Making the Replant Decision: Utilization of an Aerial Platform to Guide Replant Decisions in Tennessee Cotton

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Blessed is the one who perseveres under trial because, having stood the test, that person will receive the crown of life that the Lord has promised to those who love him. James 1:12

Abstract

The interest of unmanned aerial systems (UAS) to support management decisions through the use of quantitative data is evaluated in efforts to estimate emerged cotton plant population and stand uniformity. Results suggest plant population and stand uniformity may be successfully estimated from low altitudes of when utilizing an UAV equipped with a multispectral sensor. The provided chapters detail developed methods to determine plant population and stand uniformity through a novel and simplistic process, encompassing efficient geospatial tools. Upon estimation of stand establishment, the provided manuscripts also provide a model for understanding yield potential based upon plant population and planting date. Results indicate stands with uniformity greater than 90% provide optimum yields. Increased plant populations provide optimum yield if planted earlier in the planting window, but reduced stands may become acceptable upon emergence if planted later in the planting window. This dissertation hopes to provide producers an avenue to utilize quantitative UAS data to make the decision of whether to accept or replant a cotton stand more simplistic.

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Part I. Proposal

Introduction

Often one of the most difficult decisions we make in various aspects of life is some form of a committal. One could argue that this holds true when gauging whether to accept a cotton stand or replant. Cotton producers in Tennessee typically target plant populations between 74,000 to 148,000 plants hectare^{-1} in order to achieve optimum yield potentials. In order to provide ample time to produce and mature their crop, growers target planting dates between April 20th and May 10th. However, growers occasionally face poor environmental conditions prior to or after planting which stress emerging seedlings. If these stresses are severe enough to kill a substantial number of the emerging seedlings, a decision of whether to accept or replant the crop must be made. It has been demonstrated that accepting a uniform, lower plant population may provide adequate yields, especially if seeded earlier in the recommended planting window and environmental conditions are favorable (Siebert et al., 2006; Wrather et al., 2008). However, suboptimal populations may delay maturity, increase risk of poor fiber quality, and must be managed for earliness (Jones & Wells, 1998; Wrather et al. 2008). Little has been reported on the effect of poor stand uniformity, although it is theoretically assumed to greatly impact yield potential (Wrather et al., 2008). A model considering cotton plant population, planting date, and stand uniformity to predict lint yield potential may greatly assist in the replant decision making process and provide guidance towards management requirements throughout the season.

Emerged plant counts, commonly referred to as stand counts, are the most utilized method to determine plant population across a given area by today's crop consultants and field scouts. This method consists of selecting and measuring a linear distance of crop row, counting the number of plants within this selected distance, and repeating this practice in random locations throughout a field to estimate the mean plant population. Although this method is fast, the accuracy of this approach is reliant upon a highly uniform plant population across the entire field and quality of the data is highly correlated with the number of measurements collected across the area of interest. Human bias in selecting representative areas of the field also can influence the estimated plant population, naturally skewing the estimation to favor either replanting or accepting a given stand. The described method of stand assessment, however, does not provide an estimation of plant stand uniformity or provide any spatial information within the area of interest. In order to accurately and precisely determine if a cotton plant stand is acceptable or needs to be replanted, an assessor must be able to quickly evaluate the entire field spatially for both plant stand uniformity and population.

One proposed use of unmanned aerial systems (UAS) is to produce quantitative data to support replant decisions by spatially assessing plant stands and uniformity. It has been demonstrated that cotton plants can be sensed remotely utilizing red, green, and blue, near infrared and red edge spectral bands (REF). Theoretically, an aerial approach could provide spatially dense information on these parameters across large areas quickly and remove human bias. Currently, no known aerial assessment tools have been developed to estimate cotton plant population and uniformity.

Upland Cotton

Upland cotton, *Gossypium hirsutum*, is an indeterminate, perennial, dicotyledonous plant grown agriculturally for multiple purposes (Turner et al. 1986). Upland cotton produces a dehiscent fruit that is harvested primarily for lint, but seeds and bracts also provide economic benefits. Upland cotton is grown in primarily 17 states across the southern half of the United States including Alabama, Arkansas, Arizona, California, Florida, Georgia, Kansas, Louisiana, Mississippi, Missouri, New Mexico, North Carolina, Oklahoma, South Carolina, Tennessee, Texas, and Virginia. These states collectively make up what is termed as the “Cotton Belt” in the

U.S (Cotton Inc., 2017). Numerous management decisions, including plant population and planting date, greatly influence growth and development (Jones & Wells, 1998; Smith et al., 1979; Siebert et al., 2008; Wrather et al., 2008). Few studies have been conducted determining the interaction effect of planting date and plant population on cotton lint yield (Wrather et al., 2008). Galanopoulou-Sendouka et al. (1980) first demonstrated effect of population density, planting date, and genotype on growth and development of cotton in Greece. Planting date had the strongest influence on maturity and earliness, while density had the strongest impact on morphological characteristics and yield components. No significant impact was observed amongst the interactions of planting date, population, or selected cultivar on lint yield (Galanopoulou-Sendouka et al., 1980). Wrather et al. (2008) conducted similar work in the Mississippi River Delta Region. The interaction of planting date and plant population was significant, suggesting as population decreased and at later dates, lint yield decreased. Interestingly, lint yield harvested from 17,000 seed hectare^{-1} planted in late April was significantly greater than or equal to all plant populations planted in mid-May. While densities greater than or equal to 2.25 plants row m^{-1} did not significantly impact cotton lint yield, fiber color and maturity was negatively affected (Wrather et al., 2008). It is generally recommended, when making a replant decision, to accept stands when densities are uniform and greater than or equal to 3 plant row m^{-1} (Craig, 2010; Supak, 1990).

