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SITE-SPECIFIC APPLICATION OF COTTON HARVEST AIDS USING REMOTELY SENSED IMAGERY

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Abstract

Application of chemical harvest aids is necessary to improve harvestability and lint quality of the cotton crop. When applied properly to the crop, these chemicals stimulate leaf loss and promote boll opening. Traditionally, harvest aids have been applied at a constant rate across a field, resulting in over-application to areas that may have matured faster than others due to soil type, insect pressure, or disease.

In 2003, a project was conducted in the San Joaquin Valley of California to evaluate the use of remotely sensed imagery for site-specific applications of cotton harvest aids in both Acala and Pima cotton. Remotely sensed imagery from airborne and satellite sources was obtained over the study area and analyzed to determine the most appropriate method for harvest aid prescription generation. Variable rate applications were applied via a commercial aerial applicator and compared to traditional blanket aerial applications. Seed cotton yield and harvest aid performance were not significantly decreased through the use of variable application technologies.

Introduction

Cotton is a perennial plant that has an indeterminate growth habit resulting in inconsistent maturation of the fruit and leaves (Supak et al., 2001). The use of chemical harvest aids (i.e., defoliants, boll openers, desiccants) provides more timely leaf removal and boll opening compared to the natural process of senescence and abscission in cotton (Cothren et al., 2001). Foliage remaining on the plant at harvest time not only reduces picker efficiency (Williford, 1992), but also increases trash content and discoloration (stain) of lint (Crawford et al., 2001).

In 2000, approximately 5.4 million kg (12 million lb) of chemical harvest aids were applied to the 5.8 million hectares (14.4 million acres) of cotton grown in the United States (National Agricultural Statistics Service, 2001). Roberts et al. (2001) notes that pre-harvest and harvest practices in the western cotton growing regions have been criticized for their impact on air quality. Use of variable rate application technologies has the potential to decrease the quantity of harvest aid chemicals used and possibly reduce negative impacts on air quality.

Growing conditions in the San Joaquin Valley are different from those in the Midsouth and use of the same defoliation practices typically results in unacceptable harvest aid performance (Roberts et al., 2001). As a result, two applications are commonly used: 1) an application of a phosphate defoliant (Def 6) or a tank mix of a phosphate defoliant with ethephon, and 2) a "cleanup" application using sodium chlorate or paraquat to desiccate any remaining leaf tissue.

This year's project evaluated the use of variable rate harvest aid applications in both Acala (*Gossypium hirsutum L.*) and Pima (*G. babadense L.*) cotton grown in the San Joaquin Valley of California. The growth patterns of the two cottons vary considerably: Pima cotton exhibits a more indeterminate and rank growth pattern than does the Acala cotton (Hutmacher et al., 2001; Silvertooth, 2001). As a result, the Pima crop is typically more difficult to defoliate (Roberts et al., 2001; Hutmacher et al., 2001). Plant parameters that are indicative of the amount of harvest aid to apply (i.e., plant height, leaf area index (LAI), and percent open bolls) were measured at georeferenced sampling points and correlated to remotely sensed imagery. Variable rate applications were performed using aerial variable rate technologies.

During the 2002 growing season, a field-scale experiment was conducted to investigate the use of remotely sensed imagery for variable rate application of cotton harvest aids in the Mid-South United States. Measures of plant biomass (i.e., leaf area index (LAI) and plant height) were correlated with the normalized difference vegetation index (NDVI) and the percentage of open bolls was mapped using a linear discriminant function with NDVI (Institute for Technology Development, 2002). When compared to traditional blanket applications, variable rate applications reduced chemical use by 17-18% while effectiveness, yield, and fiber quality were maintained.

The goals of this project are to: 1) test the effectiveness of remotely sensed imagery for site-specific applications of cotton harvest aids in both Acala and Pima cotton, 2) evaluate the economic benefits of variable rate harvest aid applications, and 3) develop/refine an image-based technique for aerial/ground-based variable rate applications of cotton harvest aid chemicals.

The long-term goal of the project is to develop techniques that could be utilized at a commercial scale for the development of site-specific harvest aid prescription maps.

Materials and Methods

Study Location and Experiment Design

The study was conducted on irrigated cotton grown in the San Joaquin Valley of California in Kings County (Figure 1). Two study fields (Field 5-2 and Field 7-2) were selected on Sheely Farms (Figure 2) near Lemoore, CA, allowing ITD to evaluate variable rate aerial applications of cotton harvest aids on both Acala (Field 5-2) and Pima (Field 7-2) cotton.

In each study field, a stratified block design consisting of four blocks and 12 treatment strips occupied an area of approximately 20 ha (50 acres). Each of the strips traversed the entire length of the field [805 m (2640 ft)] and had a width of approximately 21 m (70 ft). The treatments consisted of four conventional blanket application strips and four variable rate strips (Figures 3 and 4). Initially, the experiment design incorporated a second variable rate strip in each block to which a blanket application of boll opener would be applied and compared to the variable rate boll opener application. This was later removed from the study because the variable rate application system lacked the ability to apply chemicals in this manner.

After the cotton was established and actively growing (late June), treatment strips and sample points were located using a differentially corrected global positioning system (DGPS) receiver. The DGPS receiver uses signals broadcast by Coast Guard beacons to attain an accuracy of 1-m or less. Treatment strips were established by logging a DGPS point at each corner of the strip and ArcGIS (ESRI, Redlands, CA) was used to create the vertices of the polygon. Within each treatment strip, seven sample points were established at intervals of approximately 112 m (367 ft). Each sample point was marked with a flag labeled with the point identification number.

Field Data Collection

For each field, data was collected from a total of 84 sample points. Table 1 lists the field measurements that were collected at each sample point and the time at which they were collected. Leaf area index (LAI) measurements were obtained with the LI-COR LAI-2000 plant canopy analyzer (LI-COR Inc., Lincoln, Nebraska). Measurements of LAI taken with the LAI-2000 have proven to be rapid, accurate estimations of LAI, particularly when taken under diffuse light conditions (Welles, 1990; Welles and Norman, 1991). Plant height measurements were acquired prior to the defoliant application to assist with quantifying the amount of vegetation present. Additionally, Nick Groenenberg from Groenenberg Agricultural Consulting visited each sample point on the variable rate strips and provided a rate recommendation (low, moderate, or high) to be used in the process of generating the prescription.

Guidelines established by the Cotton Defoliation Work Group (1999) were used to evaluate harvest aid performance. The harvest aid performance data was collected on a 1-m stretch of row on two rows (one row on each side of the sample point). At seven and 14 days after treatment (DAT), each sample point was visited and visually ranked for the percentage of defoliation and desiccation. Also recorded at this time was the percentage of basal regrowth, terminal regrowth, and open bolls.

To determine if variable rate applications of harvest aids had any effect on lint quality, lint samples were collected from each of the treatment strips. Composite samples were obtained from each strip by randomly collecting approximately six pounds of seed cotton as the cotton was emptied from the picker into the boll buggy. Samples were only drawn from the picker passes that harvested the center eight rows of the treatment strips.

Cotton yield measurements were obtained using John Deere four row cotton pickers equipped with the AgriPlan (AgriPlan Inc., Stow, Massachusetts) commercial yield sensing system and DGPS receiver. Data were logged at 2-s intervals and written to a PCMCIA card located on the yield monitor.

Yield monitor calibration was accomplished using a boll buggy equipped with an electronic scale. Randomly selected loads were weighed and compared with the yield monitor load weight. If necessary, correction factors were then applied to the yield monitor to compensate for any errors. Errors were typically ±5% or less.

