy wheat. To scout the plots, authors used a spectrograph on which a monochromatic camera was mounted. After running the sensor over healthy plants and plants that were inoculated with yellow rust, a spectral reflectance graph showed that stressed canopies had reasonably higher reflectance than healthy canopies at wavelengths higher than 750 nm. Also researchers focused on collecting normalized difference vegetation index (NDVI) data to make an assumption about plant conditions since plant's NDVI ratio variation can provide information about the plant's health, age and leaf area index (Bravo et al., 2003). Based on

the range of NDVI ratios from one of the tests, lower and upper limits of NDVI were fixed to 0.35 and 0.69 respectively which was the potential range in which disease might be spotted. Experimental results suggested that two wavebands (750±10 nm and 630±10nm) should be used for leaf detection purposes (Bravo et al., 2003). Nilsson (1995) was also in agreement with Bravo et al. (2003) about the concept that a plant's NDVI ratio can be a good estimator of plant stress. Furthermore, Nilsson (1995) and Jackson (1986) claim that tissue spectral signature is effected by tissue's stress, disease and presence of pigments in tissue. Bronson et al. (2005) was successful in correlating cotton leaf nitrogen concentration with NDVI ratio of cotton leaves. Three plots were available for this study: one with zero nitrogen (N) applied, variable-rate and uniform N application with 63, 93, 95 kg/ha and 59, 101,100 kg/ha N applied respectively for three years 2002, 2003 and 2004. Scanning results showed that average NDVI ratio of N-fertilized plots were significantly higher compared to non N-fertilized plots.

Corn grain yield potential was successfully predicted by Teal et al. (2006) with the GreenSeeker® which was designed mainly to calculate plant's NDVI ratio. Crop NDVI ratio was collected at growth stages starting from V6 to V11; GreenSeeker® was positioned at about 0.70 meters above the canopy. Researchers came to the conclusion that a plant's growth stage was critical for scanning the field since their statistical results showed that sensor reading explained more yield variability (R^2=0.77) when the crop was scanned in a growth stage of V8. Sensor measurements that were done in growth stage V9 and later failed to estimate any difference in green biomass because of canopy closure (Teal et al., 2006).

Normalized Difference Vegetation Index (NDVI), calculated by Indian Remote Sensing Satellite (IRS-1c), was used as a ratio by which rubber plantation disease severity and recovery was monitored by Ranganath et al. (2004). The objective of the research was to map stressed rubber plantation location and prevent diseased locations from getting more severe. Research results showed clear evidence that infected rubber trees have lower NDVI ratios when compared to healthy trees. NDVI ratio of healthy rubber trees was 0.51 while NDVI ratio of infected trees was 0.27. Also, investigators observed increased NDVI ratios of stressed rubber trees after treating stressed areas with fungicides. Before the treatment, infected areas had NDVI ratio which was equal to 0.27, however, after treatment NDVI ratios increased to 0.36 (Ranganath et al., 2004). Chang et al. (2004) also used NDVI ratio to detect weed infected patches in the soybean field so that only infected areas can be treated with necessary pesticides, which can lower production cost. Beside NDVI ratio, the authors also measured spectral reflectance of weed infected areas. It was observed by the investigators that weed-infected areas had higher reflectance at 840 nm comparing to weed-free areas. NDVI had the same pattern, i.e. NDVI ratio was high in weed-infected patches. The investigators came to the conclusion that since weed-infected areas had higher biomass as opposed to weed-free patches, reflectance and NDVI is greater that in weed-free areas (Chang et al., 2004).

Several researchers were evaluating hand-held remote sensing devices (Cropscan®, Inc. Fargo, ND) in assessing disease and injury severity in some crops such as peanut, soybean and barley (Adcock et al., 1990; Forrest et al., 1996; Nutter et al., 1988; Nutter, 1989).

Relationship among pod yield reduction, percentage defoliation of peanut caused by late leaf spot disease, and percentage canopy reflectance was evaluated by Forrest et al., (1996). Percentage of reflectance was measured with Cropscan®, a hand-held multispectral radiometer, which was positioned at two meters height above peanut canopies. Percentage of leaf defoliation assessment started sixty days after planting and continued until one week before digging. Researchers used percentage of defoliation and canopy reflectance percentage as independent values that were correlated to yield as the dependent value. Using two independent predictors, percentage of defoliation and canopy reflectance, and yield as a response; critical-point yield loss models were made. Statistical results of a model showed that the optimal time to evaluate yield with either of the two predictors is 2-3 weeks before digging the plot. Lower standard error and more variation in yield reduction was explained when canopy reflectance was used as an independent predictor. Thus, research results prove that using percentage reflectance as an independent predictor explains more variability in yield loss than using percentage defoliation as an independent predictor. About 96.3-99.3% of biomass variation was explained by percentage reflectance (Forrest et al., 1996).

The relationship between peanut disease severity and canopy reflectance was studied by Aquino et al. (1992). Investigators conducted field experiments where reflectance percentage from peanut canopies, inoculated with late leafspot, was measured at 800 nm. Visual disease assessment of the late leafspot was made based on the percentage of necrotic area and defoliation percentage. Radiometric measurements were conducted with Cropscan, a hand-held multispectral radiometer, which was held at a height of nearly 1.9 m. Radiometric measurements were done in 10 to 12 day intervals; fifty five days after the peanuts were

planted. After correlating radiometric measurements with visual disease assessment, investigators noticed a pattern of decreasing percentage reflectance values at 800 nm while disease and defoliation severity increased (Aquino et al. 1992). Kobayashi et al. (2003) had similar results on scanning rice fields with a multispectral radiometer. The authors were investigating the effect of a disease occurring in rice fields, *rice blast*, to the spectral reflectance of the rice canopy. Three kinds of rice canopies were used for recording spectral reflectance: rice leaf samples infected with leaf blast, three 1/5000-a Wagner pots with inoculated rice plants, and rice plots without presence of leaf blast. Rice leaf samples infected with leaf blast were placed in Petri dishes, the reflection of which was measured in the laboratory, whereas reflection of the other two samples was measured in the field. Disease severity of the samples were assessed as well. Degree of leaf blast severity was rated from 0 to 10. Visual assessment of disease severity enabled investigators to observe spectral reflectance trends at different disease severity levels. A multispectral radiometer (MSR-7000; Opto, Tokyo, Japan) was implemented in recording reflection from rice plants. The authors observed a trend of reflectance decreasing at a wavelength of 500-570 nm and 700-900 nm as disease severity of a rice canopy (Rice blast) increased. However, reflectance at the 400-500 nm (blue), 570-700 nm (red) and 900-2000 nm wavelength increased as disease severity increased. Investigators linked reflectance increase at blue and red portions of electromagnetic portions to chlorophyll and carotenoid content reduction as an effect of blast disease (Kobayashi et al., 2003).

Adcock et al. (1990) implemented the hand-held radiometer in assessment of soybean injury caused by application of herbicides such as *paraquat* and *glyphosate*. Scanning of the

field was performed by four individuals before and after herbicides were applied to the field. Visual evaluation of the plots was made by six evaluators whose evaluating experience ranged from zero to ten years. Statistical results showed that correlation coefficients among results of evaluators who were using hand-held radiometer were more consistent, unlike visual evaluators. Correlation coefficients among remote sensor evaluators ranged from 0.98 to 1.0 whereas coefficients of visual evaluators with different experience ranged from 0.69 to 0.96. Results also proved that tissue reflectance at 800 nm was gradually decreasing as the crop injury was increasing. Nutter et al. (1993) tested disease assessment accuracy of a CropScan® radiometer (CropScan, Inc., Fargo, ND) and visual disease assessment. Nutter et al. (1993) came to the similar conclusion and had similar results as Adcock et al. (1990). Nutter et al. (1993) observed reflectance decrease from the canopy at 800 nm as bentgrass disease severity increased. However, the opposite trend occurred when the authors recorded bentgrass reflectance at 600 nm. Percentage reflectance decreased while disease severity of bentgrass increased. The authors also compared visual and sensor based disease assessment. In order to conduct this test, several $1m^2$ bentgrass plots with different disease severity were provided. Four raters visually assessed plots for disease severity. Visual assessment of the same plots was repeated by the evaluators after 24 hours, so that repeatability among evaluators could be statistically measured. Results from initial visual evaluation of disease severity *(X)* were regressed with results of a second visual evaluation *(Y).* Regression results showed that the coefficient of determination among evaluators had a linear relationship. Correlation coefficient of regression, R^2, ranged from 83.4 to 93.1 %. The same four evaluators scanned plots with CropScan two times at 600 nm and 800 nm. After regressing

initial sensor readings with the second reading, correlation coefficient showed that variation among sensor readings is less compared to visual assessment of a plot. Statistical analysis of the study concluded that: “Coefficient of determination for inter-rater reliability using the 600- and 800-nm wavelength bands ranged from 97.8 to 99.2 % and from 99.1 to 99.6% respectively” (Nutter et al., 1993).

West et al. (2003), Navalgund, (2001), Clive, (1974) and Goodwin, (1998) also confirmed that healthy canopies have lower light reflectance than stressed canopies at wavelengths ranging from 400 to 700 nm. All four studies linked that phenomenon to the fact that healthy plants have higher photoactive pigments (chlorophylls, anthocyanins, carotenoids) which absorb received light and reflect back a smaller proportion of received light. This characteristic of healthy plants enables optical sensors to distinguish between healthy and stressed plants. Nutter (1989), however, observed increase in percent reflectance while disease severity decreased. Nutter (1989) was using Cropscan, a hand-held multispectral radiometer, to detect peanut rust disease. Results of his research show that inoculated (stressed) peanut plots have lower percent reflectance at 800 nm compared to healthy plants. He explains that phenomena with the fact that stressed plants lack chlorophyll pigments, instead they have “black bodies” that absorb electromagnetic radiation and reflect back a small portion of it. Although Nutter (1989) had different results compared to West et al. (2003) and Navalgund (2001), it can be explained by the fact that Nutter, (1989) measured percentage of reflectance at 800 nm unlike West et al. (2003) and Navalgund (2001) who measured reflectance percentage at 400-700 nm. Overall results of research conducted by Nutter (1989) proved that peanut disease can be detected with a hand-held multispectral

radiometer which measures plant reflectance at 800 nm. Nutter, (1989) was able to statistically prove an obvious linear relationship between tissue percent reflectance at 800 nm and distance from infected (inoculated) location. The further the distance from the infected source the higher the reflectance percent was. Furthermore, research was able to show a significant linear relationship between percent reflectance value and pod yield ($R^2 = 97.6$). For every 1% of percent reflectance increase the pod yield increased up to 58 kg/ha. Also, research showed that green leaf area (GLA) explained 98.2% of yield variation and late leaf spot disease severity in peanuts.