Environmental conditions also play a major role on growth and development, especially in northern areas of the cotton belt, such as Tennessee, in which reduced heat accumulation results in shorter growing seasons (Gwathmey and Craig, 2003). In Tennessee, producers have approximately 20 days to plant cotton and ensure stands are adequate (Craig, 2010). Wanjura (1971) developed an emergence model to predict germination and emergence of cotton using an empirical approach. Inputs of temperature, moisture, and physical impedance and outputs of seed moisture and seedling elongation are required by the model. The relationship between radicle emergence and hypocotyl elongation was used to predict emergence. Generally, cotton plants germinate and emerge within 5 to 12 days after planting, leaving limited time to assess plant populations to determine if they are acceptable (Wanjura et al., 1969).

In Tennessee, plant populations between 74,000 to 148,000 plants hectare^{-1} are recommended for optimum yield potential (Main, 2012). Current methodology to assess plant population includes: collecting a minimum of 4 measurements from several representative areas in the field; using the 1/1,000th method where planted row spacing dictates required length of row to count plants from counting the number of plants within this linear distance of row and multiplying by 1,000; and finally averaging these numbers to estimate representative plant population per hectare of the assessed field (Godfrey et al., 2010). Limited reports on the effect of stand uniformity and skip length exist today although Jost (2005) suggested yield reductions may occur with excessive skip lengths greater than 1 meter.

Remote Sensing

As the adoption and integration of precision agriculture increases in crop production, the interest in remote sensing methods continues to rise (Gwathmey et al., 2010). Remote sensing is considered to be an inexpensive source of data for tactical and strategic crop management decision making (Plant et al., 2001). The use of remote sensing in agriculture generally relies on multispectral reflectance data from visible and near infrared ranges of the electromagnetic spectrum to calculate vegetative indices (VI). Vegetative indices are algebraic manipulations of spectral bands with consistent responses to vegetative characteristics of plants (Plant et al., 2001). The most commonly used vegetation index, known as the Normalized Difference Vegetation Index

(NDVI), uses red (650 nm) and near infrared (NIR) (800 – 1100 nm) spectral bands to monitor plant biomass and physiological status (Tucker, 1979).

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

NDVI is highly correlated to the green and red linear relationships of photosynthetically active vegetation, essentially providing the ability to differentiate between living and dead emerged plant tissue. Wiegand et al. (1994) found a significant relationship between yield and seasonal accumulated NDVI values. Plant et al. (2000) demonstrated a positive correlation between cotton yield and NDVI-days. One of the first VI developed was known as the leaf area index (LAI) which is based upon the principle that leaves absorb more red than near infrared light (Jordan, 1969). Jordan used a ratio of 800 nm to 675 nm to create LAI, in which the greater the value, the more leaf area present. LAI quantifies the amount of area of photosynthetic foliage per unit of ground surface area. Another useful vegetative index using red, green, and blue spectral bands, which does not require a multi-spectral reflectance sensor, is the Excess Green Index (ExG) (Torres-Sanchez et al., 2015; Woebbecke et al., 1995). Woebbecke et al. (1995) used this modified hue to distinguish weeds from non-plant backgrounds.

$$ExG = 2G^* - R^* - B^*$$

$$R^* = \frac{R}{R + G + B} \qquad G^* = \frac{G}{R + G + B} \qquad B^* = \frac{B}{R + G + B}$$

Stand Evaluation with Aerial Imagery

When crop scouts and consultants look to evaluate cotton plant stands today, they typically will use what is referred to as the 1/1000th method, however, this method relies on a consistently uniform stand across the entire field, can be heavily influenced by human bias, and is limited both spatially and temporally. Models have been developed to calculate plant populations or stand uniformity in some cotyledonary-stage, major agronomic field crops using aerial imagery. Shrestha and Steward (2003) first successfully created an automated corn plant population measurement by segmenting and singulating corn plants within sequenced video frames from a vehicle-mounted digital video camera. Total number of plants pixels and their median positions were extracted from each pixel row, grouped together and iterated to count corn plants between the V3 and V4 stages. Work was continued (2005) for attempted improvement by using image segmentation to detect plant boundaries using chain code methodology and accounting for spatial structure of the crop row. Thorp et al. (2008) expanded upon this work by utilizing the developed segmentation tool combined with hyperspectral reflectance data to estimate corn plant density in various vegetative and reproductive stages of corn. Various spatial resolutions were utilized to evaluate reflectance of segmented plants within each raster to estimate the number of plants contained. Principal component regression was utilized for assessment of plant stand density and hyperspectral reflectance at the varying spatial resolutions. Huang et al. (2010) successfully predicted soil and crop canopy coverage variability using aerial multispectral images and spatial regression modeling. The use of ordinary least squares (OLS) multiple linear regression, spatial regression, and REML-geostatistics indicated that aerial images could be used for spatial prediction of soil and crop canopy coverage.

Other practical uses for estimating emergence include field based crop phenotyping. Sankaran et al. (2015) demonstrated the ability to strongly correlate aerial evaluations of winter wheat emergence and spring stand to ground-truthed visual ratings through the use of the Green Normalized Difference Vegetation Index (GNDVI) for breeding efforts. Some issues have been noted when attempting to determine plant density using stitched orthomosaic datasets. Jin et al. (2017) estimated wheat density using Meyer-Neto Vegetation Index (MNVI), which is the difference between ExG and Excess Red Index (ExR) (Meyer & Neto, 2008). Additionally, they identified the significant degradation of image quality when using orthomosaics, and used orthorectified images for plant density estimations, allowing work on original, undistorted images (Jin et al., 2017).