After harvest, the yield data files were downloaded from the PCMCIA cards and exported to shapefiles for further analysis and processing. Data points that were logged when the picker had stopped and/or momentarily reversed its direction of travel (i.e., due to plugging) were removed from the data set. After editing was complete, the file was saved and exported as a comma-delimited ASCII file.

Next, the yield data was processed using algorithms similar to those described by et al. (1996). These algorithms were implemented in software developed by the USDA-Agricultural Research Service (ARS) in Columbia, Missouri (Drummond, 2003). The software was used to correct the yield data for the time delay, removal of outliers, and to clean up the ends of the field were the picker entered and exited the crop. To maintain data integrity, yield data from each cotton picker (three pickers were used to harvest the study fields) was processed individually. After all the individual data files were processed for each study field, the files were merged for further analysis.

Although each treatment strip was 24 rows wide, only the center eight rows were used to determine yield, thus creating a buffer between the treatment strips. The mean yield for each sample point was calculated by extracting all of the data points from an 80-m segment (40-m before and after the sample point) of the two center picker passes. Finally, the mean yield values were merged with their respective treatment designation and exported to a comma-delimited ASCII file for statistical analysis.

Image Data and Pre-Processing

The ITD RDACS/Model II (Mao and Kettler, 1995) airborne camera system was used to collect multispectral imagery with a 1-m spatial resolution. The RDACS is equipped with three Kodak Megaplus cameras each fitted with a specific band pass filter (Table 2). Imagery was collected periodically throughout the growing season beginning in June and ending in October.

In addition to the data collected with the ITD RDACS system, Digitalglobe's QuickBird satellite data was provided by NASA. The QuickBird imagery consisted of four bands (Table 2) with a 2.4-m spatial resolution. Acquisition of QuickBird data began in May and continued periodically throughout the growing season concluding in October.

After the RDACS data was acquired, it was downloaded from the portable hard drive that the system uses to store data during acquisition. The frames that covered the study fields were selected and imported into ERDAS Imagine format. Because the RDACS sensor consists of three separate Kodak cameras, the resulting image frames are not co-registered. Instead of performing band-to-band registration and then georeferencing the imagery, each individual band was georeferenced separately using panchromatic data from the QuickBird satellite. Nearest neighbor resampling was used in the georeferencing process and accuracy was to the sub-0.5 pixel level. After all bands were georeferenced, they were layer-stacked to form the three-band multispectral composite image. Use of this process eliminated the need for a second resampling by essentially merging the band-to-band registration and georeferencing process into one step. Data were output in Universal Transverse Mercator (UTM) coordinates (WGS-84, zone 11 north).

Next, the imagery was calibrated to relative reflectance using the empirical line method (Smith and Milton, 1999). Reference spectra were obtained from two permanent calibration targets with differing reflectance values (approximately 8% and 65%) located adjacent to the study site. Actual reflectance values of the placards were measured several times throughout the growing season with an ASD FieldSpec spectroradiometer (Analytical Spectral Devices Inc., Boulder, CO). To develop calibration equations, pixels were first extracted from the centers of each calibration target and paired with the spectroradiometer data. Dark current values were also obtained for the camera system and used in the calibration process as the digital number (DN) that represents 0% reflectance. Regression analysis was then performed to develop calibration equations for each band in the imagery. A second order equation was used for all dates of imagery because the first order equation did not account for the nonlinear response of the camera system at higher reflectance values (Figure 5). Use of the first-order equation resulted in negative reflectance values in all image bands.

QuickBird imagery is typically delivered as radiometrically corrected data that includes a dark offset subtraction and a non-uniformity correction (DigitalGlobe, 2003). To convert the data to top-of-atmosphere spectral radiance, the QuickBird Radiance calibration utility was used in ENVI (Research Systems Inc., Boulder, CO). This utility uses the calibration factors supplied in the QuickBird metadata file to convert the values from corrected counts to spectral radiance [$W \text{-} m^{-2} \text{-} sr^{-1} \text{-} \mu m^{-1}$].

Although the QuickBird data is provided in a georeferenced format, its accuracy is often inadequate for site-specific applications. Thus, the next step in processing the QuickBird data was to georeference the imagery to obtain the desired accuracy (±0.2 pixel). A second-order polynomial model and nearest neighbor resampling was used to georeference the data.

The final step in the preprocessing of the QuickBird imagery was to perform a date-to-date normalization on the data. The top-of-atmosphere calibration to radiance does not remove atmospheric noise and therefore does not account for day-to-day differences in atmospheric conditions. A technique similar to that described by Jensen et al. (1995) where multiple dates of imagery were normalized to a reference image was applied to the QuickBird image data. QuickBird imagery acquired on 20 May 2003 served as the reference data to which all other dates would be normalized. For each date of imagery, pixels from the normalization targets (i.e., asphalt, concrete) were extracted via regions of interest and regressed against the spectral radiance values of the targets in the reference image. The resulting coefficients were then used to compute a normalized data set that had approximately the same spectral calibration as the 20 May 2003 dataset.

The final step in pre-processing of both airborne and satellite imagery was to mask the image to the field boundary. To ensure that pixels from outside of the field were excluded from any further analysis, each field was subset from the image using a mask. Masking was accomplished using a field boundary that had been buffered by a distance of 10 m.

Image Analysis

Masked image datasets from each of the study fields were subjected to several types of analyses and processing techniques. Vegetation indices, including the normalized difference vegetation index (NDVI) (Tucker, 1979), green NDVI (Gitelson et al., 1996), and soil adjusted vegetation index (SAVI) (Huete, 1988) were calculated from the image data.

Supervised and unsupervised classification techniques were performed on the datasets and thresholding of the appropriate vegetation indices were used in the prescription generation process. Supervised classification was conducted using the Maximum Likelihood algorithm (Jensen, 1996), while the ISODATA algorithm (Tou and Gonzalez, 1974) was used to perform unsupervised classification. For the QuickBird datasets, the blue band was excluded from all classifications performed.

Supervised classification was conducted only with the image dataset acquired immediately prior to the prescription application. Ground truth data collected by ITD personnel in conjunction with Nick Groenenberg was used to develop the training and accuracy assessment datasets. Data were randomly split into two groups: two-thirds of which was to be used in training the classification algorithm, and the remaining one-third to be used in the accuracy assessment.

Unsupervised classification was conducted on several different datasets: 1) multispectral composite acquired immediately prior to the prescription application; 2) multispectral composite acquired immediately prior to the prescription application with the inclusion of an NDVI image; and 3) multitemporal data set consisting of a multispectral composite acquired immediately prior to the prescription application and a multispectral composite acquired at the time of peak vegetative growth (as determined from the NDVI growth curve). The ISODATA algorithm was used initially generate 12 classes for each dataset. Next, transformed divergence was computed to evaluate the spectral uniqueness of each of the classes. Transformed divergence is a measure of spectral separability with values scaled to lie between 0 and 2000 (Kumar and Silva, 1977). Jensen (1996) recommends that values below 1700 indicate poor separation between classes, while classes with a transformed divergence value of 1700 or higher are spectrally distinct.

Comparisons of the spectral classes were made, and the pair of classes having a transformed divergence below 1700 was merged. Often, a spectral class could exhibit poor separability with more than one other spectral class. When this occurred, the two spectral classes with the lowest transformed divergence value were selected for merging. After the classes were merged, transformed divergence values were computed again, comparing the newly merged classes with the original unmerged classes. The process was iteratively repeated until three spectrally distinct classes were defined.

