BLUEBERRY CROP GROWTH ANALYSIS USING CLIMATOLOGIC FACTORS AND MULTI-TEMPORAL REMOTELY SENSED IMAGERY

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Abstract. Blueberries are a type of vegetation with spectral signatures similar to that of forest and grass. Due to their size, they are difficult to distinguish when intermingled with tall grass. Blueberries are grown in the vicinity of evergreen forests to shield them from the wind and save them from freezing. It is also difficult to distinguish blueberries from forest by normal classification methods. Advanced image processing procedures have already been developed by the authors to distinguish blueberry plants from similar land-uses. Tracking the growth of blueberries throughout a season is another difficult task. Blueberry plants start coming to life by March from their dormant stage in winter. In April, the plants reach full vigor with small fruit developing. In May, the plants have matured and the fruit is ready to harvest. By September, the plants start coming into their dormant stage also known as the post harvest stage. One of the objectives of this study is to use multi-temporal SPOT imagery to distinguish the growth stages of blueberry plants in one orchard in Southeast Georgia in a single year. Another objective was to use high resolution National Agriculture Imagery Program (NAIP) imagery from several years to track the growth of post harvest stage blueberry plants in the orchard. Spot panchromatic images dated March, April, May, and September 2004 were used for blueberry growth analysis within a growing season. NAIP imageries of 2005, 2006, 2007, and 2009 were used to analyze the multi-year blueberry plant growth. Two-meter resolution NAIP imagery of 2005 and 2006 were resampled (pan-sharpened) to 1-meter resolution to compare directly with the 1-meter resolution imagery of 2007 and 2009. Weather parameters like air temperature, solar radiation, and precipitation are other pertinent features that contribute towards the blueberry growth. Spectral signatures (Digital Number) of the blueberry orchard (study area) along with the corresponding climatologic data for all four dates were used to develop relational models for predicting blueberry plant growth. The study results established that the combination of remote sensing information and climatologic parameters can track blueberry growth within a growing season and in multi-year comparisons. This study procedure can also be used for yield estimation or determining areas with disease affected blueberry plants.

INTRODUCTION

Site Specific Crop Management (SSCM) is very common in field crop management like that of maize, wheat, rice, cotton, soybeans, and other row crops (Casanova et al., 1998; Panda, 2003; Magri et al., 2005; Baez-Gonzalez et al., 2005; Lobell et al., 2005; Li et al., 2009). However, SSCM usage for non-traditional horticulture crops is not very common (Panda et al, 2009). Horticultural crops like fruits and nuts are high value crops for which SSCM may potentially increase net returns and optimize resource use (Panda et al., 2009). Oranges, peaches, pecans, apples, grapes and blueberries are a major component of the agricultural production system in United States (US) and elsewhere around the world. Blueberries are one such high value horticultural crop produced in southeast US and ranks second to only to the pecan.

The number of blueberry orchards for commercial production has increased in Georgia and other southeastern states during the past few years. For Blueberry orchard SSCM, crop growth stage analysis during a production year and crop production comparison from year to year are necessary. Understanding the impact of weather including soil moisture, precipitation, air temperature, and other features would help plan for the blueberry crop's management. Application of remote sensing techniques, geographic information systems (GIS), and global positioning systems (GPS) would aid for such blueberry SSCM.

Blueberries are a type of vegetation with spectral signatures similar to that of forests, shrubs, and grass. These land uses are present in a blueberry orchard or in the surrounding areas. Blueberry plants are generally established in locations that have recently been cleared of shrubs and forests. Blueberry orchards are intermingled with tall and short grasses. Therefore, use of high resolution and cost-effective remotely sensed imagery and advanced digital image processing techniques are essential for distinguishing blueberry plants from these mixed land-uses for the site specific crop management (SSCM) purpose.

The application of high resolution remote sensing data, *e.g.*, aerial or satellite imaging, along with GPS and GIS is the first step towards the goal of SSCM in fruit and nut crops (Sevier, 2005). Torres et al. (2008) conducted a study to distinguish olive tree orchards using remote sensing images by clustering assessment or image classification techniques. Scientists in the Space Application Center of the Indian Space Research Organization successfully used low resolution IRS LISS III and IRS AWiFS (23 m and 55 m, respectively) images to characterize apple orchards in India (Sharma and Panigrahy, 2007). Shrivastava and Gebelein (2006) performed a study in Florida classifying the land-use to delineate citrus groves in order to analyze the economic assessment. They were successful with the use of Landsat Enhanced Thematic Mapper Plus imagery, although Landsat ETM + satellite does not work properly at present. O'Connel and Goodwin (2005) have used remotely-sensed imagery to identify the tree canopy of a peach orchard for orchard yield forecasting and future crop water requirement estimation.