Although cotton plant stand uniformity is critical to ensure adequate yield potential, a consistent, practical method of determining uniformity has not been developed and adopted. Without a quantifiable means of identifying the uniformity of a cotton crop stand, it is impossible to understand the magnitude of which in-row skips maybe be negatively impacting yield potential. Methods of determining uniformity have been developed in a few other row crops. Tang and Tian (2008) developed image processing algorithms that utilized corn plant color, morphological features, and crop row center to automatically quantify corn plant spacing measurements through the use of color-based segmentation. In order to successfully quantify skip length and stand uniformity, one must first be able to recognize the crop row. The Hough transformation is often used to detect complex patterns of points and has successfully been utilized to detect crop rows by its reliance on parameterization (Duda & Hart, 1972; Perez-Ortiz et al. 2015). Object-based image analysis (OBIA) has also been demonstrated as a successful method to identifying crop rows (de Souza et al., 2017; Perez-Ortiz et al., 2016; Torres-Sanchez et al., 2015). OBIA approach identifies similar spatial and spectral objects, created by grouping in a segmentation process, that can be used as the basic elements for analysis (de Souza et al., 2017). De Souza et al. (2017) were able to successfully create maps identifying and quantifying skip lengths in sugarcane through a process of obtaining images, calculating NDVI, filtering and thresholding, identifying rows, segmenting, removing outliers, classifying crop rows, classifying sugarcane rows and then erasing, and creating maps including areas in which should have been encompassed by a sugarcane row (de Souza et al., 2017).

Objectives

1. Investigate the ability of an unmanned aerial system to accurately determine varying plant populations of cotton.
2. Determine the influence of planting date and plant population on cotton lint yield potential.
3. Assess the ability of an unmanned aerial system to estimate cotton stand uniformity.

Studies will be conducted under field conditions with heavy reliance on image analysis and potential developed scripted programming. All developed programs will be generated considering the severity of turn-around time, such that methods may not possess value if processing is extended over multiple days. The outlying goal upon completion of the proposed work is to develop a streamlined software program for distribution to cotton scouts and producers, allowing a platform to upload field images and generate prescription maps with supporting data suggesting where and when to replant cotton stands.

Hypotheses

Objective 1

It is hypothesized that:

1. The use of multi-spectral reflectance data will accurately predict cotton plant population.
2. Population estimation accuracy will decrease as image acquisition altitude increases due to reduced spatial resolution.

Objective 2

It is hypothesized that:

1. Dependent on field environmental variability, cotton lint yield will decrease as plant population decreases to less than 1 plant row m^{-1}.
2. Cotton lint yield will steadily decrease as plant date increases.

Objective 3

It is hypothesized that:

1. The use of multi-spectral reflectance data will more accurately predict cotton stand uniformity.
2. As skip length and amount of large skips increase, uniformity and cotton lint yield will decrease.

Part II. Making the Cotton Replant Decision: A Novel and Simplistic Method to Estimate Cotton Plant Population from UAS-calculated NDVI

Abstract

One proposed use of unmanned aerial systems (UAS) in crop production is to produce quantitative data to support replant decisions by assessing plant stands. Theoretically, analysis of UAS imagery could provide spatially dense information on plant populations across large areas quickly and remove human bias. Therefore, the objective of this research was to investigate the ability of UAS to accurately determine varying plant populations of cotton (*Gossypium hirsutum*, L.). Field studies were planted in Jackson, Milan, and Grand Junction, Tennessee in three consecutive growing seasons. Treatments were replicated four times and included five seeding rates of 8,500 to 118,970 seeds hectare^{-1} producing a range of plant populations. After emergence, cotton plant stands were manually counted and images were obtained from two cameras, in respective years, mounted beneath a quad-copter UAS flying at altitudes of 30, 60, 75, and 120 m. Spectral properties of soil, residue and plant material were assessed to generate NDVI thresholds which were used to limit the analysis to only plant material. Images were then processed and analyzed for estimated number of plants and compared to actual plant populations within each plot. Images obtained from lower altitudes proved to be more successful, with greatest correlations to actual ground-truthed plant population at altitudes of 30 meters. Based on results, the utilization of the described novel, yet simplistic, method of estimating cotton plant population from NDVI-calculated UAS imagery may improve upon spatial and temporal efficiency in comparison to current methodology.

Introduction

Upland cotton (*Gossypium hirsutum*, L.) is an indeterminate, perennial dicotyledonous plant grown agriculturally for multiple purposes (Turner et al. 1986). Upland cotton produces a dehiscent fruit that is harvested primarily for lint, but seeds and bracts also provide economic benefits. Upland cotton is grown in17 states across the southern half of the United States including Alabama, Arkansas, Arizona, California, Florida, Georgia, Kansas, Louisiana, Mississippi, Missouri, New Mexico, North Carolina, Oklahoma, South Carolina, Tennessee, Texas, and Virginia. These states collectively make up what is termed as the “Cotton Belt” in the U.S. Numerous management decisions, including plant population and planting date, highly influence cotton growth and development. Environmental conditions also play a major role on growth and development, especially in northern areas of the Cotton Belt such as Tennessee, in which reduced heat accumulation results in shorter growing seasons (Gwathmey and Craig, 2003). In Tennessee, producers have an approximately 20-day window to plant cotton and insure stands are adequate, with dates ranging from April 20 to May 10 (Craig, 2010). Generally, cotton plants germinate and emerge within 5 to 12 days after planting depending on conditions, leaving limited time to assess if plant populations in fields are acceptable (Wanjura et al., 1969). Wanjura (1971) developed an emergence model to predict germination and emergence of cotton using a general “black box” analysis approach. Inputs of temperature, moisture, and physical impedance and outputs of seed moisture and seedling elongation were known. Dynamic relationships were formed within radicle emergence and hypocotyl elongation modeling to predict emergence. With upland cotton, establishing plant populations between 75,000 and 150,000 plants ha^{-1} is recommended for optimum yield potential (Main, 2012).