In similar research Nutter et al. (1988) used a hand-held multispectral radiometer to assess the relationship between green leaf area (GLA) and barley disease severity, caused by *Rhynchosporiumsecalis*. Barley plots were inoculated at different growth stages in order to obtain plots with different disease severity. Visual assessment of the barley plots were correlated with the plot's GLA measured by a hand-held radiometer, the Cropscan®. Correlation results showed that reflectance percentage increased linearly as the plot's GLA increased (Nutter et al., 1988). Nutter et al. (1990) implemented multispectral hand-held radiometers in evaluating fungicide use efficiency in controlling late leaf spot in peanuts. Peanut canopy reflectance at 800 nm was compared to visual disease severity rating. Analysis of variance proved the research hypothesis and concluded that: "Analysis of variance and mean separation test for visual versus remotely sensed assessments revealed that percent reflectance-based measurements had lower coefficient of variation than visually based assessment schemes" (Forrest et al., 1990). The authors also observed a linear relationship between sensor readings and visual disease assessment, as disease severity

decreased, percent reflectance increased (Forrest et al., 1990).

1.4 Active and Passive Sensors

There are basically two types of sensors; active and passive, available in precision agriculture for making assumptions about different aspects of a particular crop. The main difference between these two sensors is that active sensors generate and transmit their own light and capture reflectance from the target (Yunseop et al., 2010), whereas, passive sensors detect natural reflectance of the target caused by ambient illumination. Several works have been done on the effect of ambient light on the data collected by different types of sensors. Bravo et al., (2003) used a passive sensor for disease detection on wheat and observed that solar elevation and presence of clouds had quite a strong effect on the signal received from a target. This observation was further supported by Ranson et al., (1985), who tested whether sun-view angle had any effect on reflectance received by a passive sensor.

Yunseop et al., (2010) tested the effect of different conditions to the reflectance signal received by an active sensor, GreenSeeker®. In one of the tests, investigators tested the solar bidirectional effect on the NDVI ratio of target leaves by mounting a GreenSeeker® on a goniometer. The NDVI ratio was recorded while the angle of the goniometer was changed in increments of 10 degrees. Based on the observations the changes were not significant in the NDVI ratio when the sensor was positioned from 0 to 60 degrees relative to target the leaves. Bell et al., (2002) applied an active sensor to measure NDVI ratio of turfgrass and the authors stated that: “Optical sensors were not sensitive to solar radiation. Therefore, cloud cover or time of a day were not important” (Bell et al. 2002). Yunseop et al., (2010), however, claimed that diurnal solar radiation could have a minor effect on the NDVI ratio collected by

an active sensor. After collecting the data with two GreenSeekers®, one placed under direct solar radiation and another one placed under a trap, test outcomes showed that NDVI was lower when solar radiation increased. Thus NDVI ratio had a strong correlation with solar radiation. Although, the range of variation of NDVI due to solar radiation was quite low (0.07-0.08), it could have a significantly effect on detecting a plant's stress in the early phase of its development (Yunseop et al. 2010).

Evaluation of optical sensors crop quality assessment

Even though there are many areas of agriculture where optical sensors were applied in a variety of processes, only a few researchers compared the results that were based on the data collected by an optical sensor to results based on visual observations of a particular crop. Bell et al. (2009) worked on evaluation of a GreenSeeker® in quality assessment of three types of turfgrass and compared results with visual quality ratings of those crops. From the three types of tested turfgrass, bermudagrass had quite a strong correlation between two types of quality assessment i.e. optical sensor and human evaluator. Moreover, evaluations conducted visually took 2.4 times longer than an evaluation conducted with an optical sensor. Bell et al. (2002) conducted similar research on tall fescue and creeping bermudagrass and had similar results as (Bell et al. 2009). Researchers used an active optical sensor PhD 600 to capture red and near infrared reflectance from the above mentioned crops and converted the collected data on the NDVI ratio. There was a strong correlation between data collected with the optical sensor and data collected by three human turf evaluators with different years of experience in turf evaluation. Human evaluators rated turf based of three factors which are: color, texture and percent live color (PLC). NDVI ratio had more correlation with turf color

than any other types of data collected by visual evaluators, furthermore, NDVI ratio was more consistent than visual data for different crop aspects (color, texture, PLC) which varied among three human evaluators.

Results of the above-mentioned studies indicate that active and passive optical sensors can be used in canopy disease detection. Moreover, it was proved that optical sensors are faster and more consistent in disease detection than human evaluators.

REFERENCES

Adcock, T.E., Nutter, F.W. Jr, Banks, A. Ph. 1990. Measuring herbicide Injury to Soybeans (*Glycine max)* Using a Radiometer. *Weed Science.* 38:625-627.

Aquino, V. M., Shokes, F. M., Berger, R. D., Gorbet, D. W., Kucharek, T. A. 1992. Relationship Among Late Leafspot, Healthy Leaf Area Duration, Canopy Reflectance and Pod Yield of Peanut. *Phytopathology,* 82:546-552.

Bell, G.E., Howell, B.,M., Johnson G.V., Raun, W.R., Solie J.B., Stone M.,L. 2004. Optical sensing of turfgrass chlorophyll content and tissue nitrogen.*Hort Science*, 39(5): 1130-1132.

Bell, G.E., Martin, D.L., Wiese, S.G., Dobson, D.D., Smith, M.,W., Stone M.L., Solie J.B. 2002. Vehicle-mounted optical sensing: An objective means for evaluating turf quality. *Crop Science*, 42: 197-201.

Bell, G.E., Martin D., L., Koh, K., Han H.R. 2009. Comparison of turfgrass visual quality rating with rating determined using a hand held optical sensor. *Hort Technology*, 19(2): 309 -316.

Bravo, C., Moshou D., West J., McCartney, A., Ramon, H. 2003. Early disease detection in wheat fields using spectral reflectance. *Biosystems Engineering 84(2): 137-145.*

Bronson, F., K., Booker, J.,D., Keeling, W., Boman, R., K., Wheeler, T., A., Lascano, R., J., Nichols, R., L. 2005. Cotton Canopy Reflectance at Landscape Scale as Affected by Nitrogen Fertilization.*American Society of Agronomy 97:654-660.*

Chang, J., Clay, S., A., Clay D., E., Dalsted, K. 2004. Detecting weed-free and weed-infested areas of a soybean field using near-infrared spectral data.*Weed Science 52: 642-648.*

Cibula, W.G., Carter, G. A. 1992. Identification of far-red reflectance response to ectomycorrhizae in splash pine.*International Journal of Remote Sensing* 13(5): 925-932.

Clive, W., J. 1974.Assesment of Plant Diseases and Losses.*Phytopathol.* 12:27-48.

Forrest, W., Nutter, Jr., R. H. Littrell. 1996. Relationship between defoliation, canopy reflectance and pod yield in the peanut-late leafspotpathosystem. *Crop Protection.*15(2): 135-142.

Forrest, W., Nutter, Jr., Littrell, R., H., Brenneman, T., B. 1990.Utilization of a Multispectral Radiometer to Evaluate Fungicide Efficiency to Control Late Leaf Spot in Peanut.*Pathology 80: 102-108*.

Goodwin D., G. 1998.Seasonality of finely-resolved spatial structure of NDVI and its component reflectances in tallgrassprairie.*Remote Sensing 19(16): 3213-3220.*

Jackson, Ray, D. 1986. Remote Sensing of Biotic and Abiotic plant Stress. *Phytopathol*. 24: 265-287.

Jordan, D. L., R. L. Brandenburg, A. B. Brown, S. G. Bullen, G. T. Roberson, B. Shew, J. F. Spears. 2011. 2011 Peanut Information. *North Carolina Cooperative Extension Service.Collage of Agriculture & Life Science.North Carolina State University.105-132.*

Krezhova, D.D, Iliev, I.T., Hristova D. P., Yanev, T. K. 2009. Spectral remote sensing measurements for detection of virtual infections in tobacco plants (Nicotianatabacum L.).*Fundamental Space Research:* 43-46.*J Gen Plant Pathology:69: 17-22.*

Kobayashi, T., Kanda, E., Naito, S., Nakajima, T., Arakawa, I., Nemoto, K., Honma, M., Toujyou, H., Ishiguro, K., Kitada, K.,Torigoe, Y. 2003. Ratio of rice reflectance for estimating leaf blast severity with multispectral radiometer.

Navalgund, R. R. 2001. Remote sensing.*Resonance:* 51-60.

Nutter, F., W., Jr. 1989.Detection and Measurement of Plant Disease Gradients in Peanut with a Multispectral radiometer.*Phytopathology.*79:958-963.

Nutter, F., W., B. M. Cunfer. 1988. Quantification of Barley Yield Losses Caused by RhynchosporiumSecalis Using Visual versus Remote Sensing Assessment. *Phytopathology*.78:1530.

Nutter, F., W., Gleason, M., L., Jenco, J., H., Christians, N., C. 1993.Assessing the Accuracy, Intra-rater Repeatability, and Inter-rater Reliability of Disease Assessment Systems.*Phytopathology.80(8):806-812.*

Nilsson, Hans-Eric. 1995. Remote Sensing and Image Analysis in Plant pathology. *Phytopathology.*15: 489-527.

Ranson, K. J., Daugh, C. S. T., Biehl, L. L., Bauer, M. E. 1985. Sun-view angle effects on reflectance factor of corn canopies. *Remote Sensing of Environment* 18:147-161.

Ranganath, B. K., N. Pradeep, V. B. Manjula, B. Growda, M. D. Rajanna, D. Shettigar, P. P. Nageswara. 2004. Detection of Diseased Rubber Plantations Using Satellite remote Sensing. *Journal of the Indian Society of Remote Sensing*, 32(1): 50-58.

Roberson, R. 2007. Variety is key to peanut diseases. *Southeast Farm Press*. 34(13):18-19.

SAS for Windows, version 9.2. SAS Institute, Cary, NC.

Shew, B. 2004. Management is the key to peanut disease control. *Southeast Farm Press.*31(12): 12-13.

Teal, R. K., B. Tubana, K. Girma, K. W. Freeman, D. B. Arnall, O. Walsh, W. R. Raun. 2006. In-Season Prediction of Corn Grain Yield Potential Using Normalized Difference Vegetation Index.