However, no studies have yet been specifically conducted to distinguish blueberry orchard from mixed vegetation for the purpose of SSCM and crop growth analysis. Panda et al. (2009) have shown the efficiency of high resolution remotely sensed data (2.15 m Quick Bird imagery) to distinguish blueberry bushes from mixed vegetation. Panda et al. (2010) have used 1 m resolution National Agriculture Imagery Program (NAIP) orthoimagery along with Self-organizing Map (SOM) neural classification technique to successfully classify all three stages of blueberry plants from mixed land uses of grass, bare soil, shrubs, and forest cover. Therefore, it is hypothesized that high resolution remote sensing images can be analyzed to distinguish blueberry orchards to track the plant growth stages. Thus, subsequent management decisions can be taken with the use of other geospatial technology applications for higher productivity. Blueberry orchard delineation and spatial analysis using geospatial technology can provide means for management decision making, such as fruit yield determination, exact and proper fertilizer and irrigation need quantification and scheduling, and diseases treatment. At the same time, it would maximize profits for farmers (Panda et al., 2009).

The main objective of this study was to use multi-temporal SPOT imagery to analyze different growth stages of blueberry plants during a single crop production year and compare the remote sensing information to the available weather conditions during those stages of growth. Another objective of the study was to use weather parameters and high resolution NAIP orthoimagery based spectral information of several years to track the growth of post harvest stage blueberry plants in the orchard.

MATERIALS AND METHODS

Study Area. The study was conducted in an established blueberry orchard in southeast Georgia, located few miles from the city of Woodbine in Camden County (Figure 1). The orchard is surrounded by a large and thick pine plantation with open and bare land separating the blueberry plants from the surrounding pine forest (Figure 1). The orchard is relatively small in size measuring only 4.5 ha. The orchard has an established weather station located at the northern border that is part of the Georgia Automated Environmental Monitoring Network (AEMN, www.Georgiaweather.net). The single production year plant growth analysis was conducted in 2004, when the AEMN weather station was not set up in the orchard. National Weather Service (NWS) operated weather station in Brunswick, GA weather data was used in our analysis for the year 2004. The NWS weather station is within 15 miles from the orchard. The weather data from the AEMN weather station was used for the multi-year blueberry crop growth analysis modeling.

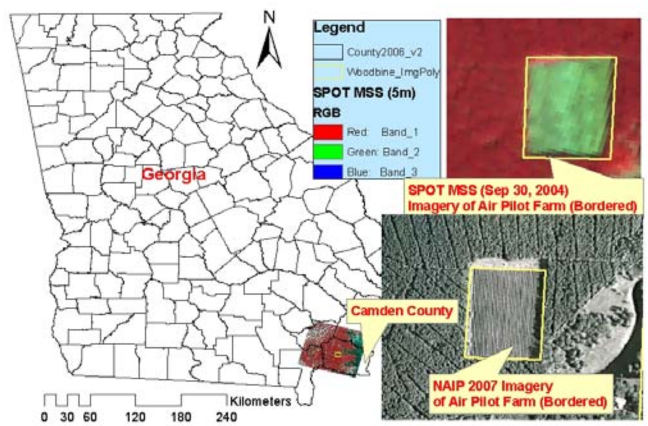
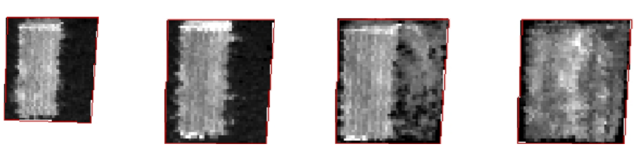


Figure 1: The study area in Camden County of southeast GA, shown over 2009 NAIP imagery.