As the adoption and integration of precision agriculture continues to increase in crop production, the interest in remote sensing methods continues to increase (Gwathmey et al., 2010). Remotely sensed data can be an inexpensive source for tactical and strategic crop management decision making (Plant et al., 2001). The use of remote sensing in agriculture generally relies on multispectral reflectance data from visible and near infrared ranges of the electromagnetic spectrum to calculate vegetation indices (VI). Vegetation indices are algebraic manipulations of spectral bands with similar responses to vegetative characteristics of plants (Plant et al., 2001). One of the first VI developed was known as the leaf area index (LAI) which is based upon the principle that leaves absorb more red than near infrared light (Jordan, 1969). Jordan used a ratio of 800 nm to 675 nm to create LAI, for which the greater the value, the more leaf area present. LAI quantifies the amount of area of photosynthetic foliage per unit of ground surface area. The most commonly used VI, known as the Normalized Difference Vegetation Index (NDVI), uses red (~600 to 700 nm) and near infrared (NIR) (~700 to 800 nm) spectral bands to monitor plant biomass and physiological status (Tucker, 1979).

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

NDVI is highly correlated to the green and red linear relationships of photosynthetically active vegetation, essentially providing the ability to differentiate between living and dead emerged plant tissue. In-season NDVI data has been shown to correlate to cotton yields. Weigand et al. (1994) found a significant relationship between yield and seasonal accumulated NDVI values. Plant et al. (2000) demonstrated a positive correlation between cotton yield and NDVI-days modeling.

From our knowledge, no models have been developed to calculate plant populations of cotyledon stage cotton. With respect to other crops, Shrestha and Steward (2003) first successfully created an automated corn plant population measurement by segmenting and singulating corn plants within sequenced video frames from a vehicle-mounted digital video camera. Total number of plant pixels and their median positions were extracted from each pixel row, grouped together and iterated to count corn plants between the V3 and V4 stages. Work was continued (2005) for attempted improvement by using image segmentation to detect plant boundaries using chain code methodology and accounting for spatial structure of the crop row. Thorp et al. (2008) expanded upon this work by utilizing the developed segmentation tool combined with hyperspectral reflectance data to estimate corn plant density in various vegetative and reproductive stages of corn. Various spatial resolutions were utilized to evaluate reflectance of segmented plants within each raster to estimate the number of plants contained. Principal component analysis was utilized for assessment of plant stand density and hyperspectral reflectance at the varying spatial resolutions. Huang et al. (2010) successfully predicted soil and crop canopy coverage variability using spatial regression modeling on aerial multispectral images. The use of ordinary least square (OLS) multiple linear regression, spatial regression, and restricted maximum likelihood (REML)-geostatistics indicated that aerial images could be used for spatial prediction of soil and crop canopy coverage (Huang et al., 2010). Other practical uses for estimating emergence include field-based crop phenotyping. Sankaran et al. (2015) demonstrated the ability to strongly correlate aerial evaluations of winter wheat emergence and spring stand to ground-based visual ratings with the Green Normalized Difference Vegetation Index (GNDVI). Jin et al. (2017) estimated wheat density using Meyer-Neto Vegetation Index (MNVI), which is the difference between Excess Green Index (ExG) and Excess Red Index (ExR) (Meyer & Neto, 2008).

Today, emerged plant counts, commonly referred to as stand counts, are the most utilized method to determine plant population across a given area (Godfrey et. al., 2010; Main, 2012). This method consists of selecting and measuring a linear distance of plant row, counting the number of plants within this selected distance, and repeating in random locations throughout a field to estimate the mean plant population. Distances of row selected are typically based upon the 1/1000th method (Godfrey et al., 2010). When using this method, the assessor determines row m ha^{-1} and divides this number by 1000. The resulting number defines the distance in which the assessor would measure and the assessor counts the number of emerged plants within this area. Once the number of plants is obtained, the assessor multiplies by 1000 to reach an estimate of the total number of emerged plants within a hectare. Although this method requires little time, the approach is reliant upon a highly uniform plant population across the entire field and can be spatially limited. Human bias in selecting areas of the field also influence the estimated plant population, naturally skewing the estimation to favor either replanting or accepting a plant stand. The described method, however, does not provide an estimation of plant stand uniformity, or detail in a site-specific manner into the areas that possess inadequate populations. In order to accurately determine if a cotton plant stand is acceptable or needs to be replanted, an assessor must be able to evaluate the entire field for both uniformity and plant population.

Theoretically, analysis of UAS imagery could provide spatially dense information on plant population and uniformity across large areas quickly. Therefore, the objectives of this research were: (1) to develop and investigate a simplistic, novel method of processing UAS imagery for the estimation of cotton plant populations and (2) to determine optimum altitude of data acquisition for these estimations.

Material and Methods

Field Site Establishment and Management

Field studies were established in 2016-2018 at Ames Plantation in Grand Junction, TN; the West Tennessee Research and Education Center (WTREC) in Jackson, TN; and the Milan Research and Education Center (MREC) in Milan, TN. Treatments consisted of the following five seeding rates: 10.5 seed m^{-1} (118,970 seeds ha^{-1}), 6.75 seed m^{-1} (76,480 seeds ha^{-1}), 3 seed m^{-1} (33,990 seeds ha^{-1}), 1.5 seed m^{-1} (17,000 seeds ha^{-1}), and 0.75 seed m^{-1} (8,500 seeds ha^{-1}). Each trial was managed without tillage (no-till) and utilized a randomized complete block design

Table 1. Planting dates for 3 trial locations during the 2016-2018 growing seasons.

