Estimation of cotton yield with varied irrigation and nitrogen treatments using aerial multispectral imagery

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Abstract: Cotton yield varies spatially within a field. The variability can be caused by various production inputs such as soil properties, water management, and fertilizer application. Airborne multispectral imaging is capable of providing data and information to study effects of the inputs on yield qualitatively and quantitatively in a timely and cost-effective fashion. A 10-ha cotton field with irrigation and non-irrigation 2×2 blocks was used in this study. Six nitrogen application treatments were randomized with two replications within each block. As plant canopy was closed, airborne multispectral images of the field were acquired using a 3-CCD MS4100 camera. The images were processed to generate various vegetation indices. The vegetation indices were evaluated for the best performance to characterize yield. The effect of irrigation on vegetation indices was significant. Models for yield estimation were developed and verified by comparing the estimated and actual yields. Results indicated that ratio of vegetation index (RVI) had a close relationship with yield (R^2=0.47). Better yield estimation could be obtained using a model with RVI and soil electrical conductivity (EC) measurements of the field as explanatory variables (R^2=0.53). This research demonstrates the capability of aerial multispectral remote sensing in estimating cotton yield variation and considering soil properties and nitrogen.

Keywords: remote sensing, multispectral imagery, cotton, yield, nitrogen, irrigation, soil properties

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1 Introduction

Cotton yield is one of the most important factors in determining the profit received by cotton producers. Cotton yield varies spatially within a field and the variability can be introduced by various factors such as soil properties, water management, and fertilization. Producing high-yielding cotton requires careful field management practices in every production stage. Precision agriculture (PA) technology allows producers to optimize production inputs on a spatially variable basis within a field so that farm profit can be maximized. Detection of plant growth conditions and assessment of nutrient status and yield potential are essential for appropriate adjustment of the inputs in PA practices. Remote sensing (RS) has been widely used in PA for large-scale and rapid data collection including plant nutrient and yield prediction and water management. RS has been used in water management, yield prediction, nutrient management, and pest management in a number of crops[1]. RS-based water stress indices have been found to be useful in optimizing irrigation strategies for sorghum[2]. Statistical techniques for RS data were evaluated for crop yield estimation[3]. Yang et al.[4,5] found that both satellite and airborne multispectral

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imagery could be used for cotton yield estimation considering variability across a field. RS imagery was successfully used to predict FAO-56 basal crop coefficients and evapotranspiration in cotton for irrigation scheduling[6]. Airborne hyperspectral, multispectral, and thermal infrared RS data were used to determine water stress of cotton plants[7]. Vegetation indices extracted from airborne multispectral imagery have been studied for prediction of irrigated corn yield[8].

The goal of this study is to explore the relationship between the vegetation indices from airborne multispectral imagery and the cotton yield under different irrigation and nitrogen treatments. Specifically, this study was undertaken to 1) develop a method of assessing cotton yield and plant nutrient using airborne multispectral imagery; 2) investigate the effects of irrigation on cotton plant canopy reflectance characteristics; and 3) explore the possibility of estimating cotton yield using multispectral imagery combined with soil electrical conductivity (EC) measurements.

2 Materials and methods

2.1 Study area

A 10-ha cotton field in a research farm of the United States Department of Agriculture, Agricultural Research Service Crop Production Systems Research Unit at Stoneville, MS (latitude: 33°26'30.86", longitude: -90°53'26.60") was selected as the experimental site.

2.2 Experiment design and field treatment

Experimental plots were laid out in a split plot design with two irrigation treatments as main units and six nitrogen treatments (0, 39, 67, 101, 135, and 168 kg/ha) as subunits. The main units design was a randomized complete block with two blocks. There were two replications of the subunits within each main unit. A cotton cultivar (DP 0912 B2RF) was planted on May 8, 2011. Non-irrigated plots were defoliated on September 8, 2011 and irrigated plots on September 23, 2011. Cotton was machine harvested with a spindle-type picker on October 11, 2011. Seed cotton from the middle 12 rows of each 24-row plot were transferred to a load cell-equipped boll buggy and weighed for yield estimation.

2.3 Aerial multispectral imaging

An MS4100 camera (Geospatial Systems, Inc., West Henrietta, New York, USA) was used to image the cotton field. The MS4100 camera is a multispectral 3-CCD (charge-coupled device) color/color-infrared (CIR) digital camera. The camera provides a digital imaging resolution of 1920 (horizontal) × 1080 (vertical) pixels per sensor and a 114 degree diagonal angle of view when fitted with 14 mm, f/2.8 lens. The camera is available in two spectral configurations: RGB (Red Green Blue) for high resolution color imaging and CIR for multispectral applications. The camera images four spectral bands from 400 nm to 1000 nm, and acquires Near InfraRed (NIR) at 800 nm with 60 nm bandwidth, red at 670 nm with 40 nm bandwidth, green at 540 nm with 40 nm bandwidth, and blue at 460 nm with 45 nm bandwidth image planes. When running the RGB or CIR configurations individually, a base configuration supports any three-tap configuration running at 8 bits per color plane (i.e. 24-bit RGB).