Accuracy assessments were conducted on all classifications, including those developed through thresholding. Before the accuracy assessment was performed, a majority filter with a 3-by-3 kernel was applied to the resulting classification image. Accuracy assessments were conducted using the Confusion Matrix utility in ENVI. For supervised classifications, the accuracy assessment data were imported as regions of interest and paired with their corresponding classes to compute the accuracy of the classification. Accuracy assessments for classifications generated by thresholding or the ISODATA algorithm were conducted by importing all available ground truth points as regions of interest, pairing them with their corresponding classes, and then computing a confusion matrix. Overall accuracies as well as the producer's and user's accuracy were computed.

Data and Economic Analysis

To analyze differences between treatments, analysis of variance (ANOVA) was conducted using the GLM procedure in SAS (SAS Institute, 1999). Data were analyzed to determine what, if any, influence variable rate applications exhibit on net profits, effectiveness, and fiber quality. Duncan's Multiple Range test was used to make pairwise comparisons among the treatment means. For all statistical tests, a significance level of 0.10 was used.

Economic analyses were conducted with the assistance of the Fresno State University Center for Agricultural Business. An approach similar to that used by Larson et al. (2002) was used to calculate net revenues as a function of yield and fiber quality. Lint price differences for fiber quality as influenced by harvest aid treatments may be expressed as

$$P_d = P_{cls} + P_m + P_{str} + P_u, \qquad [1]$$

where P_d is the total price difference for each treatment from the base price of cotton (¢ lb^{-1}); P_{cls} is the price difference for the combination of color grade, leaf grade, and staple (¢ lb^{-1}); P_m is the price difference for micronaire ((¢ lb^{-1}); P_{str} is the price difference for strength (¢ lb^{-1}); and P_u is the difference in price for length uniformity (¢ lb^{-1}).

Net revenues (*NR*) for each treatment can then be expressed with the following partial budgeting equation:

$$NR = (P_b + P_d) \times Y - C_j \qquad [2]$$

where P_b is the base quality lint price (¢ lb^{-1}); P_d is the total price difference (¢ lb^{-1}) for each treatment as calculated with Equation 1; Y is the lint yield measured for each treatment (lb ac^{-1}); and C_j is the harvest aid material and application cost for treatment j (\$ ac^{-1}).

Results and Discussion

Image Data

There were a total of eight acquisitions of both RDACS and QuickBird imagery over the study area (Table 3). Imagery was processed as previously outlined in the image pre-processing section and vegetation indices were calculated (NDVI, GNDVI, SAVI).

Crop development was monitored throughout the growing season by calculating the mean NDVI value for each field for every image acquisition date. The resulting values were plotted versus time to obtain a growth curve for each field (Figure 6). As the crop developed and accumulated biomass, the mean NDVI increased. For both fields, biomass accumulation peaked in mid-August and then began a gradual decrease. Vegetative biomass declined rapidly beginning in mid-September as the crop had completed the boll development process. Both the RDACS and QuickBird imagery show the same general trend in plant development, although the NDVI generated from the RDACS data is substantially greater in magnitude. The differences between the two types of imagery are likely due to the calibration process that was performed on the RDACS imagery.

Pre-Application Data Collection

The pre-application field data was collected during the last week in September (Acala cotton) and during the first week in October (Pima cotton). At each sample point, five plants were selected at random, their heights measured, and the total number of bolls and the number of open bolls determined. The mean height and percentage of open bolls were determined by averaging the data from the five plants. Leaf area index measurements were obtained with the LICOR LAI-2000 plant canopy analyzer at four locations within a 3-m area around each sample point.

Image data from 25 Sep. (including vegetation indices) (Figure 7) was extracted from a 3-by-3 meter area around each sample point, averaged, and merged with the field data. Analysis was conducted to determine which image attributes correlated best with the field data (Table 4). For plant parameters sampled from the Acala crop, correlations to imagery were weak and most were not significant. Plant parameters from the Pima crop, however, had strong to moderate correlations with the image data. Similar to last year's study (Institute for Technology Development, 2002), plant height and LAI were positively correlated with the NIR band, as well as all vegetation indices. The percentage of open bolls was negatively correlated with the NIR band and all vegetation indices, as the number of open bolls is inversely proportional to the amount of vegetative biomass.

In addition to the plant parameters shown above, the georeferenced sample points on the variable rate transects were visited by a field scout that made a rate recommendation (low, moderate or high) at each point. Recommendation information was also correlated with the image data and plant parameters (Table 5). For the Acala field, the scout's rate recommendation was not significantly correlated with the plant parameters or the NIR band. However, moderate significant correlations were obtained between the vegetation indices and the scout's rate recommendation. In contrast, all correlations for the Pima field were significant and ranged from moderate to strong. The scout's rate recommendation was strongly positively correlated with plant height and LAI. The percentage of open bolls was strongly negatively correlated with the scout's rate recommendation as higher rates were to be applied to areas of the field with fewer open bolls. On both fields, GNDVI exhibited the strongest correlation with the scout's recommendation.

Image Analysis and Prescription Generation

A number of image processing techniques and image data sets were used in the prescription generation process. Supervised classification using the Maximum Likelihood algorithm was performed on the multispectral composite image acquired prior to the harvest aid application. Unsupervised classification performed with the ISODATA algorithm was performed on several data sets: 1) multispectral composite acquired immediately prior to the prescription application; 2) multispectral composite acquired immediately prior to the prescription application with the inclusion of an NDVI image; and 3) multitemporal data set consisting of a multispectral composite acquired immediately prior to the prescription application and a multispectral composite acquired at the time of peak vegetative growth (as determined from the NDVI growth curve). Each technique was evaluated with the rate recommendations provided by the field scout using a confusion matrix. The overall classification accuracy as well as the user and producer accuracy was determined for each classification (Table 6).

Of all classification methods evaluated for this study, thresholding of a GNDVI provided the highest classification accuracy. The GNDVI was selected over the other vegetation indices because it had higher correlations with the field scout's rate recommendations. For the RDACS imagery, the thresholded GNDVI had an overall accuracy of 68% and 86% for the Acala and Pima fields, respectively. Accuracies obtained with a thresholded GNDVI from the QuickBird data were similar to those obtained from the RDACS imagery.

Mixed results were obtained with the ISODATA and Maximum Likelihood classification algorithms. Supervised classification performed with the Maximum Likelihood algorithm obtained higher classification accuracies on the QuickBird data than it did on the RDACS data. In general, classification accuracies were higher on the Pima field than they were on the Acala field. Most likely, this was due to the greater variation in plant growth (plant height, LAI, open bolls) exhibited by the Pima cotton. In comparison, the Acala field was relatively uniform and it was more difficult to distinguish the classes.

Since the highest classification accuracies were obtained with the thresholded GNDVI, it was used to develop the prescription maps for both of the study fields. The thresholds that resulted in the highest classification accuracy are shown in Table 7. Interestingly, the thresholds were somewhat similar for each of the study fields. The moderate class (class 2) tended to be a transition class from the low areas (least amount of vegetation) to the high areas (greatest amount of vegetation) (Figure 8).