Year	Location		
	Ames Plantation	WTREC	MREC
2016	10-May	-	-
2017	18-May	16-May	17-May
2018	4-May	3-May	15-May

containing 4 replications. Plot size consisted of four rows 9 m in length. Row spacing for all trials equaled 96.5 cm. DeltaPine 1522 B2XF (Monsanto Co., St. Louis, MO), was planted on the dates listed in Table 1. All in-season management practices followed the University of Tennessee Extension Service recommendations for cotton production (Main, 2012), and decisions were based upon growth and development of the 118,970 seeds ha^{-1} plots.

UAS and Ground-Truthing

After full emergence and prior to harvest, the number of plants within each row of each plot were manually counted. During 2016 and 2017, aerial imagery was collected by a custom built quad-copter equipped with a MicaSense RedEdge (MicaSense, Seattle, WA), while in 2018, aerial imagery was collected by a DJI Inspire 2 (SZ DJI Technology Co., Ltd., Shezen, Guangdong) equipped with a Sentera Double 4K (Sentera, Minneapolis, MN) multispectral sensor (Table 2.). Changes in sensors was the result of available equipment. Both sensors were set to

Table 2. UAS multispectral sensor specifications

Sensor	Ground Sampling Distance (cm/pixel)				Sensor Width (mm)	Focal Length (mm)	Image Width (pixels)	Image Height (pixels)
	Flight Altitude (m)							
	30	**60**	**75**	**120**				
RedEdge	2.1	4.2	5.2	8.3	4.8	5.4	1280	960
Double 4K	0.9	1.72	2.2	3.4	6.2	5.4	4000	3000

Sensor	Spectral Resolution			
	Red Band (nm)		Near-Infrared Band (nm)	
	Center Wavelength	Bandwidth	Center Wavelength	Bandwidth
RedEdge	668	10	840	40
Double 4K	650	70	840	20

factory designated settings for spatial resolution. In 2016 and 2017, autonomous flight patterns were generated using Mission Planner (ArduPilot, Indianapolis, IN), while in 2018, Sentara's proprietary flight program, Field Agent, was used to generate grids. Flights were arranged in a serpentine "lawn-mower" pattern perpendicular to the planted rows at altitudes of 30, 60, 75, and 120 m above ground level (AGL) and 80% image overlap and sidelap. Upon acquisition, images were collected and stored to portable microUSB drives and data was uploaded to a laptop computer for further analysis. Images were subjected to Pix4Dmapper (Pix4D Inc., San Francisco, CA) and orthomosaics were generated, resulting in a 16-bit geotiff file (.tif) with a single image of the plot area of interest and embedded metadata.

Plant Population Estimation Thresholding and Processing

Plant population estimations were generated within ArcMap 10.6 (ESRI, Redland, CA). A Python script was constructed within PythonWin (Python Software Foundation, Beaverton, CA) to streamline the analysis process (Figure 1.). The ArcPy command prompt was called for utilization of ArcGIS tools. Values within the resulting rasters were reclassified as either cotton plants, soil, or field residue using the Reclassify tool in the Spatial Analyst toolbox. Threshold values for respective cameras were developed by determining value ranges for cotton plants, soil, and field residue. Ranges were generated by manually selecting plants until maximum and minimum values were acquired. Values outside of these ranges were excluded and mean values were calculated. Ranges for each respective image classification parameter were compared, and threshold ranges were established. The raster was subjected to the Raster to Polygon tool within the Conversion toolbox producing an area measurement for each individual polygon in the attribute table, reflected as respective cotton plants. Using the Add Geometry Attributes function, a new field containing each area measurement was added to the vector layer attribute table. The Update