West, J. S., Bravo, C., Oberti, R., Lemaire, D. 2003. The potential of canopy measurement for targeted control of field crop diseases.*Annual Review of Phytopathology 41: 593-614.*

Yunseop, K., Glenn, M. D., Park, J., Ngugi, K. H., Lehman, B. L. 2010. Active spectral senor evaluation under varying conditions.*ASABE Annual international Meeting.* Paper No. 1009111. Pittsburgh, Pennsylvania.

CHAPTER 2

Material and methods

2.1 Introduction

According to previous studies (West et al. 2003), (Navalgund, 2001) and (Clive, 1974) it has been observed that stressed plants change their color and have lower chlorophyll content than healthy plants, hence the reflected light from a stressed plant will be affected by the smaller amount of chlorophyll content and plant color. Also, peanut soilborne diseases occur in patchy patterns in relatively the same location every season. Consequently, as was suggested by peanut extension specialists, mapping disease locations would be very beneficial for farmers in order to make necessary management decisions to treat only stressed areas in peanut fields (Jordan et al., 2011).

2.2 Equipment used

2.3 GreenSeeker®

One of the primary devices that was implemented in collecting the data was GreenSeeker®-505 (Figure 1), an active spectral sensor, which was designed by NTech Industries Inc., Ukiah, CA. The sensor was designed to enable variable rate applicators (VRA) to apply nitrogen fertilizer based on the plant's requirement by remotely sensing reflectance of light from tissue. For the current research, the GreenSeeker® was implemented in scanning peanut plots and calculating the plant's NDVI ratio. The NDVI ratio was correlated to visual disease assessment and yield from scanned plots.

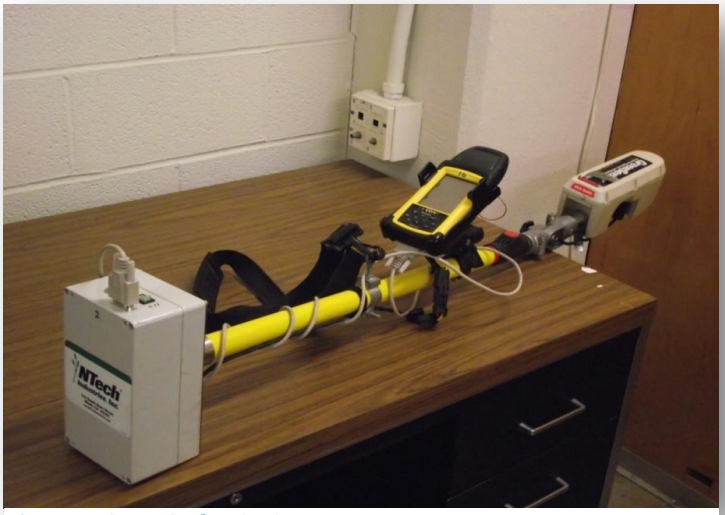

Figure 1. GreenSeeker® 505

Figure 2. GreenSeeker® 505 connected to hand-held computer and DGPS

2.4 GreenSeeker® characteristics

GreenSeeker® is considered an active sensor since it generates its own red light at 660±12 nm and near infrared light at 770±12 nm, this makes the sensor independent of ambient illumination. Suggested height at which sensor should be held above the target ranges from 30-50 inches (75-127 cm).

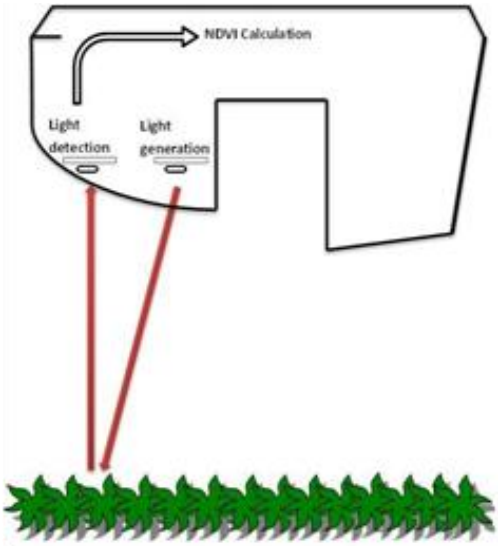

Figure 3. GreenSeeker® side view

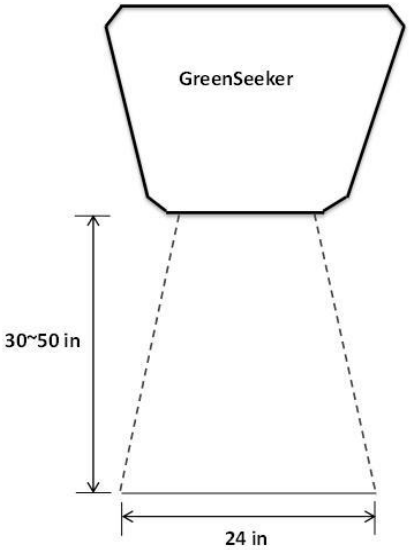

Figure 4. GreenSeeker® front view

The advantage of a hand held or tractor mounted sensor, such as GreenSeeker®, over other remote sensing methods, such as aerial photography, satellite remote sensing or hand held radiometers, is this instrument does not require a clear sky or sunny day to make measurements in the field. Furthermore, readings from GreenSeeker® are more up-to date since the data can be processed immediately. Satellite remote sensing or aerial photography can be a month old or even older. Scanning of the field with GreenSeeker® can be done in conjunction with other field operations such as pesticide spraying or cultivation.

2.5 Hand-held computer and Global Positioning System (GPS)

All data collected by the sensor were stored in a Nmad® hand held computer produced by Trimble® (Figure 5). The hand held computer also served as a device which synchronized sensor readings with data from a backpack global positioning system (GPS), the Trimble AgGPS 162® (Figure 6) which determined longitude and latitude coordinates for every data point.

Figure 5. Hand-held computer

Figure 6. Backpack DGPS antenna

2.6 Software

2.7 Farm Works mobile™

Hand-held computers which were used for data collection had Farm Works Mobile™ software installed which was used for logging GreenSeeker® and GPS data. The mobile

software was also able to convert stored data to ArcMap or Farm Works Office™ file formats.

2.8 Farm Works Office™

For transferring data from the hand-held computer and making disease maps of the field, geographic information system based software, Farm Works Office™ was implemented. Although Farm Works is capable of writing prescription maps and making disease maps of a field (Figures 7-14), it did not have the necessary functions to extract the NDVI ratio of each row and upload it to statistical software. Thus, in order to extract NDVI ratio from each plot and upload it to a statistical program, sensor readings were exported to ArcMap.

2.9 ArcMap

Thus, all sensor measurements from Farm Works were imported to GIS based software, ArcMap (ESRI), which allowed extracting NDVI ratio of each scanned row and further uploading those ratios to SAS 9.2 software (SAS Institute Inc., Cary, NC). Data uploaded to ArcMap was in shapefile format, the attribute table of which had NDVI ratio of each collected data points. By default, compass headings and sequential numbers of data points were logged in the attribute table of the shapefile. Compass headings allowed identifying walking direction while scanning the field. Since data points between plots were close to each other and sometimes overlapped, it made it difficult to differentiate between plot NDVI ratios. Compass headings and sequential numbers of data points were used in differentiating between plots. A new column identifying plot numbers was created in the

attribute table of the shapefiles for each scanning days. Using “Select by attribute” and “Statistics” tools, the NDVI ratio for each plot was extracted to make further correlations with visual disease assessment.

2.9.1 SAS

SAS 9.2 software (SAS Institute Inc., Cary, NC) was implemented to correlate sensor readings with yield and visual disease assessment of a field. PROC CORR command was used to make all correlations to test if there is any relationship between response variable *Y*, average plot NDVI ratio, and explanatory variable *X*, visual disease severity assessment. Correlation coefficient determines if change in one variable effects the other variable, in this study NDVI and visual disease assessment. The closer the correlation coefficient to 1 or -1, the stronger is the relationship between two variables. Correlation is considered positive if values of *y* increase as values in *x* increase. Whereas, correlation is considered negative if values of *y* tend to decrease as values of *x* increases (Ott et al. 2010).

2.9.2 Visual disease assessment

Visual disease severity of scanned plots was assessed on a scale from 0 to 100 percent severity where 0% indicates minimum/no disease and 100% is maximum disease severity respectively. Also, yield from each scanned row was calculated. These two datasets (yield and visual disease assessment) were used as basis for comparison to which sensor readings were correlated in order to observe the relationship between sensor readings, visual disease severity assessment and pod yield. Visual disease ratings were focused on a combination of two types of diseases; Cylindrocladium Black Rot (CBR) and Tomato Spotted Wilt Virus

(TSWV). Visual ratings were made twice (September 23rd, 2011 and October 9th 2011) throughout the growing season when disease symptoms became visually obvious.