Once the classes were established for each field, the next step in the prescription generation process was to create the actual prescription map. A spray grid with a cell size of 21 m (70 ft) wide by 61 m (200 ft) deep was created and overlaid on the classified GNDVI maps. To determine the rate for a given cell, the Zonal Statistics function in ArcGIS was used to determine what class (i.e., 1, 2, or 3) was the majority in that particular cell. The resulting prescription maps were recoded to represent the spray rate in gallons per acre (Figure 9) and modified to include the conventional blanket application strips. The prescription maps were converted to geographic coordinates (latitude/longitude) and to the appropriate format for the Satloc controller using Satloc MapStar software.

The harvest aid chemicals selected for use were Def 6 (S,S,S-Tributyl phosphorotrithioate) and Prep (Ethephon). Def 6 is an emulsifiable concentrate that is used to remove leaf tissue, while Prep is an ethephon-based product that promotes boll opening and more complete defoliation (Brecke et al., 2001). Application of the cotton harvest aids took place on 02 Oct. 2003 and 09 Oct. 2003 for the Acala and Pima fields, respectively. The prescriptions were applied with an AirTractor AT-802 (AirTractor, Inc., Olney, TX) airplane equipped with a Satloc (Satloc, LLC, Scottsdale, AZ) navigation and sprayer control system using the rates shown in Table 8.

<u>Post-Application Data Collection and Analysis</u>

Harvest aid performance was evaluated at seven and 14 days after treatment (DAT). The percentage defoliation, desiccation, open bolls, basal regrowth, and terminal regrowth were determined at each of the grid sample points. Analysis of variance was conducted to determine if there was a difference between treatments.

Results of the seven and 14 DAT evaluations on the Acala field are presented in Figures 10 and 11, respectively. At both evaluations, the variable rate strips had a significantly higher percent defoliation than did the conventional blanket strips. The percent desiccation and open bolls were also significantly different at seven DAT. Basal and terminal regrowth was minimal at both dates, with the variable rate strips having significantly less regrowth (both basal and terminal) at 14 DAT.

The same parameters were measured on the Pima field and the results are presented in Figures 12 and 13. No significant differences existed between the treatments at both seven and 14 DAT. When compared to the Acala cotton (Field 5-2), the percent defoliation was considerably less at both seven and 14 DAT, most likely because the Pima cotton is much more difficult to defoliate (Roberts, 2003). On both fields, a greater amount of basal and terminal regrowth was noted at 14 DAT.

<u>Fiber Quality</u>

Cotton lint samples were acquired during harvest, bagged, and shipped to USDA for ginning and classification. Acala cotton samples will be ginned with a saw-type gin, while Pima samples will be ginned using a roller-type gin. Fiber analyses will be conducted with the High Volume Instrument (HVI) (USDA-AMS, 2001) to determine fiber length, uniformity, strength, micronaire, and color. At the time of writing, results of the fiber quality analysis were not yet available.

<u>Yield Data and Net Revenues</u>

Harvest of the study field took place during the last week in October and the resulting yield maps are shown in Figure 14. Analysis of variance was conducted on the yield data for both fields (Figure 15) and no significant differences were found. Analysis of net revenues cannot be performed at this time because the lint quality data is required to determine the appropriate market value for the crop. Upon completion of the lint quality analysis, the net revenues will be determined for each treatment strip and the results will be analyzed.

Conclusions

At this time, the hypotheses pertaining to cotton lint quality and net revenues are not yet tested, as the results of the fiber quality analysis have not been received. Once obtained, the lint data will be analyzed for differences between the variable rate and conventional treatments and an analysis of net revenues will be conducted. The fiber quality data will also be used to determine the appropriate market value for the crop that will be used in the analysis of net revenues and economics.

Plant parameters measured on the Pima cotton (Field 7-2) exhibited strong correlations with the remotely sensed data, while the plant parameters measured on the Acala cotton (Field 5-2) exhibited weak correlations with the image data. Most likely, this was due to the lack of variability present in the Acala study field. For the Pima cotton, LAI and plant height were positively correlated with vegetation indices (NDVI, GNDVI, SAVI), while the percentage of open bolls exhibited a negative relationship with the same indices.

A number of image processing techniques were evaluated for creating harvest aid prescriptions from both airborne and satellite imagery. Mixed results were obtained from both supervised and unsupervised classification algorithms, while thresholding of a GNDVI tended to provide the highest classification accuracies using airborne or satellite image data. A thresholded GNDVI map was used to generate variable rate harvest aid prescriptions that were successfully applied via aerial application methods.

Analysis of seed cotton yield and harvest aid performance evaluation data revealed that variable rate applications did not significantly impact cotton yields, and for the most part, effectiveness was maintained. This year's results correspond to work conducted last year in the Mississippi Delta in terms of yield and harvest aid performance.

Disclaimer

Mention of trade names or commercial products is solely for the purpose of providing specific information and does not imply recommendation or endorsement by the National Aeronautics and Space Administration (NASA), the Institute for Technology Development (ITD), University of California Cooperative Extension, or AZCAL Management.

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Table 1. Harvest aid field measurements.

Measurement	Timing[†]
Leaf Area Index (LAI)	BT
Plant Height	BT
Percent Open Bolls	BT, 7, and 14 DAT
Percent Defoliation	7 and 14 DAT
Percent Desiccation	7 and 14 DAT
Percent Basal Regrowth	7 and 14 DAT
Percent Terminal Regrowth	7 and 14 DAT

[†] BT = before treatment; DAT = days after treatment

Table 2. Wavelengths and bandwidths for the RDACS camera system and the QuickBird satellite.

	Wavelength	Bandwidth
Image Band	nm	
RDACS		
Green	560	40
Red	660	30
Near-infrared	830	70
QuickBird		
Blue	485	35
Green	560	40
Red	660	30
Near-infrared	830	70

Table 3. Image acquisition dates for the RDACS camera system and Digitalglobe's Quickbird satellite.

	Date of Acquisition	
Acquisition	RDACS	QuickBird
1	20 June 2003	20 May 2003
2	26 June 2003	02 June 2003
3	11 July 2003	08 July 2003
4	25 July 2003	26 July 2003
5	11 Aug. 2003	18 Aug. 2003
6	18 Sep. 2003	05 Sep. 2003
7	25 Sep. 2003	23 Sep. 2003
8	06 Oct. 2003	06 Oct. 2003

Table 4. Correlation coefficients for plant parameters and image data for the Acala and Pima cotton study fields.

	Plant Height	LAI	Open Bolls (%)
Image Data	Correlation Coefficient (*r*)		
Acala			
Green	0.03 ns[†]	-0.06 ns	0.10 ns
Red	-0.05 ns	-0.12 ns	0.02 ns
NIR	0.21 ns	0.40	-0.02 ns
NDVI	0.21 ns	0.41	-0.03 ns
GNDVI	0.18 ns	0.43	-0.07 ns
SAVI	0.21 ns	0.41	-0.03 ns
Pima			
Green	-0.55	-0.58	0.66
Red	-0.68	-0.72	0.75
NIR	0.76	0.78	-0.75
NDVI	0.88	0.88	-0.88
GNDVI	0.87	0.87	-0.89
SAVI	0.88	0.88	-0.88

[†] ns = not significant

Table 5. Correlation coefficients for plant parameters and image data with the field scout's rate recommendation.

Field	Plant Height	LAI	Open Bolls (%)	Green	Red	NIR	NDVI	GNDVI	SAVI
	Correlation Coefficient (r)								
Acala	0.21 ns[†]	0.11 ns	-0.38 ns	-0.52	-0.38	0.35 ns	0.57	0.66	0.57
Pima	0.78	0.84	-0.79	-0.53	-0.63	0.75	0.83	0.84	0.83

[†] ns = not significant

Table 6. Accuracy assessment results for Acala and Pima study fields using RDACS and QuickBird imagery.