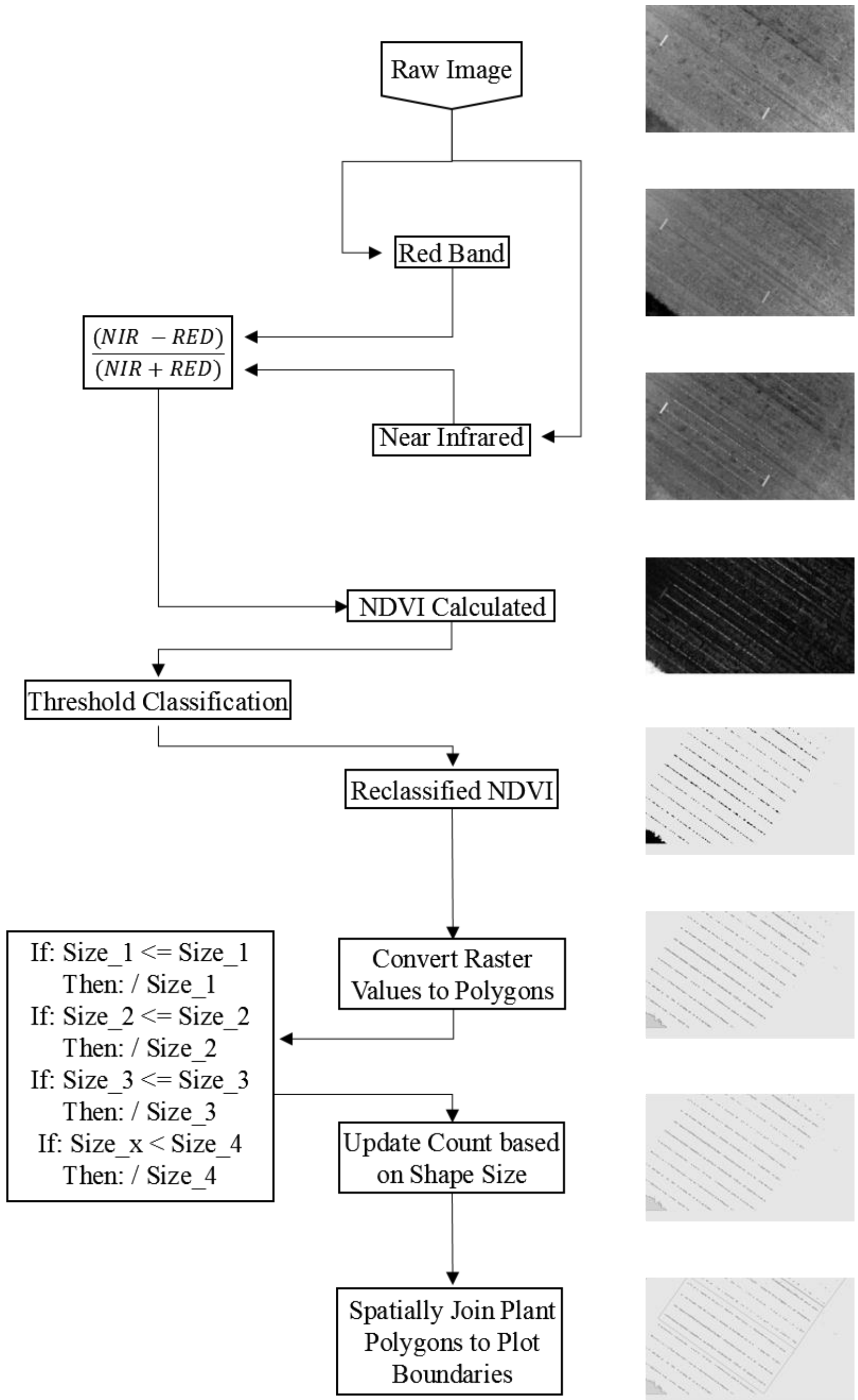

Figure 1. Flowchart illustrating stages of cotton plant population estimations for UAS imagery. First step: calculating NDVI, second step: thresholding image to select for cotton cotyledons, third step: convert raster data to vector data, resulting in polygons for individual or groups of plants, fourth step: update count based on size of plants to account for overlapping cotyledons, final step: summate number of estimated plants within boundary of interest

Cursor feature was used to threshold plant areas to minimize the number of plants represented by multiple pixels within the prior raster. The Search Cursor function was then used to identify areas for each polygon within the attribute table. To distinguish multiple plants within a row that may have closely bordered or overlapped their neighbor, a *for* loop was coded, where each of the 4 smallest areas were divided by themselves such that they would equal to one. All areas larger than the 4th smallest polygon area were divided by the value of the 4th smallest polygon area and products were recorded within the attribute table. Polygons with resulting values greater than 1 were considered to be overlapping or closely bordering cotton cotyledons. Polygons were constructed for each individual plot area and data was spatially joined from the concluding layer feature class to each plot; plants were counted by calculating the sum within each plot.

Statistical Design and Analyses

To understand the accuracy of the threshold and method across increasing altitude, estimated plant populations for each respective altitude were subjected to dummy regression (indicator variable) statistical analysis in SAS v 9.4 (SAS Institute, Cary, NC). Dummy regression is particularly beneficial when both analysis of variance (ANOVA) and regression terms are of interest. Upon evaluating the full model in which all parameters are unequal, non-significant terms were identified and removed. Significance levels were set at an alpha-level equal to 0.05. Slopes were compared for trueness, with values closest to 1 representing greater accuracy. To evaluate accuracy of the described method to current scouting methods, all actual plant populations for each trial location were summated to be considered a simulated field. One row from the first replication of each treatment at each location was selected and plant populations ha^{-1} were calculated using the 1/1000th method described in Section 1. Current stand count estimations and simulated field populations were subjected to simple linear regression in JMP 14 (SAS Institute, Cary, NC).

Coefficient of determination and slope values amongst the two methods were compared for accuracy differences.

Results and Discussion

Cotton Plant Identification

The described simplistic method to identify emerged cotton plants using calculated NDVI proved to be successful, consistent with previous work on corn, sunflower, sugarcane, and wheat (de Souza et. al., 2017; Torres-Sanchez et. al., 2015). For analysis of images acquired from the RedEdge sensor, NDVI values ranging from 0.24 to 1.0 were considered plants, while values less than 0.24 were not included in further analyses (Table 3.). For the Double 4K sensor, NDVI values ranging from 0.23 to 1.0 were considered plants, while values less than 0.23 were not included for further analyses. The described method of thresholding bordering or neighboring plants based upon pixel size was noted to have the least scatter at lower plant populations. Accuracy at lower populations is of greater importance in that these plant density ranges will most commonly provoke the decision of replanting or accepting the emerged stand. Soil type, light intensity, plant reflectance, and other factors may influence values from field to field or site to site within a field. Calibration methods or the use of training data has been demonstrated to improve accuracy and detection of plant density and in-row skip lengths (Perez-Ortiz et. al., 2016; Souza et. al., 2017). The development of a calibration procedure may have the potential to improve accuracy using the described method when analyzing imagery in different environments.