Image data acquisition and processing. As mentioned previously, two blueberry crop growth analyses were conducted in this study. One analysis was conducted to find the blueberry crop's single year growth phenomena and its relationship to weather and remotely sensed spectral characteristics. This analysis was conducted for the year 2004 with SPOT multitemporal imageries. The SPOT imageries were low cost and high resolution cloud free images. They were only available for that year. The second analysis was conducted to observe the blueberry crop growth over the years. High resolution NAIP orthoimagery data was used for this study as all the imagery was available for a single corresponding growth stage (post harvest) of the blueberry crop.

Multitemporal SPOT imagery acquisition and processing. For the Year 2004 single season crop growth analysis model, SPOT data was collected in four dates as shown in Table 1 from the SPOT Image Corporation, Chantilly, VA via the support of America View (http://americaview.datadoors.net/datadoorsweb/order.aspx). The image was a single scene of Scene K/J 618/288 (Path and Row, respectively), which covered the entire Camden County, in which our study area is located. Four panchromatic (0.51 - 0.73 µm (Visible)) images with 5 m resolution with nominal cloud cover were collected. One scene of 10 m resolution Multispectral (MSS) band imagery was also collected for September 30. The 10 m resolution September 30 imagery that consists of four bands of R (0.61 - 0.68 µm), G (0.50 - 0.59 µm), NIR (0.79 - 0.89 µm), and SWIR (1.53 - 1.75 µm) was pan-sharpened to 5 m resolution using the Resample tool in ArcGIS 9.3 with the 'Bilinear Interpolation' technique. This, method offered us a good reduction in pixel size while maintaining contrast and geometry of the original image. The resampled MSS imagery of September was used in the multi-year model that used NAIP imageries. All these SPOT images were georeferenced to the study area in ArcGIS 9.3.

The SPOT image acquisition dates are mentioned in Table 1 along with the cloud cover, incident angle, and data quality. All these dates were chosen in accordance with the different growth stages of blueberries in a single season. The March 12th date coincides with the early blooming stage in early spring, April 23rd date coincides with the budding stage, May 24th date coincides with the fruit bearing stage of the crop which is ready to be harvested, and the final September 30th date coincides with fully harvested stage with matured blueberry plants in the orchard. The study area boundary feature file was used to clip the SPOT imageries to the size of the study area (orchard) using the Extract by Mask tool of ArcGIS 9.3. Figures 2a- d represent the SPOT images of the orchard in the four different dates of the year.



(a) (b) (c) (d)

Figure 2: Clipped orchard size SPOT panchromatic raw image of (a) March 12, (b) April 23, (c) May 24, and (d) September 30, 2004.

Remote signature extraction from the study area. The four SPOT panchromatic images were classified using the hybrid ISODATA classification technique in ArcGIS 9.3 using IsoCluster and Maximum Likelihood tools to the appropriate number of classes that would render the field as a cohesive class. Figure 3 represents the classification of the September 30, 2004 SPOT panchromatic image with the Blueberry field shown in green. As shown in Figure 3, the class that represents the blueberry field (in green) was assigned a value of 1 and the remaining classes were assigned 0. The classification of the imagery to separate blueberry orchard was fairly successful with 91% accuracy (Figure 3). Raster Calculator was used to multiply the reclassified image and the original image. The resulting calculated raster represented only the original cell values of the blueberry field class. This process was completed for the remaining three images. The calculated rasters were made into permanent ESRI GRID format so that it automatically included a 'Count' field for all rasters. Then the statistics (Mean and Standard Deviation) of the 'Count' field were obtained for all four dated images. In the blueberry orchard, different land uses like bare soil, grass, and shrubs other than only blueberry plants were present. These land uses were comparatively less in the orchard. The Mean and standard deviation of the spectral signatures of the blueberry field combined all these spectral signature values to a single entity and helped us to use them in the crop growth model development. These parameters were transferred to the MSExcel (Microsoft Corporation, Bellevue, WA) file for easier handling and graphical analysis with the corresponding weather data.

Figure 3: Example of the unsupervised classification of the blueberry field from SPOT September 30, 2004 covering the field and surrounding area.