Field	Dataset	Method	Accuracy Overall	Producer's	User's
			%		
Acala	RDACS	Maximum Likelihood	45	56	48
		ISODATA – 25 Sep. Composite Image	29	30	11
		ISODATA – 25 Sep. Composite Image + NDVI	32	33	11
		ISODATA – 25 Sep. Composite Image + 11 Aug. Composite Image	36	36	44
		GNDVI Threshold	68	60	63
	QuickBird	Maximum Likelihood	64	55	71
		ISODATA – 23 Sep. Composite Image	50	44	38
		ISODATA – 23 Sep. Composite Image + NDVI	32	33	11
		ISODATA – 23 Sep. Composite Image + 18 Aug. Composite Image	32	33	11
		GNDVI Threshold	70	64	67
Pima	RDACS	Maximum Likelihood	56	58	56
		ISODATA – 25 Sep. Composite Image	61	63	73
		ISODATA – 25 Sep. Composite Image + NDVI	71	71	74
		ISODATA – 25 Sep. Composite Image + 11 Aug. Composite Image	36	31	33
		GNDVI Threshold	86	85	85
	QuickBird	Maximum Likelihood	73	67	48
		ISODATA – 06 Oct. Composite Image	71	64	52
		ISODATA – 06 Oct. Composite Image + NDVI	68	65	68
		ISODATA – 06 Oct. Composite Image + 18 Aug. Composite Image	61	62	46
		GNDVI Threshold	89	87	87

Table 7. GNDVI thresholds used develop the prescription maps for the study fields.

Field	Low (Class 1)	Moderate (Class 2)	High (Class 3)
	GNDVI		
Acala	< 0.53	0.53 – 0.59	> 0.59
Pima	< 0.50	0.50 – 0.62	> 0.62

Table 8. Application rates for the harvest aid chemicals.

Class Id	Carrier Volume gal. acre^{-1}	Def 6	Prep
		lb. a.i. acre^{-1}	
1	8	1.0	1.0
2	12	1.5	1.5
3	15	1.9	1.9

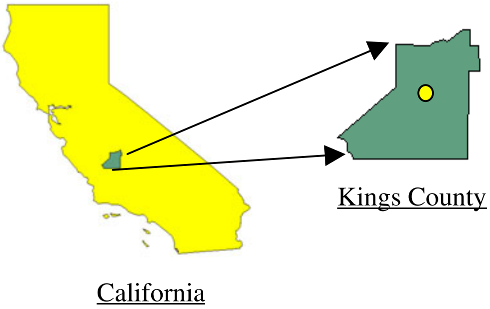

Figure 1. Location of the study site in Kings County near Lemoore, CA.

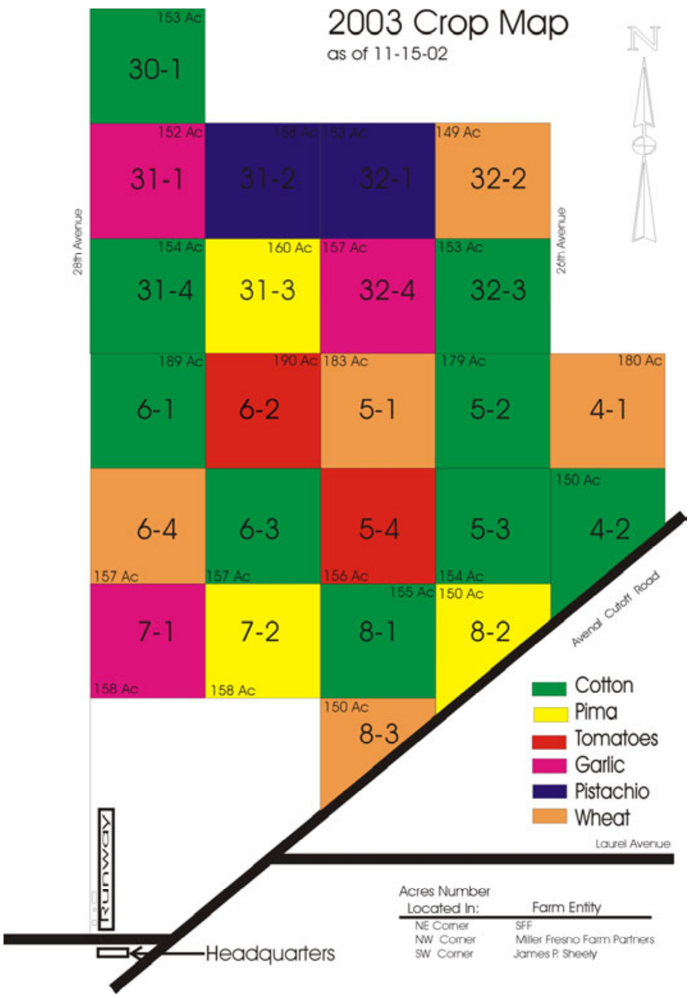

Figure 2. Sheely Farm crop map for the 2003 growing season.

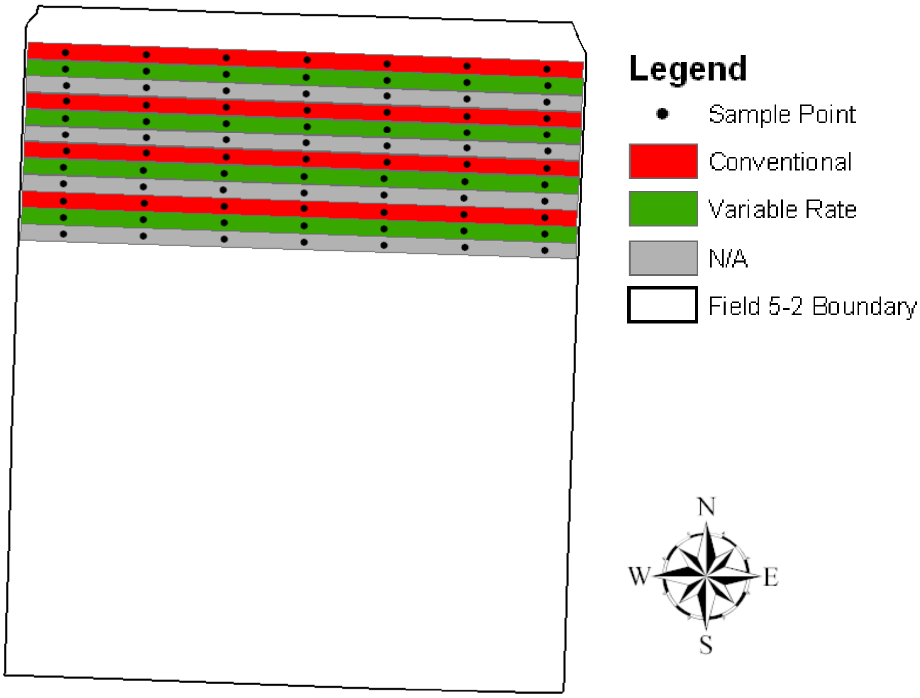

Figure 3. Experiment layout for the Acala cotton study field.