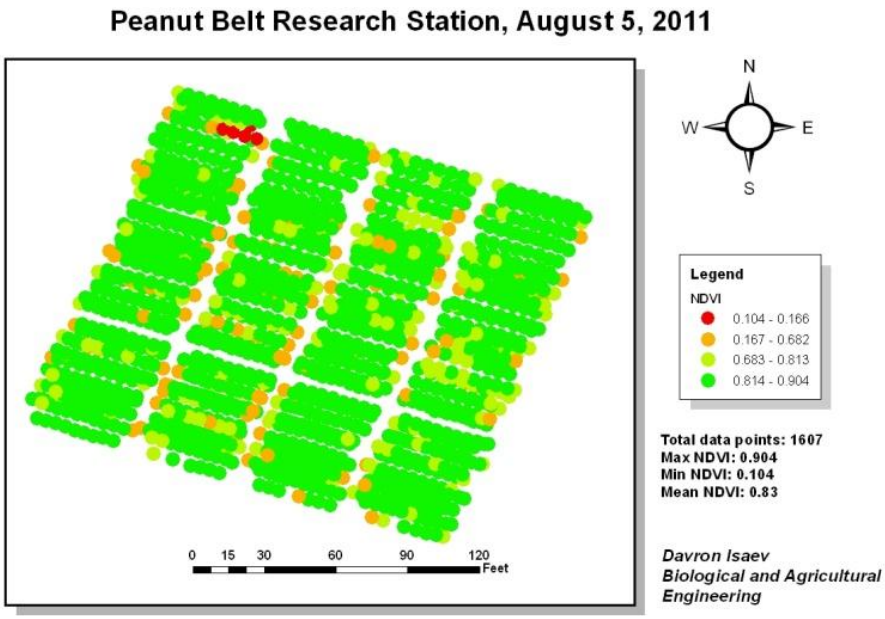

Figure 7. NDVI map of a plot for August 5, 2011

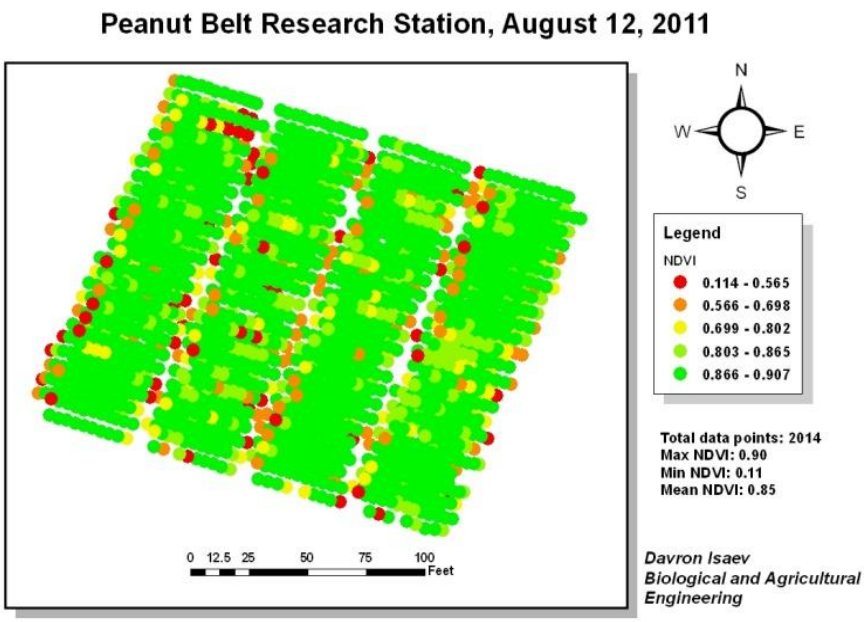

Figure 8. NDVI map of a plot for August 12, 2011

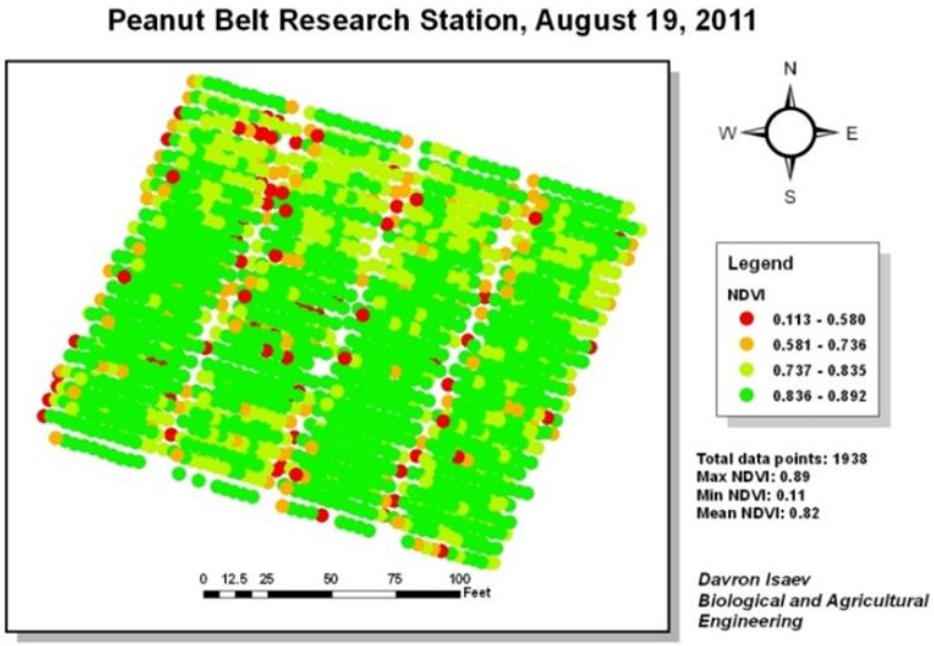

Figure 9. NDVI map of a plot for August 19, 2011

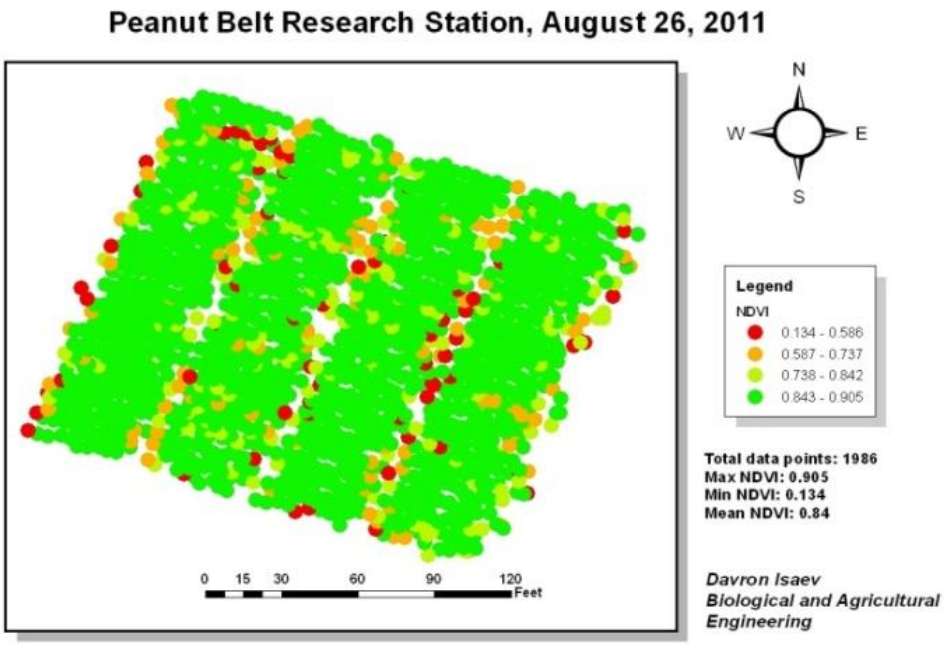

Figure 10. NDVI map of a plot for August 26, 2011

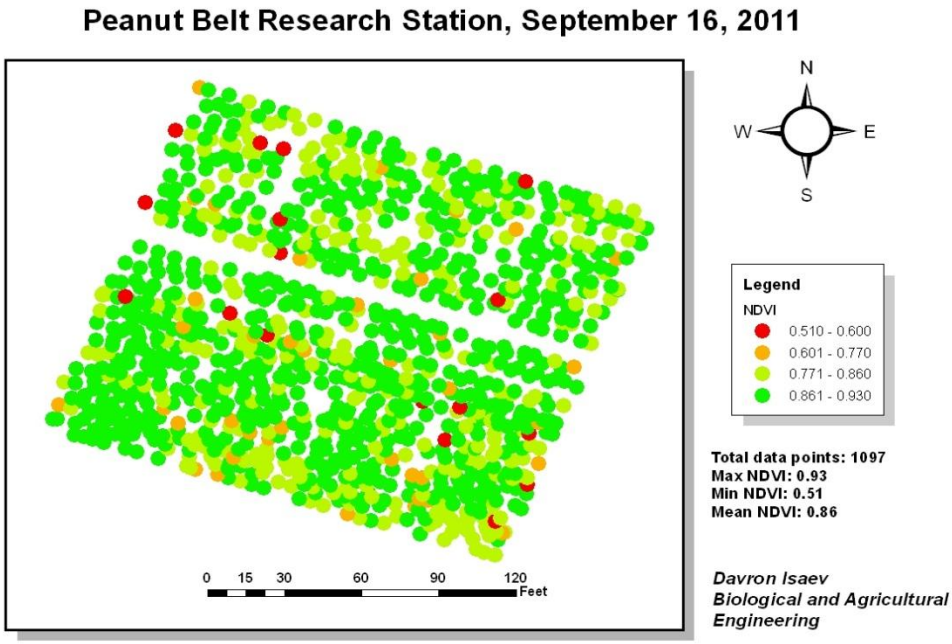

Figure 11. NDVI map of a plot for September 16, 2011

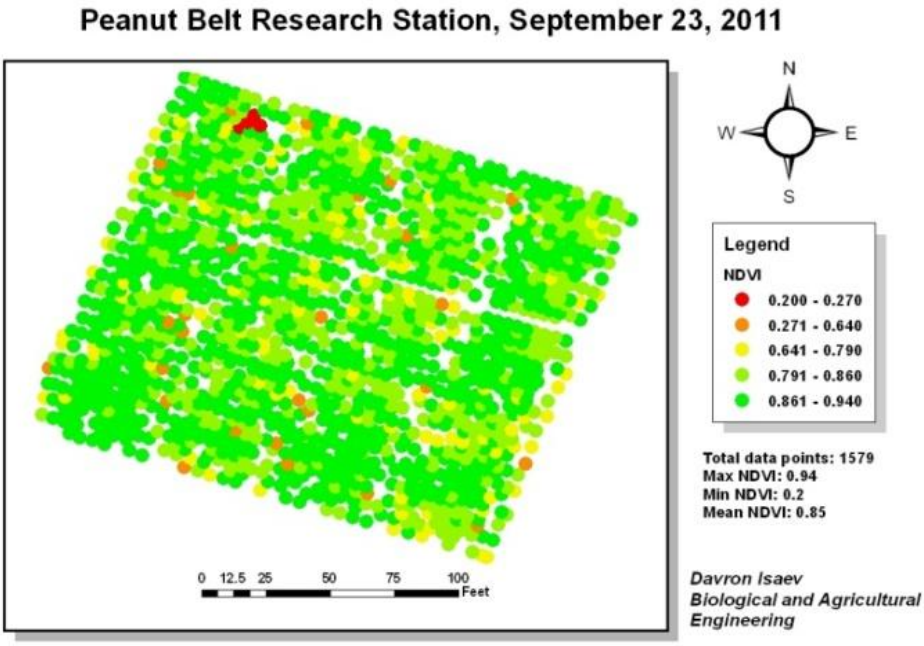

Figure 12. NDVI map of a plot for September 23, 2011

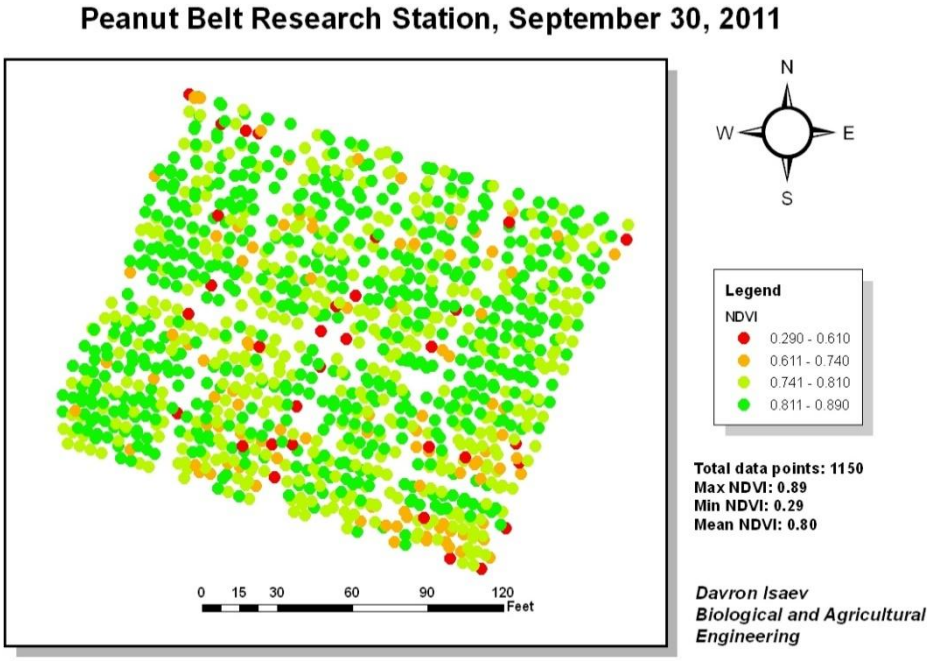

Figure 13. NDVI map of a plot for September 30, 2011

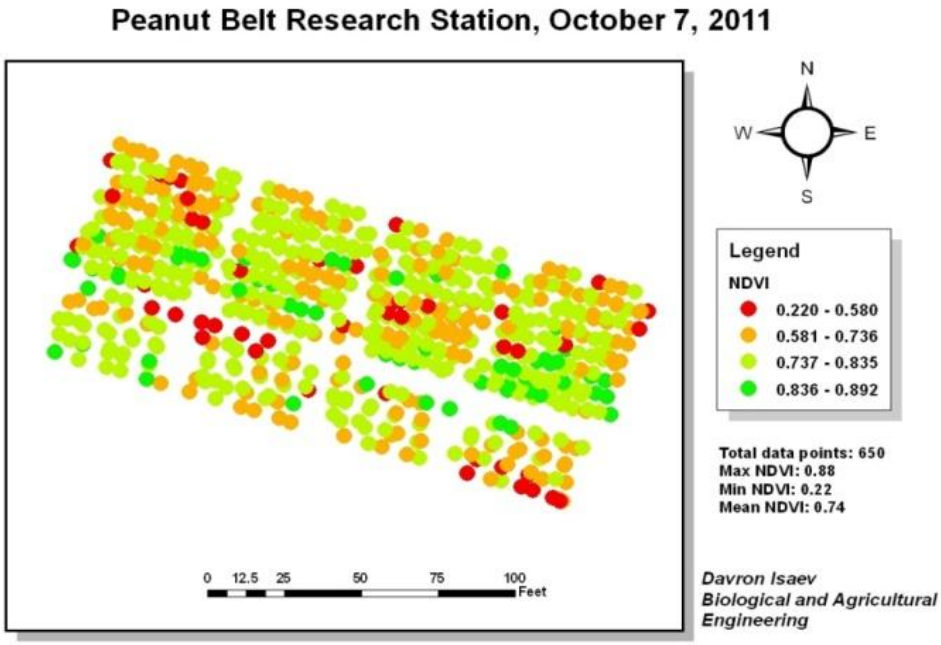

Figure 14. NDVI map of a plot for October 7, 2011

REFERENCES

Clive, W., J. 1974. Assesment of Plant Diseases and Losses. *Phytopathol.* 12:27-48.

Navalgund, R. R. 2001. Remote sensing. *Resonance:* 51-60.

Ott, R., Layman, longnecker, M. 2010. An Introduction to Statistical Method and Data Analysis, Sixth Edition. Canada, Brooks/Cole, Cengage Learning.

SAS for Windows, version 9.2. SAS Institute, Cary, NC.

West, J. S., Bravo, C., Oberti, R., Lemaire, D. 2003. The potential of canopy measurement for targeted control of field crop diseases.*Annual Review of Phytopathology 41: 593-614.*

Jordan, D. L., R. L. Brandenburg, A. B. Brown, S. G. Bullen, G. T. Roberson, B. Shew, J. F. Spears. 2011. 2011 Peanut Information. *North Carolina Cooperative Extension Service.Collage of Agriculture & Life Science.North Carolina State University.105-132.*

CHAPTER 3

3.1 Data collection

Data collection was conducted at Peanut Belt Research Station (PBRS), Lewiston, NC and Upper Coastal Research Station, Rocky Mount, NC. The selected plots were scanned with a hand held version of Greenseeker-505® (GreenSeeker®, NTech Industry Inc., Ukiah, CA) at approximately 1 m. height. Total area of the two selected plots was about 1 acre (0.5 acres each), every row of which was scanned. Scanning of the plot in Peanut Belt Research Station was done between 10 am to 11 am every seven days starting from August 5 until the plot was dug on October 7. Due to the late start of scanning the plots in Upper Coastal Plains Research Station, there were fewer scanning days compared to PBRS. Fields in Peanut Belt Research Station and Upper Costal Plains had 96 plots each of which comprised of two rows with the same peanut variety. During the digging process, two rows with the same peanut variety were dug into one windrow which constitutes one plot. Yield and visual disease assessment was done for every plot. Plots in both sites had six different peanut cultivars: Florida-07, Phillips, CHAMPS, Bailey, Sugg and Gregory.

Light reflected from the peanut canopy was converted to a normalized difference vegetation index (NDVI) ratio and was logged in the hand held computer (Nomad) connected to the optical sensor, GreenSeeker®. The standard NDVI equation (equation 1) was used for conversion of received light to NDVI ratio:

Equation 1. NDVI Equation

$$NDVI = \frac{NIR - VIS}{NIR + VIS}$$

Where, NIR is near infrared light at 770±12nm generated by sensor

and VIS is visible red waveband at 660±12nm.

Every collected data point was georeferenced with longitude and latitude coordinates that were provided by a differentially corrected GPS receiver connected to the hand held computer along the with Greenseeker®.

3.2 Sensor Limitations

One of the hypotheses of the research was that stressed peanut canopy would have a lower NDVI ratio when compared to healthy tissue. Although this fact was confirmed by previous researchers, there are some limitations that exist and should be considered. During the data collection process it was noticed that a plant's NDVI ratio does not always correlate with the plant's health status, instead NDVI ratio might also be effected by drought and mechanical damage that can decrease a plant's NDVI ratio and color.