Multi-year NAIP orthoimagery acquisition and processing. Mosaiced county size NAIP imagery was obtained for our study from the Natural Resources Conservation Service Data gateway server (http://datagateway.nrcs.usda.gov/). All the images came with three visible (R, G, and B) bands. According to Hoffman et al. (2008) NAIP acquires images during the agricultural growing season for the continental US. The images are obtained normally between the middle of April and the middle of September when most of the traditional row crops are grown (Hoffman et al., 2008). These NAIP orthophotographs are of very high resolution (1 m to 2 m) and are taken from fixed wing aircraft. They are later orthorectified with United States Geological Survey (USGS) Digital Ortho Quarter Quadrangles (DOQQs) and mosaiced together for data dissemination on a county basis Hoffman et al., 2008). Prior to supplying the NAIP images to the public, they are geometrically registered to North American Datum (NAD) 1983 Universe Transverse Mercator (UTM) coordinate systems Hoffman et al., 2008). NAIP imagery for Camden County, GA was collected from USDA NRCS geospatial data gateway (http://datagateway.nrcs.usda.gov/). The images were collected for 2005, 2006, 2007, and 2009. There was no NAIP imagery program in 2008 for Georgia. The images of 2007 and 2009 were of 1 m resolution and the rest were of 2 m resolution. All four years of imagery were georeferenced to the NAD 83 UTM Zone 17N coordinate system (USDA, 2008).

As stated earlier, the images are geometrically registered by United States Department of Agriculture (USDA). It is to be noted that the NAIP images are also radiometrically corrected by USDA prior to release. The radiometric corrections are conducted with solar correction (i.e., centered on ground position where solar illumination and camera view angle are coincident), dark area subtraction, gain measurement, and mid-tone color alignment (Hoffman et al., 2008). Therefore, these images are suitable for image segmentation and analysis.

The study area boundary feature file was used to clip the NAIP images to the size of the study area (orchard). At the same time, the 2 m resolution study area imagers of 2005 and 2006 were resampled to 1 m resolution rasters. The resampling was conducted for facilitating geocomputation only as it does not add any extra information to the image. Principal component analysis (PCA) was conducted in ERDAS Imagine 10 (ERDAS Inc, Norcross, GA) on all four NAIP imageries (3-visible bands) and the resampled September 2004 SPOT MSS imagery (4-bands) to reduce data redundancy. PCA is a linear transformation that reorganizes the variance in a multi-band image into a new set of image bands (Byne et al., 1980). Each individual band in the output PCA image receives some contribution from all of the input image bands. Therefore, PCA was used to solve the computational problems associated with multi-dimensional digital imagery data. The highly correlated First Principal Component (PC1) band images of all five years (2004, 2005, 2006, 2007, and 2009) were used in the analysis. Similarly, following the processes as conducted with SPOT data, statistical (spectral mean and standard deviation) features were obtained from these PC1 bands. These data were used along with the weather data collected during the respective periods to correlate with the multi-year post harvest stage growth.

Weather data collection and processing. The weather data that were expected to be contributors towards the blueberry crop growth were collected from the weather stations as mentioned previously. Precipitation and temperature (max, min, and average) data were the major contributing data collected for the study. The weather data for year 2004 were collected corresponding to the four months for which we had SPOT imagery. The data were collected in a two week range (1 week behind and 1 week ahead of the image acquisition date) and averaged. The weather data was collected from the weather station as daily average. For example, the precipitation and temperature records were obtained from March 5 to 19 to correspond the March 12, 2004 imagery data. As mentioned previously, for the year 2004, the climatic data were collected from the NWS operated weather station in Brunswick, GA.

The NAIP for the study area was acquired in different dates. According to USDA Farm Service Agency (FSA), Salt Lake City, UT that deals with NAIP image acquisition, the images in all four years were acquired in different dates as shown in Table 2. The weather data for these four years were collected from the AEMN weather station located at the side of the farm within the two weeks range period (Table 2) as done in case of year 2004. The precipitation and temperature data were averaged to be used in the analysis with the orthoimagery spectral information.

Statistical correlation of spectral and weather data. Several visual and statistical comparison and correlation studies were conducted to establish relationships among weather data (precipitation and temperature), remotely sensed spectral digital statistics, and blueberry crop growth stages.

One analysis was conducted by putting Mean DN (digital number), DN standard deviation (StDev), maximum temperature ($Temp_{max}$) (in ^{0}C), minimum temperature ($Temp_{min}$) (in ^{0}C), and precipitation (in mm) side by side for all four image acquisition dates in 2004 that represent four growth stages of blueberry crop. The growth stages are young foliage (mid March), mature foliage (late April), mature fruit bearing (Late May), and post harvest (late September). The data were mapped in MSExcel program and analyzed visually to see how the spectral characteristics change with different stages of the blueberry plant within a year or how the temperature or precipitation impacts the growth stage of the plant.