The MS4100 camera was mounted on an Air Tractor 402B airplane (Air Tractor, Inc., Olney, Texas, USA) to fly over and acquire CIR images of the cotton field after the canopy was closed. Figure 1 shows the georeferenced CIR images of the field on August 30, 2011. The flight line was from south to north. The flight altitude was about 760 m, which gave a 40 cm horizontal ground spatial resolution and 90 cm vertical ground spatial resolution.

To convert digital numbers of the CIR images to percent reflectance, an IRR 180 irradiance radiometer (TerraVerde Technologies, Inc., Stillwater, Oklahoma, USA) was used to record solar irradiance. The radiometer was equipped to record the sun’s irradiance in the field to normalize images. This radiometer was set in the field on the day of field imaging and the signals were automatically recorded at a preset interval. After imaging, the data were uploaded to the computer. With the uploaded data, the dedicated image correction software, Image Correction Center software (TerraVerde Technologies, Inc., Stillwater, Oklahoma, USA), was used to filter out anomalies caused by clouds and normalize the images to acquire reflectance images without the conventional standard reflectance panels.

Figure 1 CIR image of the cotton field acquired on August 30, 2011

The image provides three original bands (NIR, Red, and Green). Based on the three bands, three vegetation indices, NDVI (Normalized Difference Vegetation Index), RVI (Ratio Vegetation Index) and GNDVI (Green NDVI), were generated for analysis in the study. They are calculated as follows:

$$NDVI = \frac{NIR - Red}{NIR + Red} \tag{1}$$

$$RVI = \frac{NIR}{Red} \tag{2}$$

$$GNDVI = \frac{NIR - Green}{NIR + Green} \tag{3}$$

2.4 Soil electrical conductivity mapping

Soil apparent EC was measured in the cotton field at shallow (0 to 0.3 m) and deep (0 to 0.9 m) depths using a Veris 3000 EC system (Veris Technologies, Inc., Salina, Kansas, USA). The measurements are expressed in the unit of milliSiemens per meter (mS/m).

2.5 Statistical analysis

One plot which is in the low area of the field was flooded several times due to accumulation of rainfall and irrigation water. Excessive soil water content made the plants grow in an undesired pattern and caused cotton flowers and boils to be shed. Cotton yield in the plot was not representative, thus, the yield collected in this plot was treated as an outlier and removed from the data set prior to data analysis.

The effect of irrigation on spectral reflectance characteristics was statistically analyzed. The analysis of relationship between cotton yield and vegetation indices from image and soil EC measurements was further conducted. The calculations of ANOVA and regressions were performed using SAS for Windows software (version 9.2) (SAS Institute Inc., Cary, North Carolina, USA).

3 Results and discussion

Table 1 shows the Duncan mean separation on yield and vegetation indices in the plots of with and without irrigation treatment. The results indicated that the means of all variables were significantly different between the two irrigation treatments.

Table 1 Duncan mean separation of irrigation treatment on yield and vegetation indices ($\alpha = 0.01$)

Irrigation treatment	Yield/kg ha^{-1}	*NDVI*	*RVI*	*GNDVI*
Irrigated	3398.57^{a*}	0.59^{a}	3.83^{a}	0.55^{a}
Non-Irrigated	2975.38^{b}	0.53^{b}	3.27^{b}	0.51^{b}

Note: *Different letters indicate that the means are significantly different between two irrigation treatments.

The yield mean separation revealed that irrigated plots did have significantly higher yields than non-irrigated plots (Table 1). However, the effect of the nitrogen application rates used in the experiment on yield was not significant. This was most likely due to high residual nitrogen in the experimental plots. Plants in the field had sufficient nitrogen to grow; therefore, effects of the nitrogen application rates used in the experiment on the vegetation indices and yield were diminished. Table 1 indicated that mean values for NDVI, RVI and GNDVI were all higher for irrigated plots.

In order to model cotton yield, vegetation indices of NDVI, RVI, and GNDVI from the aerial CIR image and shallow soil EC (SSEC) and deep soil EC (DSEC) from VERIS soil EC mapping were used as explanatory variables in regression modeling. For linear model fitting, the yield, NDVI, RVI, GNDVI, SSEC and DSEC were natural-log (ln) transformed to produce new dependent and explanatory variables. All the dependent and explanatory variables were used to perform progressive multiple regression based on R^2 selection to find subsets of variables that best estimated the yield.

In the process of progressive regression to model ln(yield), the explanatory variables were plugged into the model starting with one variable, then two variables, and so on up to ten variables (five base variables plus their cross combinations). Table 2 shows the best three models for one, two, and three explanatory variables in the process of multiple R^2 selection regression.