3.3 Frequency of data logging

One of the limitations of a GreenSeeker® is the frequency of data logging. GreenSeeker® itself is programmed to log data faster than 1.0 HZ, however, Farm Works Mobile can log data once every second and this factor can have a negative effect on the accuracy at which sensor can map disease locations. Since this research implemented the hand-held sensor for data collection, logging frequency did not have a noticeable negative impact to the process because of slow walking speed. However, in the case of using tractor mounted sensors, because of the higher speed there might be long gaps between data points which can negatively effect disease assessment accuracy. Thus, speed at which data is

collected should be considered. Table 1 shows estimated distance between data points if collected at various ground speeds. For this study average distance between data points was 28.3 inches collected at walking speed (4 mph).

Table 1. Distance between data points collected at various speed

Average distace between data points (inches)	14.2	21.3	28.3	35.4	42.5	49.6	56.7	63.8	70.9
Ground speed	2mph	3mph	4mph	5mph	6mph	7mph	8mph	9mph	10mph

3.4 Solar radiation effect on NDVI ratio collected by GreenSeeker®

GreenSeeker® generates its own red at 660± 12 nm and near-infrared (NIR) at 770 ± 12 nm wavelength; therefore, it is assumed that the sensor's measurements are not affected by ambient light. To confirm the performance of the sensor in various conditions (i.e. day time vs. night and different solar radiation), the hand held sensor was used to scan the same path on a lawn five times a day in three hour increments starting at 9 AM and finishing at 9 PM. The sensor was held at a height of about 3 feet above the ground. Statistical analysis using Analysis of Variance (ANOVA) was performed to test research and hull hypothesis stating that NDVI ratio collected during different time of a day does not vary significantly versus NDVI ratio collected during different time of a day does vary significantly.

Table 2. Scanning time

Scanning time	9:00 am	12:00 PM	3:00 PM	6:00 PM	9:00 PM
Weather conditions	Cloudless/ slight dew on a grass	Cloudless	Cloudless	Cloudless	Cloudless

The results of the statistical analysis showed that the grass's NDVI ratio, captured during different time of a day, does not differentiate significantly. The null hypothesis was accepted with a p-value=0.83. Even though there is considerable evidence that NDVI ratio is not affected by the time of a day it was calculated, there were still some slight variations of NDVI ratio due to solar radiation (Fig. 6). The lowest NDVI ratio was observed when the solar radiation was high at 12:00 and 3:00 PM. Yunseop et al. (2003) had similar results on testing a correlation between data captured with a NDVI sensor and diurnal solar radiation. In their experiment NDVI ratio changed from 0.07 to 0.08 due to diurnal solar radiation. Unlike the current experiment, Yunseop et al. (2003) tested the NDVI sensor in a fixed position. Moreover, Yunseop et al. (2003) tested NDVI sensor in three experimental setups: different temperature of NDVI sensor, varying target temperature and different light level. The experiment results indicated that NDVI ratio remained the similar and stable in three different experimental setups.

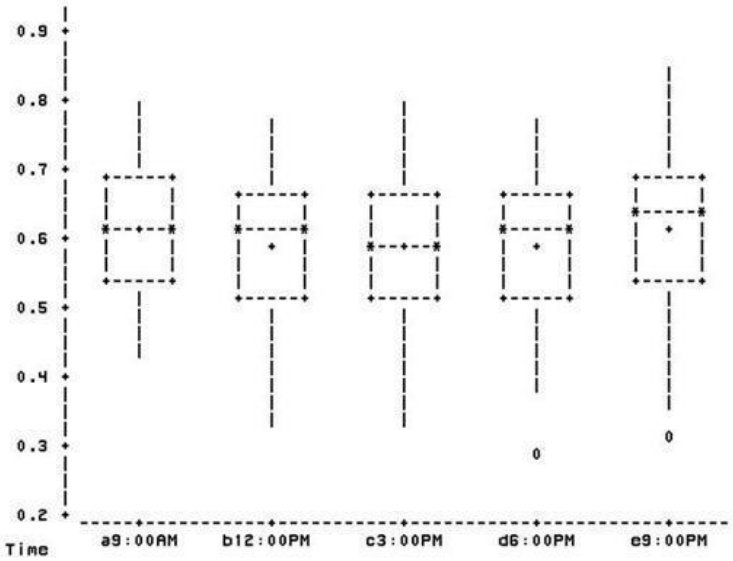

Figure 15.Boxplot of NDVI ratio vs. scanning time

Table 3. ANOVA table for solar radiation effect on sensor reading

Source	DF	Sum of	Mean	F-value	Pr>F
Model	4	0.014488	0.003622	0.36	0.8386
Error	163	1.65194	0.010135		
Corrected	167	1.666428			

REFERENCES

Yunseop, K., Glenn, M. D., Park, J., Ngugi, K. H., Lehman, B. L. 2010. Active spectral senor evaluation under varying conditions.*ASABE Annual international Meeting.* Paper No. 1009111. Pittsburgh, Pennsylvania.