Another analysis was conducted by constructing the line graph in MSExcel with the line passing thru each of the parameters described above for individual growth stages in a year. Using these five parameters, a 4^{th} order polynomial trendline was generated in MSExcel. The polynomial equation constructed through this analysis showed that if these five parameters are obtained through remotely sensed imagery and weather data, one can easily figure out the growth stage of blueberry plant.

Similar analysis was conducted for the multi-year (four years and five years) growth stage study. It is to be noted that the NAIP images were acquired in four different dates in individual year starting from September 14 to October 16 and the SPOT MSS was obtained in September 30. Although, the blueberry plants are in post harvest stage during that range but the maturity of plant varies in years. Hence, we postulated to have a difference in DN values in these four years. The bar graph and the line graph with trendline analysis provided us with information to correlate the blueberry growth to spectral characteristics and weather data over the year. In this analysis, we studied the east and west part of the study area separately for 2005 and 2006 (2005 East, 2005 West, 2006East, and 2006 West) due to the distinct growth patterns as shown in Figure 2.

Finally, another relationship was studied to compare the growth stages in blueberry plants within a year and over the years to that of spectral characteristics obtained from remotely sensed imagery. A 3rd order polynomial was constructed to establish a relationship between the mean DN values and the matured post harvest stage blueberry plants (in an orchard) using the spectral data of Septmber 30, 2004, October 16, 2005, July 19, 2006, September 14, 2007, and September 28, 2009 with split (East and West) information for 2005 and 2006.

RESULTS AND DISCUSSION

Weather and corresponding spectral data. The Mean and StDev of the study area DN and the corresponding $Temp_{max,}$ $Temp_{min}$, and precipitation data of the year 2004 are shown in Table 3. The blueberry growth stages are also shown in the table referring to the dates of image acquisition. Similarly, the multi-year (2005 – 2009) weather and DN values are shown in Table 4.

The line graph analysis (Figure 4) shows that the spectral characteristics shows significant differences for within a year blueberry growth stages. The young foliage (mid March) stage have a higher DN (spectral reflectance) in panchromatic or visible bands of electromagnetic spectrum compared to the mature foliage stage (Late April) when the plant started to bear flowers. But the DN values increased with the next two stages of the plant, mature fruit bearing stage and post harvested stage, respectively. Unfortunately, we did not study other orchards to confirm the trend. The temperature as usual improves over the year and decreased in post harvest stage. Precipitation does not bear any relationship trend to the growth stages. It is also understandable because farmers rely on irrigation in less rainfall condition and water drains out quicker in high precipitation conditions because blueberry is grown in well drained soil only. Figure 5 shows the weather and spectral parameters comparison of blueberry growth in the multi year analysis. As the spectral and weather data refers to only the post harvest stage of blueberry, there was not much difference in temperature and rainfall. However, significant changes were observed with the DN values. It is concluded that with annual growth, blueberry plants show different spectral characteristics. The average DN values along with temperature can provide the blueberry growth stage information in a orcahrd. On another note, in 2005 and 2006, the orchard had two distinct spectral characteristics.The west part of the orchard had already established blueberry plants while the east part had a very early stage of blueberry seedlings. By 2007, both sides had the plants in established stages and showed simialr trend in sprectral reflectance.

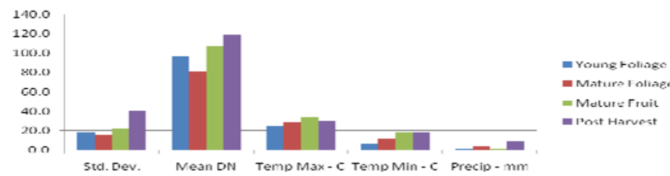


Figure 4: Side by side comparision study of weather and spectral parameters with the within year blueberry growth stages.