Table 3. NDVI Plant Thresholding Parameters

Sensor	NDVI		
	Cotton	**Residue**	**Soil**
	Value Range		
RedEdge	0.24 - 0.76	0.06 - 0.2	-0.05 - 0.1
Double 4K	0.23 - 0.91	-0.64 - 0.35	-0.34 - 0.13
	Mean Value		
RedEdge	0.55	0.11	0.08
Double 4K	0.46	-0.26	-0.04

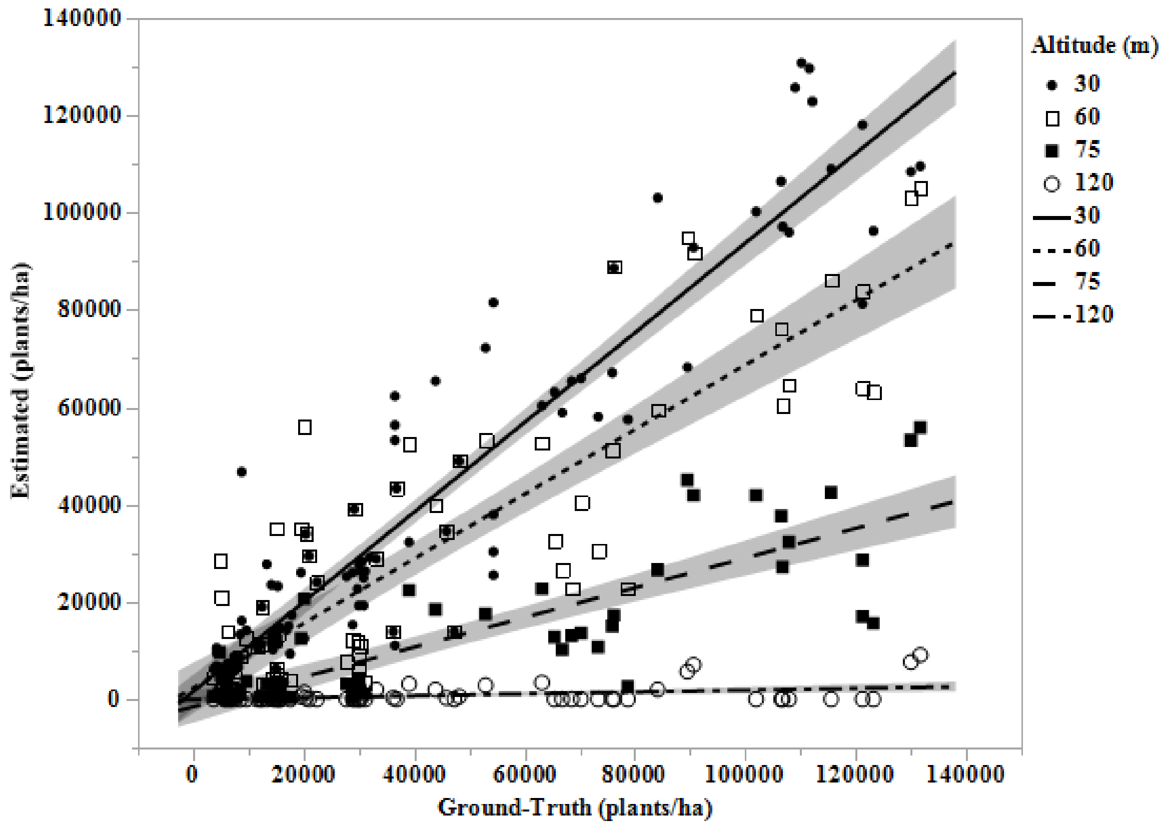

Figure 2. Dummy Regression Analysis of Estimated vs. Actual Plants by Altitude (m)

Altitude analysis

Primary differences were the result in change in spatial resolution and image quality, impacted by the increase in flight altitude. Linear regression lines separately fit flight altitudes of 30, 60, 90, and 120 meters using dummy regression modeling (Figure 2.). The model explained for approximately 88% of amongst plant population estimations at the varying flight altitudes (Table 4.). ANOVA tests demonstrated that treatment intercepts did not differ (P=0.5457), although slope differences were highly significant (P<.0001) (Table 4.). Images obtained from 30 meters were demonstrated to possess the greatest accuracy using the described methodology with a linear slope of 0.903, explained by greatest spatial resolution. As flight altitude increased and spatial resolution decreased, slope also decreased, with equaling 0 at 120 meters. The linear regression slope and coefficient of determination for plant estimations at 30 m altitude was

Table 4. Dummy Regression Analysis of Estimated vs. Actual Plant Population by Altitude (m)

Altitude (m)	Slope	Pr > F*
30	0.903	<.0001
60	0.645	<.0001
75	0.286	<.0001
120	0.000	<.0001
Intercept	Pr > F = 0.5457	
R^2	0.8771	
CV	48.506	
RMSE	10874.92	
Mean	22419.78	

***Significance levels based upon an alpha-level equal to 0.05**

nearly identical to previous work conducted by Shrestha et. al. (2001) in which a digital camera was mounted to a ground traveling vehicle at a height of 0.6 m. This decrease in slope can be directly interpreted as an increased number of false negatives (uncounted plants) as spatial resolution dissolved from increases in flight altitude. This is consistent with work conducted on wheat plant density by Jin et. al. (2017). It is suspected the increase in ground sampling size as altitude increased (Table 2) relative to the static size of each emerged plant prevented the sensor from reading reflectance values above the defined thresholds at greater altitudes. Although an acceptable level of error based on the relationship between plant population and yield must be determined, it is likely a balance between error and temporal efficiency will be reached between the 30 and 60m altitudes using factory sensor settings.