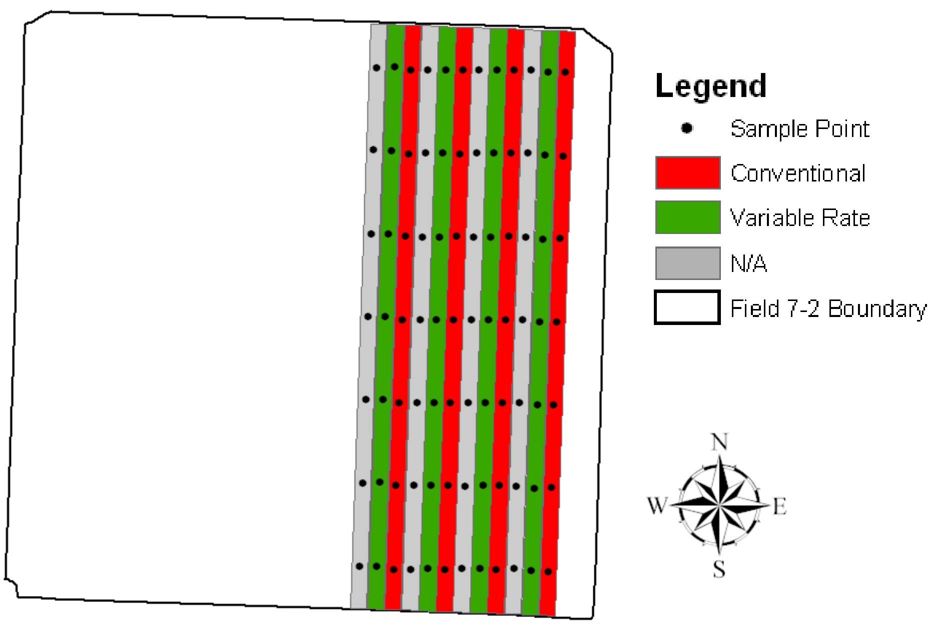

Figure 4. Experiment layout for the Pima cotton study field.

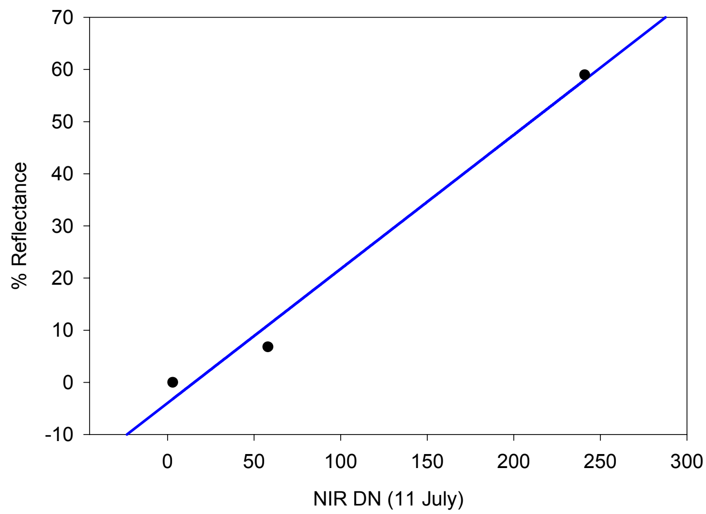

Figure 5. First-order image calibration for the RDACS NIR band on 11 July.

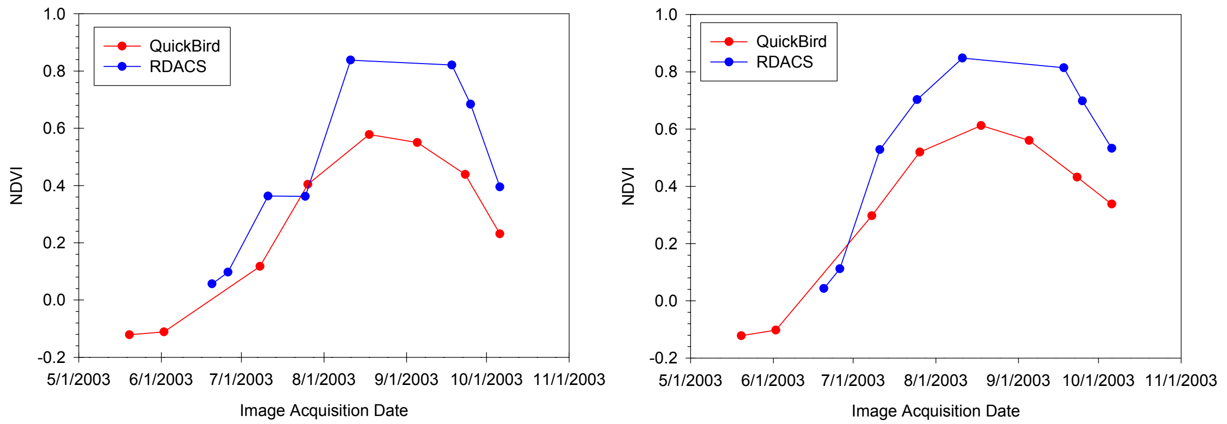

Figure 6. Plot of the field average NDVI versus the date of acquisition for the Acala field (left) and the Pima field (right).

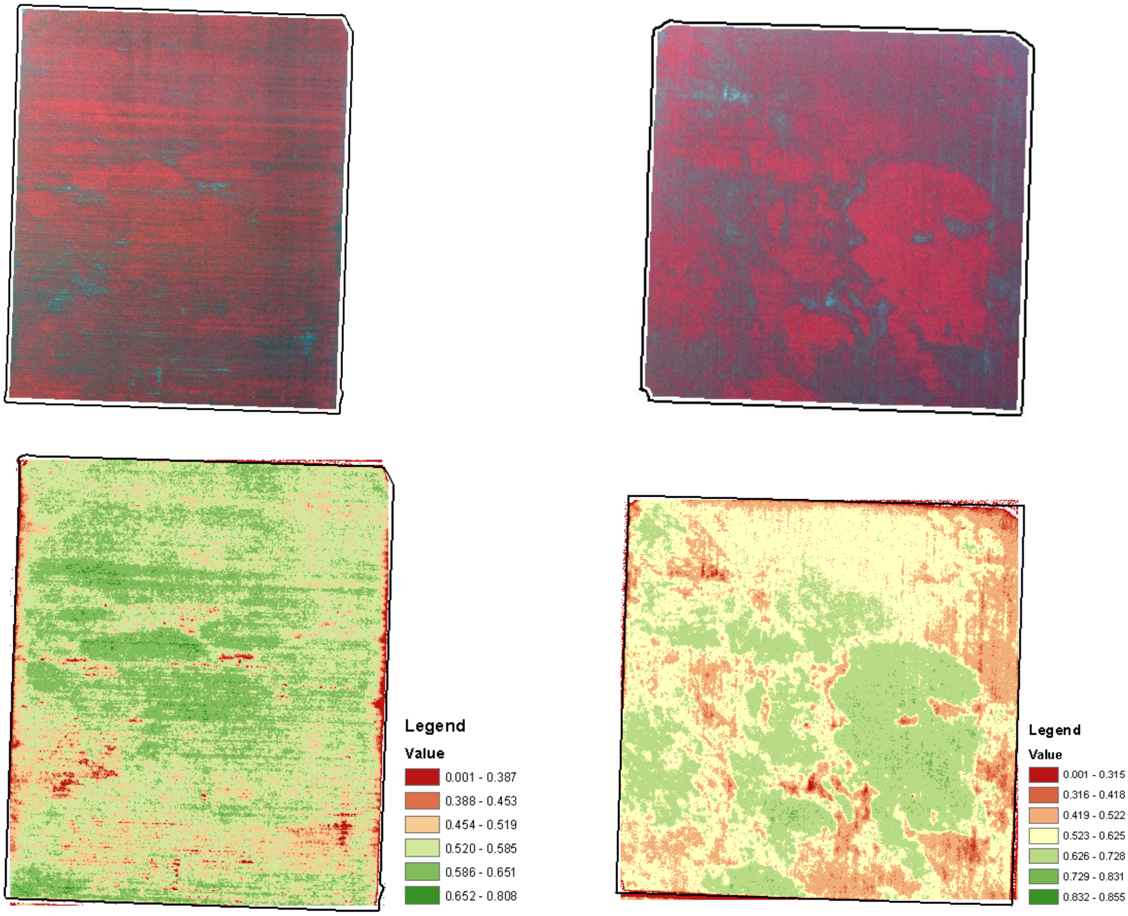

Figure 7. RDACS imagery acquired on 25 Sep. for the Acala (top, left) and Pima (top, right) fields. The GNDVI map for the Acala (bottom, left) and Pima (bottom, right) fields are also shown.