Table 2 The best three models for 1, 2, and 3 explanatory variables in the model of ln(yield) in the process of progressive multiple regression

R^2	Explanatory variable	R^2	Explanatory variable
0.47	RVI	0.52	ln(RVI) and SSEC
0.47	ln(RVI)	0.57	NDVI, ln(RVI) and ln(SSEC)
0.44	NDVI	0.57	NDVI, SSEC and ln(RVI)
0.53	ln(RVI) and ln(SSEC)	0.56	NDVI, ln(RVI) and ln(DSEC)
0.53	RVI and ln(SSEC)		

Figure 2 indicates that the model improved modestly with increased number of explanatory variables in the model. However, with more than two explanatory variables, the models would have co-linearity between variables from the CIR image and between the two soil EC measurements. The final model was determined as the best model using two explanatory variables:

$$\ln(\text{yield})=6.6717+0.8177\ln(RVI)+0.0916\ln(SSEC) \quad (R^2=0.5263) \tag{4}$$

Three-dimensional plots were generated for actual yield and estimated yield from RVI and SSEC (Figure 3). The estimated yield was inverted back to the original scale from the output of the model in Equation (4). The plots indicate that the actual yield goes to a maximum at maximum RVI and relatively mid-range SSEC (indicating medium soil texture). The estimated yield from the model follows the trend well.

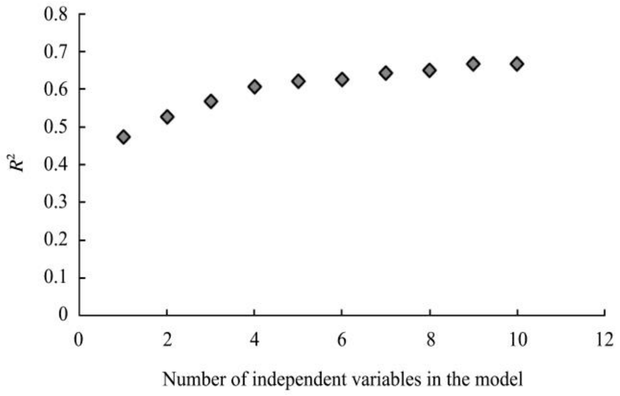

Figure 2 R^2 versus the best model with different numbers of explanatory variables in the process of selection regression modeling

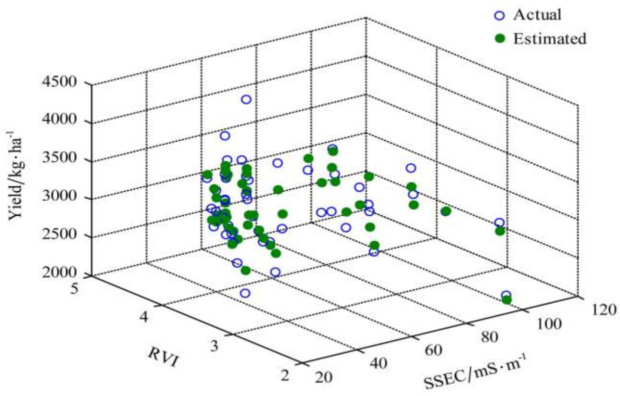

Figure 3 3-D plots of actual and estimated yield versus RVI and SSEC

The model was verified from the relationship between actual yield and estimated yield (Figure 4). The plot indicates that the model can be verified well with non-irrigated data (R^2=0.72) but not the irrigated data. The probable reason for this is that yield was in a relatively narrow range under the irrigated treatment and the scatter was high. Irrigation dominated the effects of all other variables.

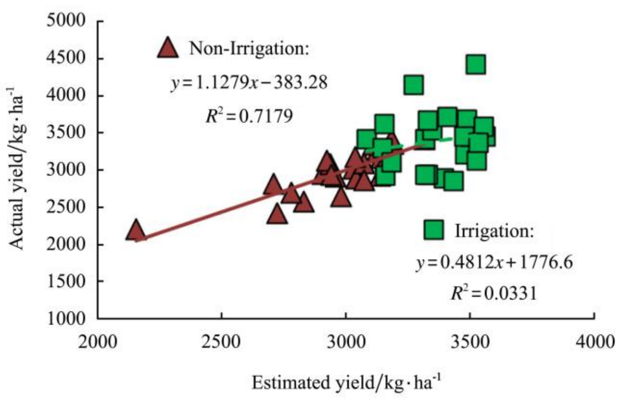

Figure 4 Model verification through actual yield versus estimated yield

4 Conclusions

1) Airborne multispectral imagery can be used to assess cotton yield with the effect of irrigation;

2) NIR band, Green band, NDVI, RVI, and GNDVI are significantly different from irrigated to non-irrigated treatment;

3) The best model of yield was achieved by ln(yield) with explanatory variables ln(RVI) and ln(SSEC). The model was verified well with non-irrigated data.

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