SAS for Windows, version 9.2. SAS Institute, Cary, NC.

Chapter 4

Statistical analysis and results

4.1 NDVI average throughout scanning period

The NDVI average of the scanned plot fluctuated from the beginning of August, 2011 to the end of September 2011 and it noticeably decreased starting from the end of September (Figure 16). Some of the assumptions made to explain subtle NDVI fluctuation in the beginning of the scanning season were pesticide spraying and irrigation of the plot. Each of these facts might affect tissue NDVI ratio. Furthermore, random error can be a reason for NDVI fluctuation.

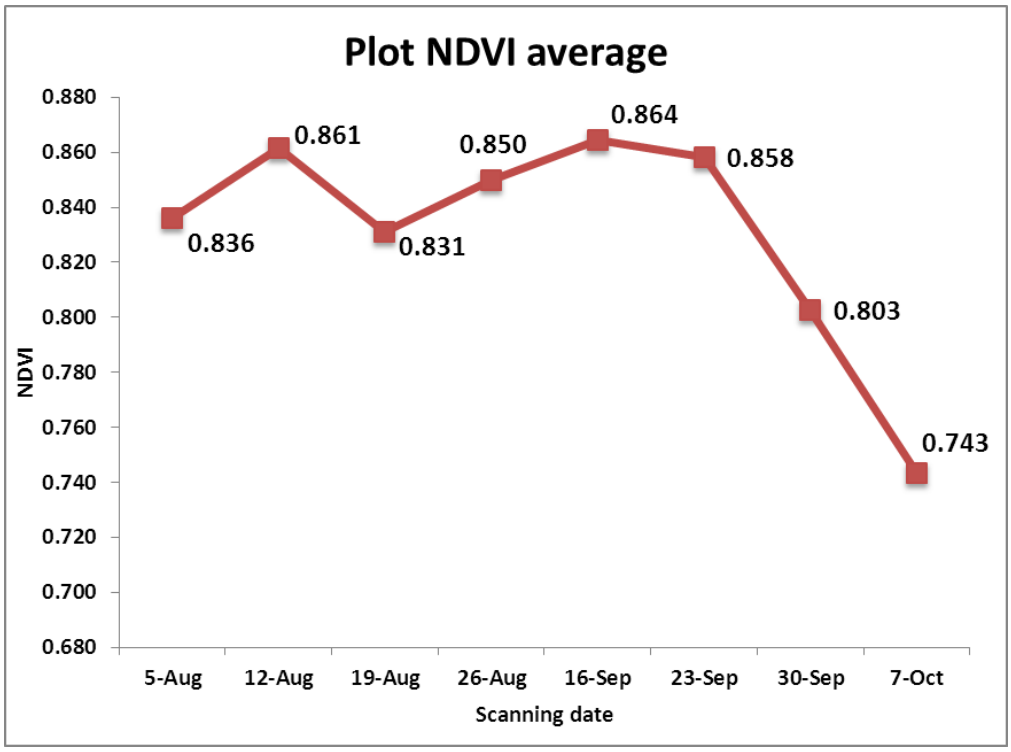

Figure 16. Average plot NDVI ratio vs. scanning date

4.2 Disease severity rating

Visual disease severity ratings of the plots in Peanut Belt Research Station ranged from 0% to 70%, with 0% being minimum observed severity and 70% being maximum observed severity respectively. Table 4 indicates the number of rows rated at each severity level.

Table 4. Row disease severity

% of disease severity	0%	2%	5%	10%	15%	20%	25%	30%	35%	40%	45%	50%	55%	70%
Number of given rows	22	2	21	6	10	11	4	7	2	5	1	3	1	1

In order to observe the NDVI ratio for a specific percentage of disease severity, the NDVI ratio for each row rated at percentage levels of 70%, 55%, 50% …0% disease severity, were combined and averaged for every scanned day starting from August, 2011 until October 2011. Average NDVI ratio vs. scanning date was plotted as shown in figure 17.

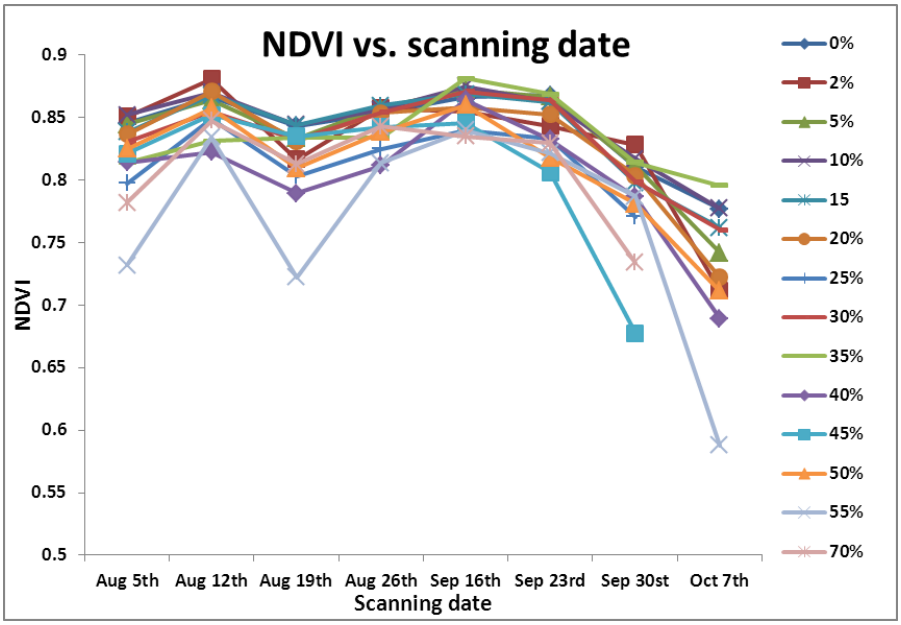

Figure 17. NDVI ratio of infected rows

For comparison, an NDVI ratio of the rows with the highest percentage of disease (average of 70% and 55%; 30%; 40%) and the rows with the lowest percentage of disease (0%), were plotted (figure 18). This figure suggests that the row having the high percentage of disease has comparatively lower NDVI ratio than rows with the lower percentage of disease for all scanning dates.

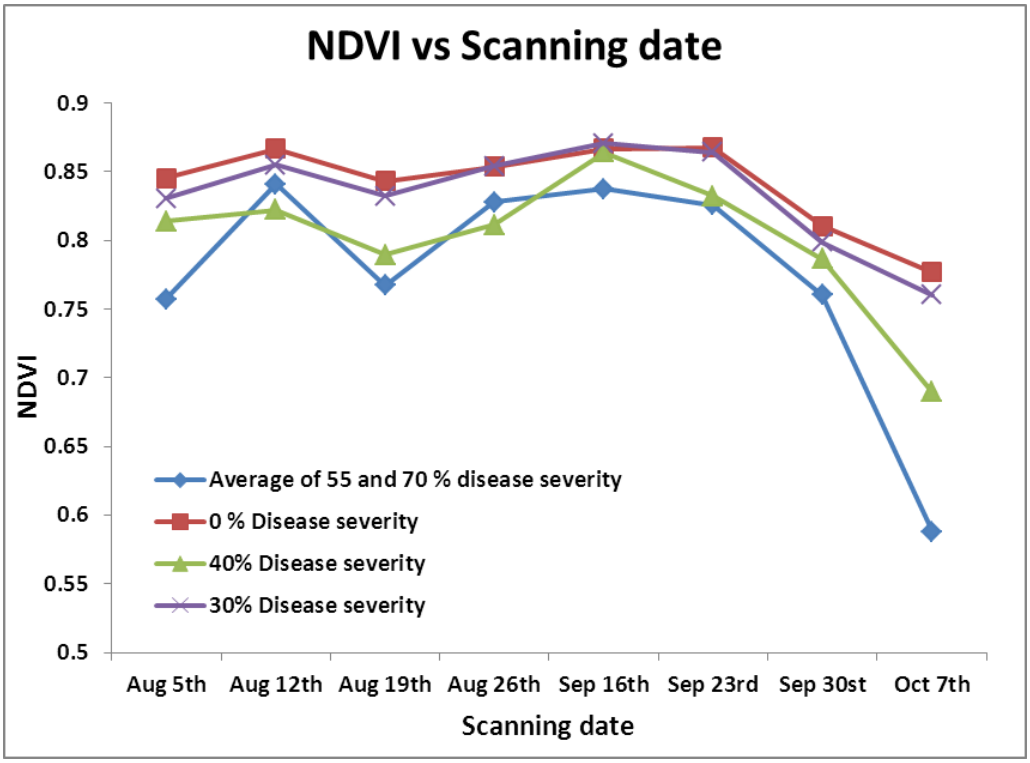

Figure 18. NDVI ratio of rows with max and min disease severity

4.3 Sensor readings and visual assessment correlations

Statistical analysis was performed to determine the correlation between sensor readings (average NDVI ratio of individual row) with visual disease assessment (percentage of disease severity for individual row) as rated on September 28th, 2011. The research hypothesis for this statistical analysis was: there is a negative linear correlation between

sensor reading and visual disease assessment. Correlation of plot NDVI ratio with plot visual disease assessment was negative and statistically significant at 95% confidence level for every sensor readings except for the correlation of NDVI ratio collected on September 16th 2011 and visual disease rating. The p-value of the latter correlation was slightly high (p-value: 0.0943) for the correlation to be statistically significant.