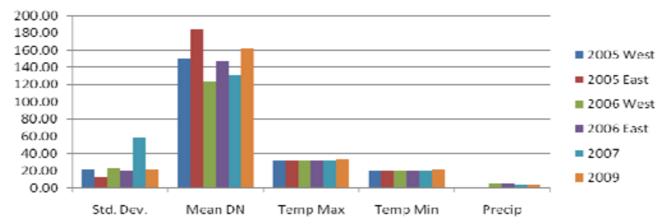


Figure 5: side by side multi-year (2005 – 2009) comparision study of weather and spectral parameters for post harvest stage blueberry plants.

Figure 6 and 7 show the trend line (shown in thin line) analysis of the same weather and spectral parameters with respect to the growth stages of blueberry within year and multi-year, respectively. The equation (constructed with 4th order polynomial) for each stage's trendline is shown below its respective parameter in the legend to the right. This trendline was constructed because it was the best fitting trendline in this analysis. We hope that these equations can be used to help identify unknown stages of blueberry plants. The x-axis parameter labels are as follows, 1 -Standard Deviation, 2 -Mean DN, 3 –$Temp_{max}$ (^{0}C), 4 –$Temp_{min}$ (^{0}C), and 5 –Precipitation (mm). The y-axis units are as specified in the parentheses to each x-axis parameter. The bold lines in the figure represent the actual data and the thin lines of the corresponding color are the best-fit fourth-order polynomial trendlines for each growth stage of bluberry.

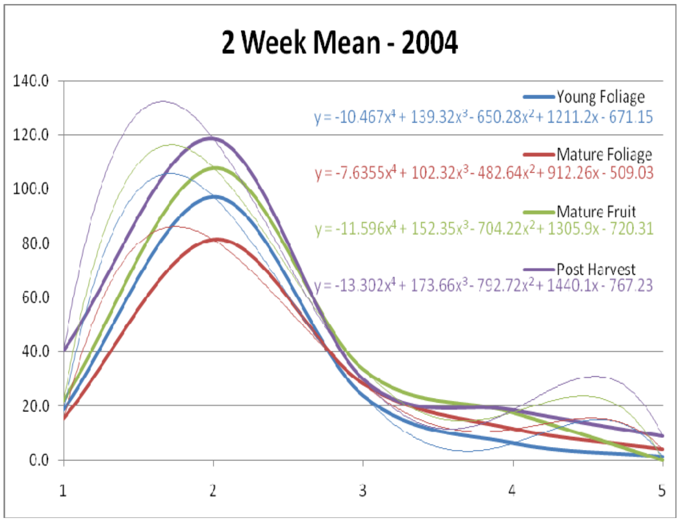


Figure 6: The trendline analysis for predicting blueberry growth stages with weather and spectral parameters with within year data.

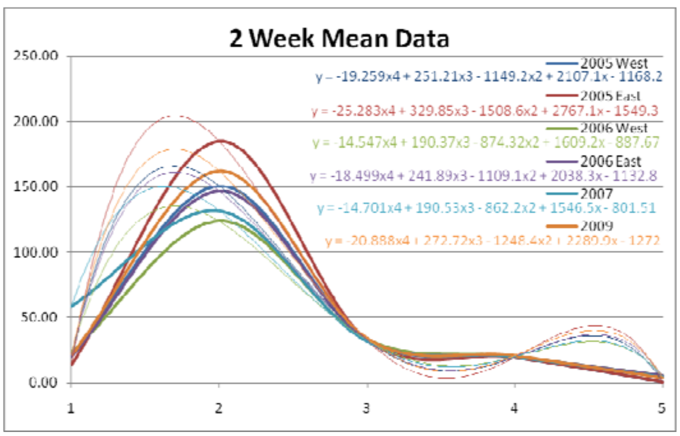


Figure 7: The trendline analysis for predicting blueberry growth stages with weather and spectral parameters with multi-year data.

As we observed from our analysis, the spectral characteristics (DN mean) shows significant relationship with different within year and multi-year growth stages, we established a trend line relationship between the DN mean values at post harvest growth stage in a multi-year scenario. Figure 8 shows the trend line curve constructed with 3rd order polynomial analysis for the data of 2005, 2006, 2007, and 2009. A coefficient of determinant (R^2) value of 0.44 was obtained for the study. It will certainly improve if the 2005 East and 2006 East data are excluded from the analysis as they are outliers. Both represent the spectral characteristics of non-established blueberry plants in post harvest stage of growth. Figure 9 shows the trend line curve constructed with 3rd order polynomial analysis with the earlier data along with SPOT spectral DN values extracted from mid September image. A coefficient of determinant (R^2) value of 0.21 was obtained from the analysis and this decrease in correlation coefficient could be attributed to the DN value obtained from another satellite (SPOT). The trend line relationship equations are put in the Figures itself. It is expected that these equations could be used for establsihing blueberry growth stages with remotely sensed digital information. The numbers in X axis represent the year as shown in the figures in the right.