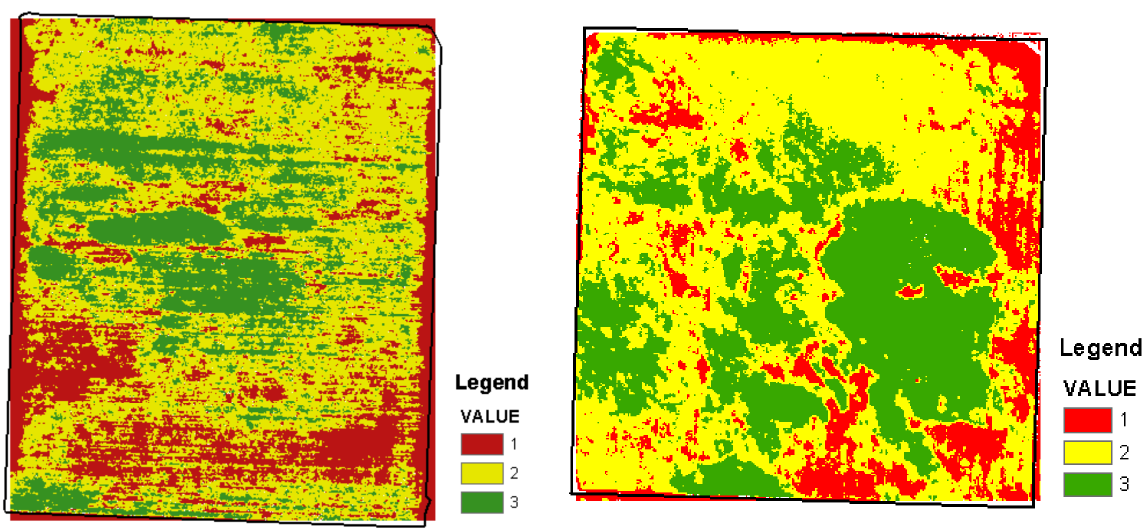

Figure 8. Classified GNDVI maps for the Acala (left) and Pima (right) fields.

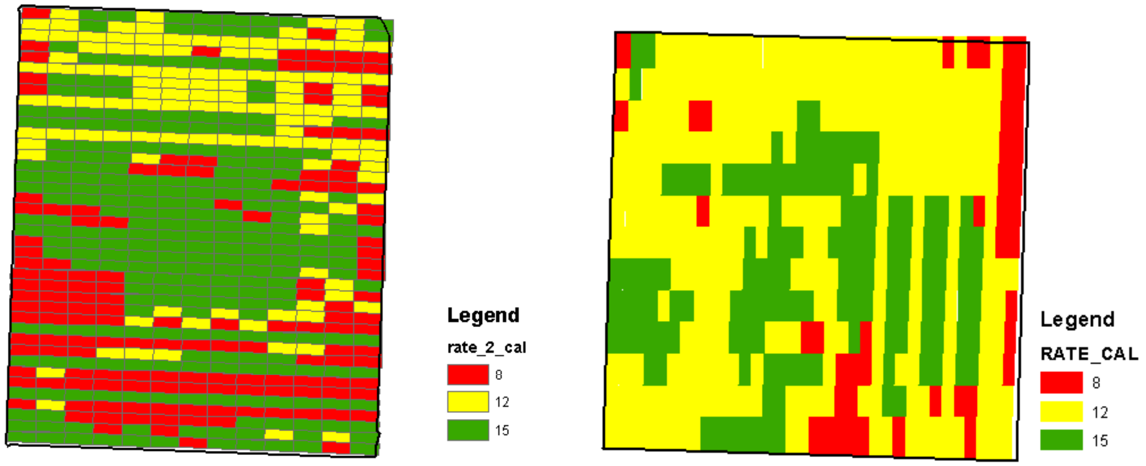

Figure 9. Harvest aid prescription maps for the Acala (left) and Pima (right) fields.

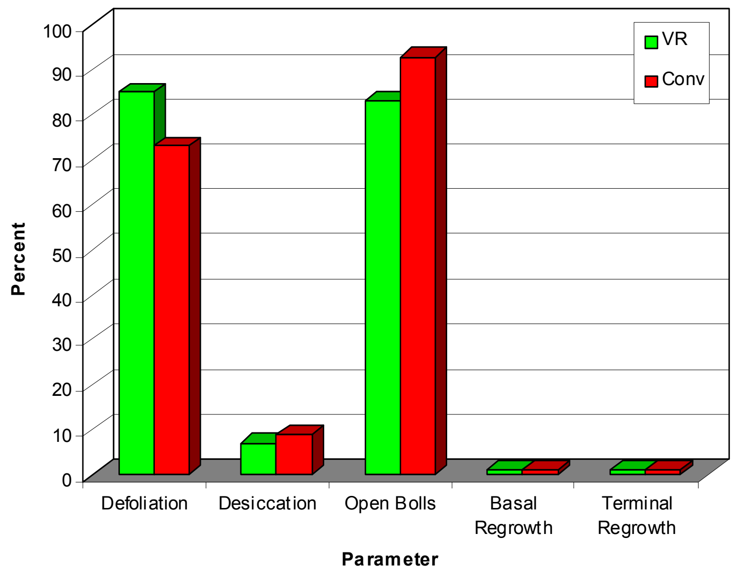

Figure 10. Results of the 7-DAT evaluation on the Acala field. Bars with the same letter are not significantly different according to Duncan's Multiple Range test (alpha = 0.10).

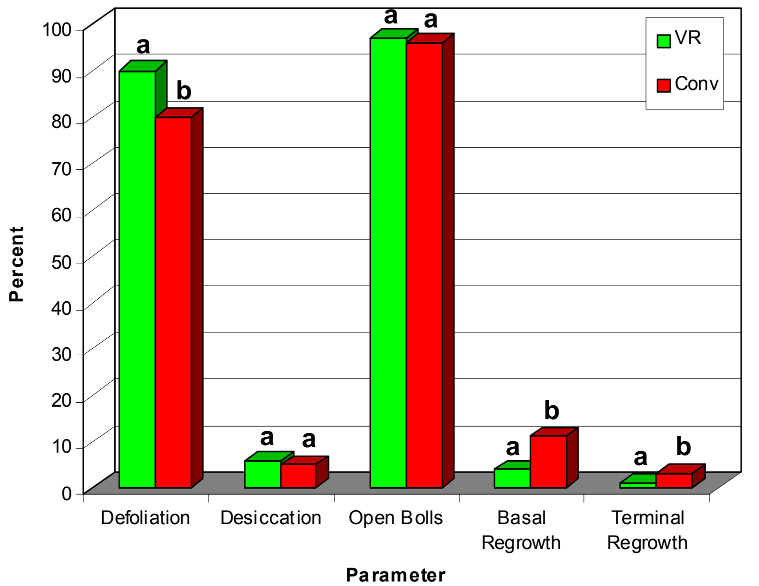

Figure 11. Results of the 14-DAT evaluation on the Acala field. Bars with the same letter are not significantly different according to Duncan's Multiple Range test (alpha = 0.10).