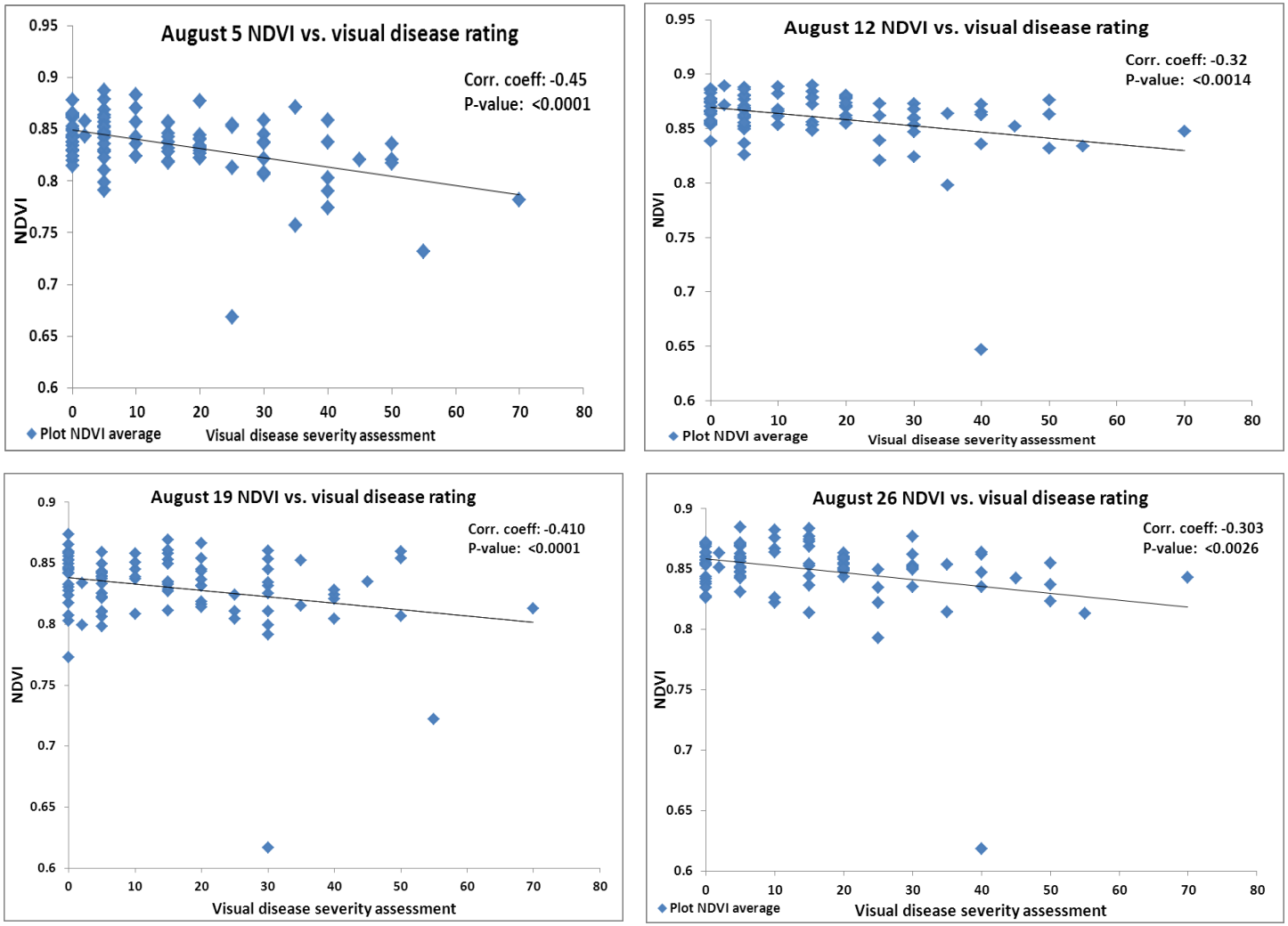

Figure 19. NDVI vs. visual disease rating correlations for August

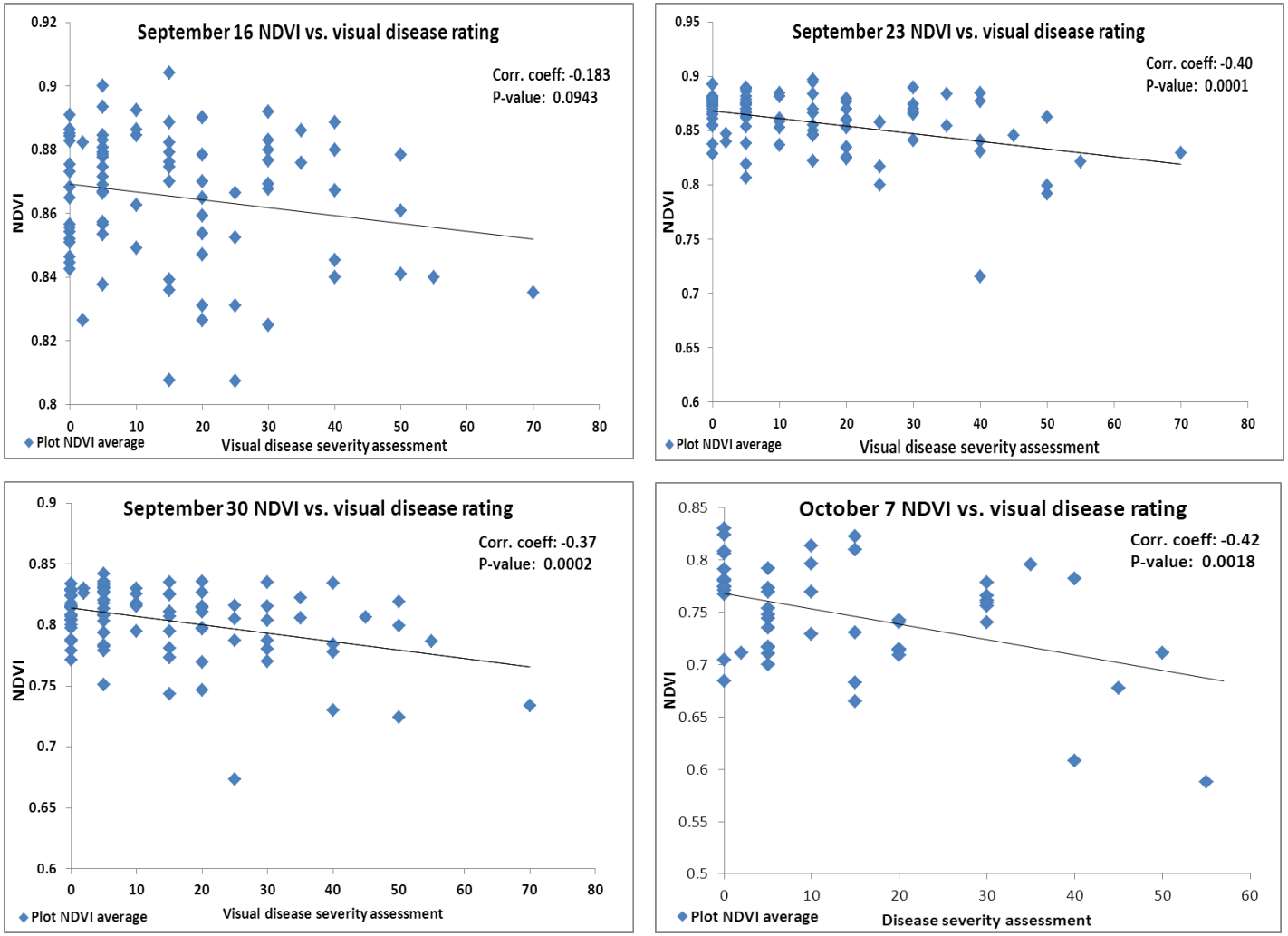

Figure 20. NDVI vs. visual disease rating correlations for September-October

4.4 NDVI and plot yield correlation

Yield of the scanned plots was also calculated (lb. /plot), and was correlated with the average NDVI ratio of each plot. Correlation results were expected to be positive because statistical results of a study showed that plots with low NDVI ratio have higher disease severity (Figure 19, 20). Consequently, plots with high disease severity should have lower yield. Correlations between average plot NDVI ratio and plot yield were positive; however, only four out of eight observations were statistically significant at 95% confidence level (Figures 21-24)