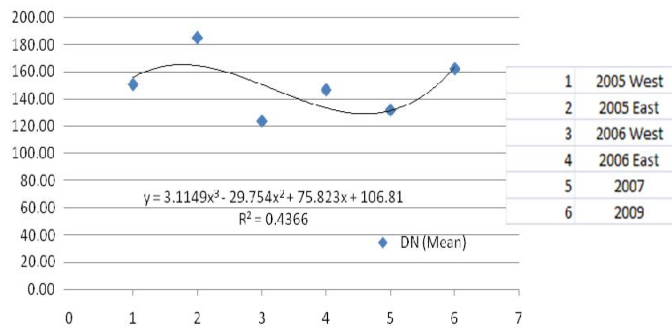


Figure 8: The trendline analysis of spectral characterisitics versus multi-year post harvest stage growth with data from 2005 - 2009.

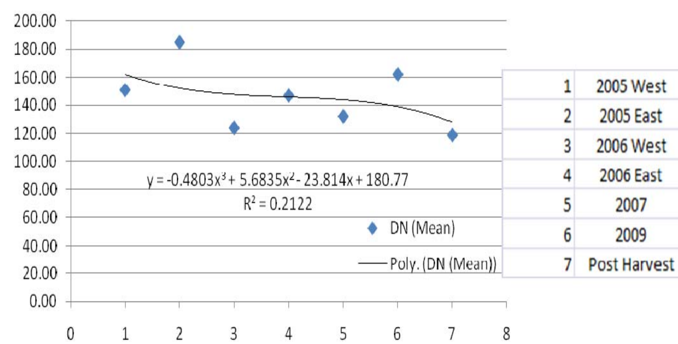


Figure 9: The trendline analysis of spectral characterisitics versus multi-year post harvest stage growth with data from 2004 - 2009.

CONCLUSION

This study is a preliminary analysis of correlating spectral characteristics and weather data to the blueberry growth stages. The study was conducted to analyze blueberry growth stages during a year and also growth rate over the years. Strong relationships could not be established bewteen weather and growth parameters as weather have similar pattern during a year and over the years. Farners also use processes to mend the damages from eratic weather patterns. We could not observe eratic weather patterns during the course of our study (2004-2009). However, a good and significant relationship was established between the blueberry plant spectral characteristics (within year and multi-year) to different growth stages of blueberry. Further studies are being conducted that include other orchards to compare with our findings.

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REFERENCES

Baez-Gonzalez, A. D., Chen, P. Tiscareno-Lopez, M., and Srinivasan R. 2002. Using satellite and field data with crop growth modeling to monitor and estimate corn yield in Mexico. Crop Science, 42: 1943-1949.

Byne, G. F., Crapper, P. F., and Mayo, K. K. 1980. Monitoring land-cover change by principal component analysis of multi-temporal Landsat data. Remote Sensing of Environment, 10: 175-184.

Casanova, D., Epema, G.F., and Goudriaan, J. 1998. Monitoring rice reflectance at field level for estimating biomass and LAI. Field Crop Research. 55: 83-92.

Hoffmann, R., Molander, C., & Bohn, T. (2008). NAIP 2008 summary briefing, Surdex Corporation. NAIP Coordination Meeting. http://www.fsa.usda.gov/FSA/apfoapp?area=home&subject=meet&topic=nai. Accessed on November 12, 2010.

Li, T., Feng, Y., and Li, X. 2009. Predicting crop growth under different cropping anf fertilizer management practices. Agricultural and Forest Meteorology, 149(6-7): 985-998.

Lobell, D. B., Ortiz-Monasterio, J. I., Asner, G. P., Naylor, R. L., and Falcon, W. P. 2005. Combining field surveys, remote sensing, and regression trees to understand yield variations in an irrigated wheat landscape. Agronomy Journal, 97: 241-249.

Magri, A. 2005. Soil test, aerial image and yield data as inputs for site-specific fertility and hybrid management under maize. Precision Agriculture, 6(1): 87-110.