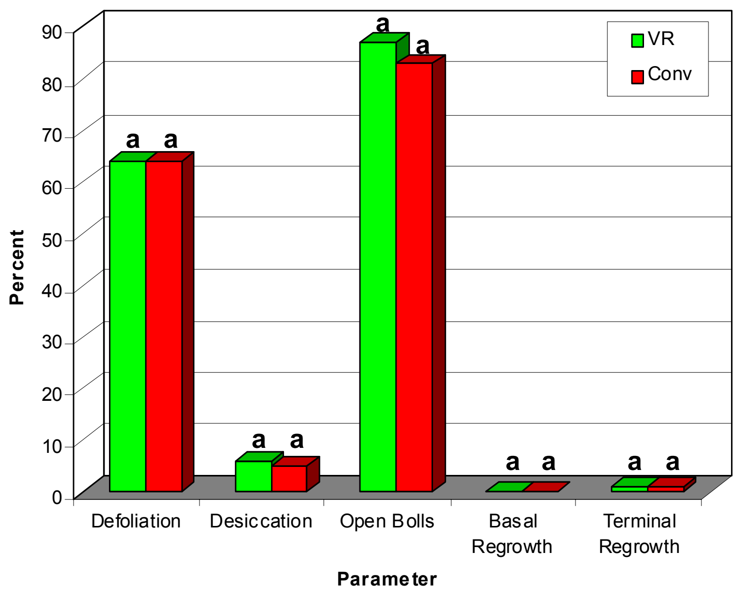

Figure 12. Results of the 7-DAT evaluation on the Pima field. Bars with the same letter are not significantly different according to Duncan's Multiple Range test (alpha = 0.10).

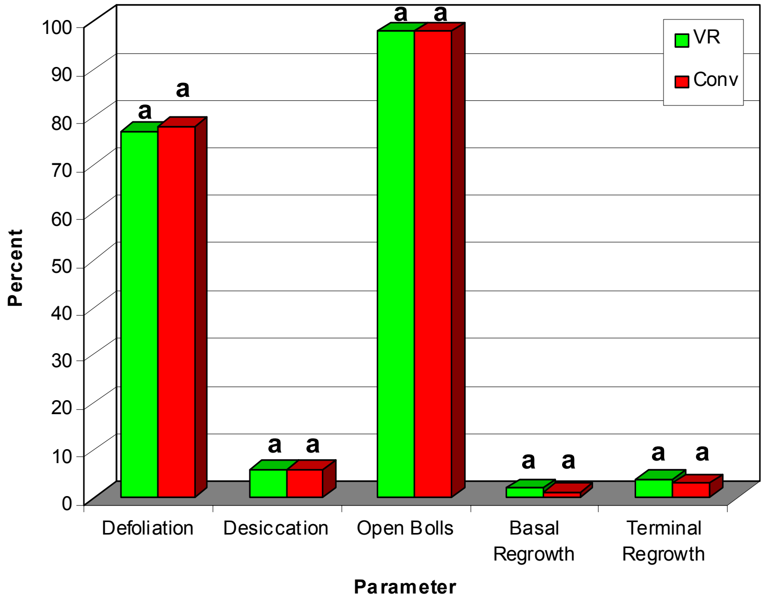

Figure 13. Results of the 14-DAT evaluation on the Pima field. Bars with the same letter are not significantly different according to Duncan's Multiple Range test (alpha = 0.10).

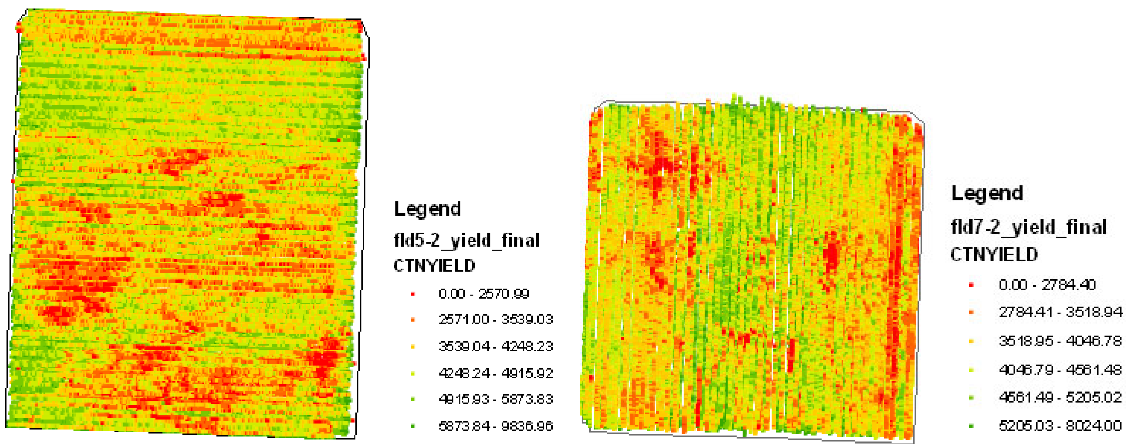

Figure 14. Yield maps from the Acala field (left) and Pima field (right).

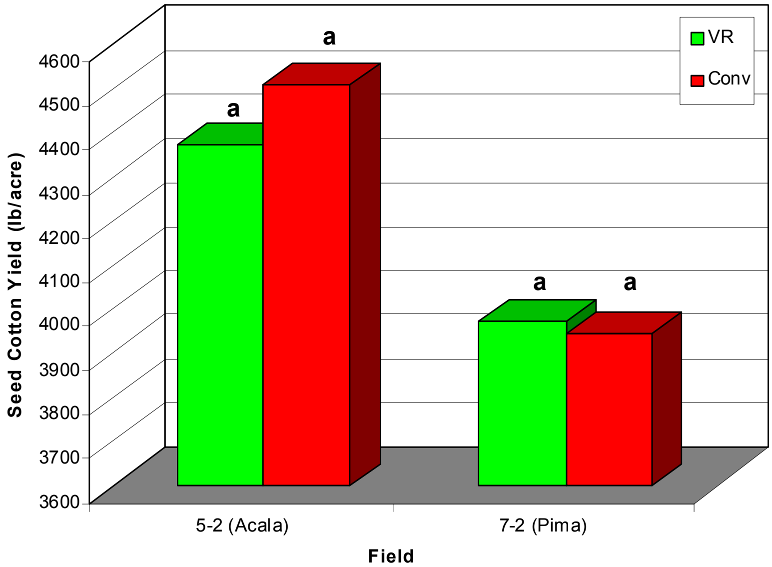

Figure 15. Mean seed cotton yield of conventional and variable rate applications from Field 5-2 (left bars) and Field 7-2 (right bars). Bars with the same letter are not significantly different according to Duncan's Multiple Range test (alpha = 0.10; N = 56).