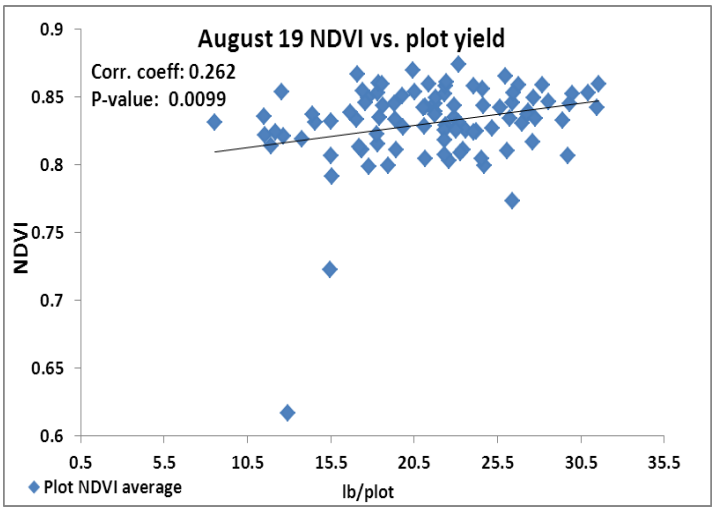

Figure 21. NDVI vs. yield correlation for August 19

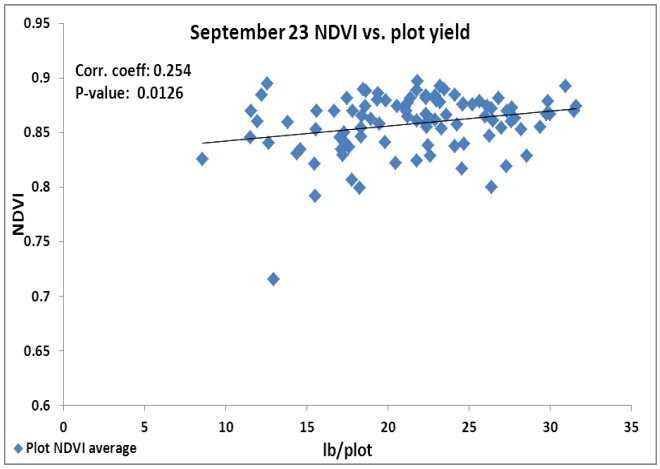

Figure 23. NDVI vs. yield correlation for September 23

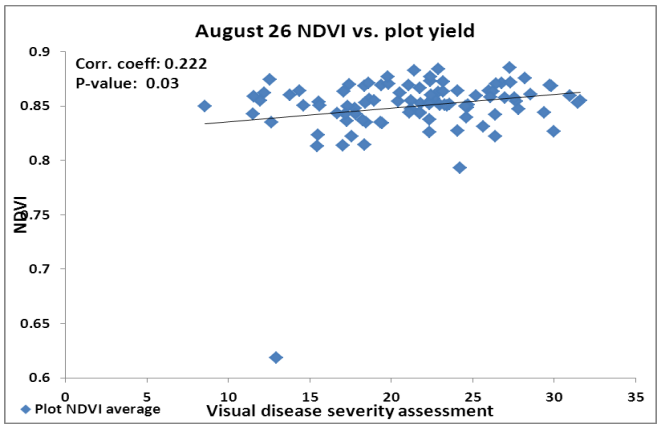

Figure 24. NDVI vs. yield correlation for August 26

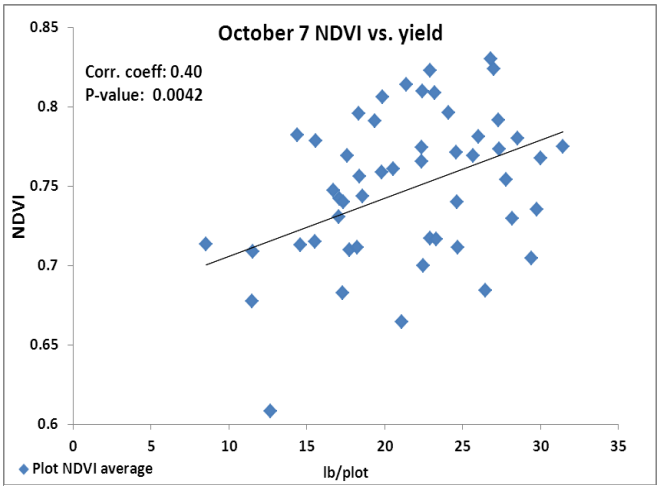

Figure 22. NDVI vs. yield correlation for October 7

4.5 Visual disease assessment and yield correlation

Visual disease ratings were correlated with pod yield in order to observe the correlation coefficient of two variables (figure 25). As was expected, correlation between yield and disease severity rating was negative i.e. the higher the disease rating, the lower the yield from a plot.

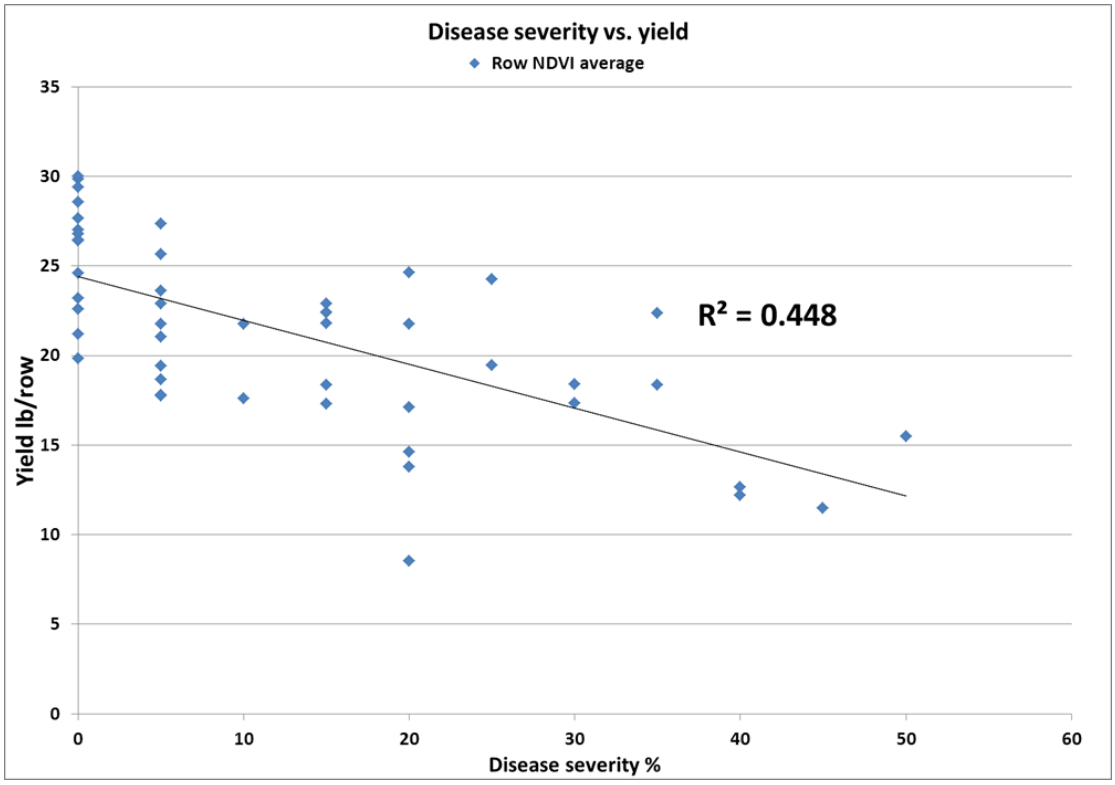

Figure 25. Disease severity vs. yield

4.6 NDVI ratio of different peanut variety

For the current study there were six varieties of peanuts available for scanning; Florida-07, Phillips, CHAMPS, Bailey, Sugg and Gregory. It was assumed that NDVI ratio might vary between different peanut varieties which might limit a GreenSeeker's ability to detect disease when different peanut varieties are scanned. NDVI ratios of all six varieties

collected the on 5th and 12th of August at Peanut Belt Research Station and collected on September 2nd at Upper Coastal Plains were averaged and potted. Figure 26 shows that NDVI ratios of different peanut varieties from two sites do not vary significantly. Table 5 shows the average difference of NDVI ratio among six peanut cultivars.

Table 5. NDVI difference of among peanut varieties

	Florida-07	Phillips	CHAMPS	Bailey	Sugg
Florida-07					
Phillips	0.018				
CHAMPS	0.016	0.002			
Bailey	0.018	0	0.002		
Sugg	0.009	0.01	0.008	0.009	
Gregory	0.022	0.004	0.006	0.004	0.014

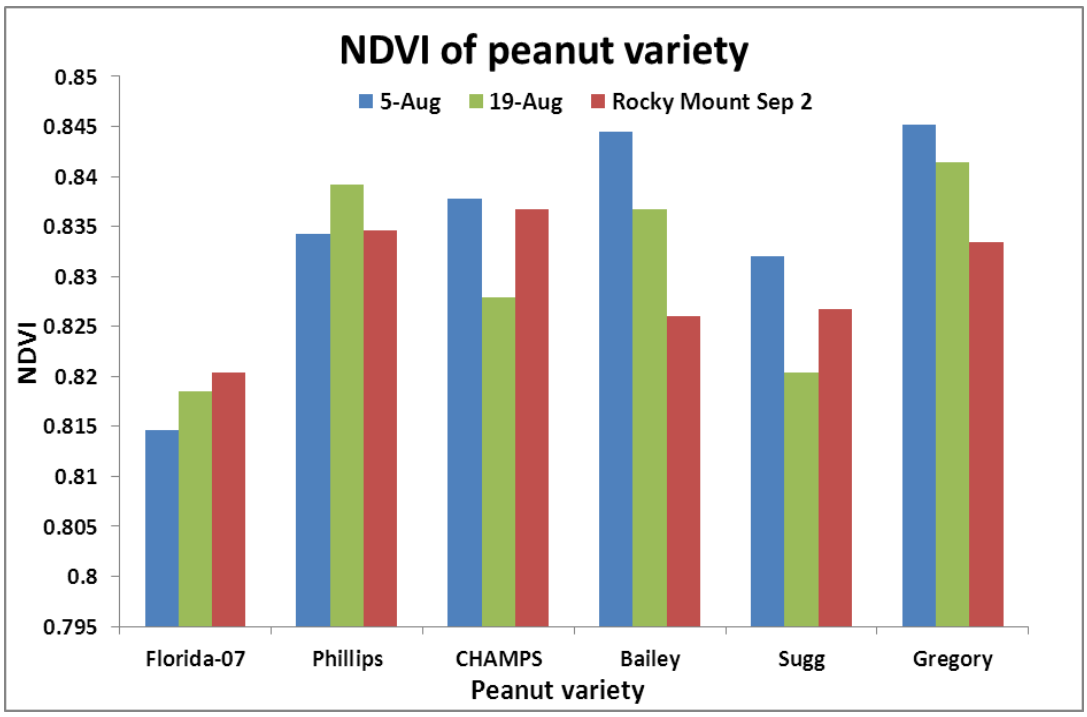

Figure 26. NDVI ratio of different peanut variety

Figure 26 depicts that Florida-07 has the lower NDVI ratio comparing to other peanut cultivars. This can be explained with the fact that average disease rating for the given peanut cultivar was higher (26.9%) comparing to other cultivars. Table 6 shows average disease ratings for all peanut cultivars.

Table 6. Average disease ratings of different peanut varieties

Variety	Average disease rating (%)
Florida-07	26.9
Phillips	10.0
Champs	15.6
Bailey	2.5
Sugg	25.0
Gregory	1.3

CHAPTER 5

Conclusion and future work

5.1 Summary

Statistical results showed a negative linear relationship between sensor NDVI readings; collected from the beginning of August until the beginning of October, and visual disease assessment. All correlations were statistically significant at 95% confidence level, except for the correlation between NDVI ratio collected on September 16th and visual disease assessment.

After plotting NDVI ratio of plots that were assigned minimum disease percentage with NDVI ratio of plots assigned maximum disease presence, the graph indicated that plots with the high disease incidence have lower NDVI ratio for all scanning dates. NDVI ratios of all six peanut varieties in both sites were also compared to one another. Results showed that NDVI ratio of following peanut varieties: Florida-07, Phillips, CHAMPS, Bailey, Sugg and Gregory are not significantly different suggesting that GreenSeeker® can be used in disease detection of above mentioned peanut varieties.

Results of this study suggest that GreenSeeker® can detect peanut diseases and can be implemented in scanning the field in order to map peanut disease patches. Disease map of a field can be useful tool for farmers to see distribution of disease patches in the peanut field so that farmers will have an idea about which areas of the field should be given extra attention when treating for disease management. Moreover, GreenSeeker® can enable farmers to make disease map at relatively low cost since scanning of the field can be done in conjunction with field operation such as pesticide application.

5.2 Future work

For more precise results, GreenSeeker® should be tested on peanut plots inoculated with peanut soilborne diseases and disease-free plots as a control. Establishing several plots with different percentage of disease severity can give more precise statistical results since sensor readings more replicas will be available. Furthermore, conducting ground truth of sensor readings would give more details on GreenSeeker® disease detection ability.