O'Connell, M. G. and Goodwin, I. 2005. Spatial variation of tree cover in peach orchard. Acta Horticulture (ISHS), 694: 203 – 205.

Panda, S. S., G. Hoogenboom,, & J. Paz, (2009). Distinguishing blueberry bushes from mixed vegetation land-use using high resolution satellite imagery and geospatial techniques. *Computers and Electronics in Agriculture*, 67 (1-2): 51-59.

Panda, S.S. 2003. Data mining for precision management of crop. PhD dissertation, North Dakota State University, Fargo, North Dakota, USA.

Panda, S.S., Panigrahi, S., & Ames, D.P. (2010). Crop yield forecasting from remotely sensed aerial images with self-organizing maps. *Transactions of ASABE*, 53(2): 323-338.

Sevier, B. J., & Lee, W. S. (2005). Precision farming adoption by Florida citrus. Producers: Probit model analysis. *University of Florida Cooperative Extension Service. Circular # 1461*.

Sharma, A., & Panigrahy, S. (2007). Apple orchard characterization using remote sensing and GIS in Shimla district of Himachal Pradesh. *Remote Sensing and Photogrammetry Annual Conference 2007*, September 11 – 14, 2007. http://www.ceg.ncl.ac.uk/rspsoc2007/papers/87.pdf. Accessed on 12 July, 2010.

Shrivastava, R.J. and Gebelein, J.L. 2006. Land cover classification and economic assessment of citrus groves using remote sensing. ISPRS Journal of Photogrammetry & Remote Sensing 61: 341–353.

Torres, L.G., Pena-Barragan, J.M., Lopez-Granados, F, Jurado-Exposito, M., and Fernandez-Escobar, R. 2008. Automatic assessment of agro-environmental indicators from remotely sensed images of tree orchards and its evaluation using olive plantations. Computers and Electronics in Agriculture, 61(2): 179-191. [doi>10.1016/j.compag.2007.11.004]

United States Department of Agriculture, Aerial Photography Field Office. (2008). National Agriculture Imagery Program. http://165.221.201.14/NAIP.html. Accessed on 28 July, 2010.

Table 1: Information on multitemporal SPOT imagery collection in year 2004 for Camden County, GA (includes Woodbine city and proximity) – Scene K/J 618/288

Date	Type/Resolution	Cloud Cover	Incident Angle	Quality
03/12/2004	Spot 5m Pan	2%	-4.92	100%
04/23/2004	Spot 5m Pan	6%	-18.79	100%
05/24/2004	Spot 5m Pan	14%	-13.38	100%
09/30/2004	Spot 5m Pan	6%	20.63	100%
09/30/2004	Spot 10m MSS	6%	20.62	100%

Table 2: NAIP image acquisition date for Woodbine NW (our study area is part of the image tile)

Year	SrcImgDate (acquisition date)	Weather data collection range
2005	10/16/2005	10/09/2005 to 10/23/2005
2006	07/19/2006	07/12/2006 to 07/26/2006
2007	09/14/2007	09/07/2007 to 09/21/2007
2009	09/28/2009	09/21/2009 to 10/05/2009

Table 3: Weather data and DN values of the study area for different growth stages in a year (2004)

Month	Std. Dev.	Mean DN	Temp Max (^{0}C)	Temp Min (^{0}C)	Precipitation (mm)	Growth Stage
March	18.6	97.3	23.9	6.3	1.31	Young Foliage
April	15.3	81.3	28.1	11.5	3.99	Mature Foliage
May	22.1	107.9	33.6	17.7	0.05	Mature Fruit
September	40.5	118.6	30.0	18.6	8.98	Post Harvest

Table 4: Weather data and DN values of the study area for post harvest stage of blueberry (mid July to mid October) in multi-year

Year	Std. Dev.	Mean DN	Temp Max (^{0}C)	Temp Min (^{0}C)	Precipitation (in)
2005 West	21.60	150.54	32.59	19.48	0.72
2005 East	13.73	184.72	32.59	19.48	0.72
2006 West	23.02	123.64	32.76	19.81	5.12
2006 East	19.82	146.56	32.76	19.81	5.12
2007	58.62	131.73	31.77	19.86	4.32
2009	21.38	161.97	34.09	20.82	3.88