NDVI versus Physical Estimations

When interpreting the simple linear regression of simulated 1/1000th method plant population estimation to the total number of plants within the trial area, data was highly correlated with a coefficient of determination equal to 0.971 (Table 5.) Trueness was also high with a slope equaling 0.9606. This strong correlation would be expected as uniform treatment populations were established in areas of very limited variability. While RMSE was better for the 1/1000th method than the UAS approach, as expected, the benefit was marginal. One noted issue with population

Table 5. Correlation of 1/1000th Method to Summated Plant Population of Trial Locations

Slope	0.9606
Intercept	2821
R^2	0.971
RMSE	3477
Pr > F	0.0003
1/1000th Mean	40573
Total Plant Mean	42358

***Significance levels based upon an alpha-level equal to 0.05**

assessment from an aerial image is overlapping cotyledons; the approach described here occasionally fails to differentiate plants which are growing very closely together. This error should be acceptable in cotton for two reasons. First, cotton planted 74,000 to 148,000 plants ha^{-1} typically results in a 7-12 cm within-row gap between cotton plants; subsequently, overlapping cotyledons should only occur occasionally. Second, actual plant population will have less of an influence on yield than the uniformity of the stand. As a compensatory plant, the yield potential of one, two or three plants in a cluster will closely match the yield potential of a single plant. The most important component of making the replant decision in cotton is the identification and quantification of skips (Craig, 2010). This is particularly beneficial in a sense that methods of distinguishing plant uniformity and spacing (skips) may also have potential to be quantified by further analysis from the existing thresholding method.

Sensor Comparison

While multiple sensors were not compared within the scope of this study, differences were noted and may have negatively impacted accuracy. Although the Sentera Double 4K imagers have much higher spatial RGB resolution than the Micasense RedEdge, lower spectral resolution prevented the Double 4K from successfully separating living plant material from soil/residue through the use of NDVI due to the constraints on returned values. The red wavelength highly influences the determination of NDVI values, and the wide bandwidth limited the imagers ability to distinguish minor differences in the reflectance of cotton plants and field residue in the red color spectrum. Comparably, the lower spatial resolution of the Micasense RedEdge factory settings caused limitations using the described thresholding method at higher altitudes. As new sensor technology is released, utilizing a camera with narrow bandwidths and high spatial resolution may improve temporal efficiency, by increasing flight altitudes without spatial resolution limitations. The Sentera Double 4K may also currently have greater potential to assess cotton plant population from higher altitudes with factory sensor settings if using RGB based imagery.

Conclusion

Cotton producers need quicker, site-specific methods to determine plant populations. The described methods of estimating plant population from multispectral images acquired from an UAS have the potential to provide growers with population estimates along with detailing in what specific areas of a field stand is inadequate. Estimations from low altitudes were highly correlated to the number of actual plants.

Estimating plant populations with aerial imagery will significantly reduce the amount of time required to assess a field and will provide more spatially dense, site-specific information. Although some error will likely be introduced with a UAS system, this error is countered by a complete assessment of all areas of the field and is contrasted by the limited spatial density of measurements collected by a field scout. The major limitation of image acquisition falls upon the utility of the UAS, such that battery life and field of view determine the amount of time required to cover the scope of the field. Other potential issues with the currently described methods include the threshold or reclassification portions of the models. Further development of the described method to include training data may not only improve overall accuracy, temporal efficiency may also be positively influenced as images from higher flight altitudes with current sensor technology may become more functional.

Program Coding

Part II Python Script

```
import arcpy, string

from arcpy import env
from arcpy.sa import*

size_1 = 0.000361
size_2 = 0.000722
size_3 = 0.001038
size_4 = 0.001369

arcpy.CheckOutExtension("spatial")

#Input Image File Location
arcpy.env.workspace = r'E:\Test'
arcpy.env.overwriteOutput = True

#Input Image File
input = r'E:\Test'

#Name File Result
result = "NDVI_Done.tif"

#Input Band Name
NIR = input + "\pop\Pop_Band4"
Red = input + "\pop\Pop_Band3"
```

```
#Name Band Result
NIR_out = "Results\NIR.tif"
Red_out = "Results\Red.tif"

arcpy.CopyRaster_management(NIR,NIR_out)
arcpy.CopyRaster_management(Red, Red_out)

Num = arcpy.sa.Float(Raster(NIR_out) - Raster(Red_out))
Denom = arcpy.sa.Float(Raster(NIR_out) + Raster(Red_out))
NDVI_Done = arcpy.sa.Divide(Num, Denom)

NDVI_Done.save(result)

#Reclassify NDVI
outReclass = Reclassify(NDVI_Done, "Value",
                    RemapValue([[-1,0.24,"NODATA"],[0.24,1,1]]))
outReclass.save("E:\Test\Results\Plnt_Rcls")

#Raster to Polygon
arcpy.RasterToPolygon_conversion(outReclass, "Rast2Poly", "NO_SIMPLIFY", "VALUE")

Rast2Poly = r'E:\Test\Rast2Poly.shp'
#Area in Attribute Table
arcpy.AddGeometryAttributes_management(Rast2Poly, "AREA", "", "SQUARE_METERS","")

if arcpy.Exists(Rast2Poly):
    outputDir = r"E:\Test\Results"
    output = outputDir + "\PolyUpd"
    arcpy.CopyFeatures_management(Rast2Poly, output)
    cursor = arcpy.UpdateCursor("PolyUpd")
```

```
    Count = "Poly_Area"
    for row in cursor:
        if row > 0 and row <=size_1:
            row.setValue(Count, row.getValue(Count) / size_1)
        elif row > size_1 and row <=size_2:
            row.setValue(Count, row.getValue(Count) / size_2)
        elif row > size_2 and row <=size_3:
            row.setValue(Count, row.getValue(Count) / size_3)
        elif row > size_3 and row <=size_4:
            row.setValue(Count, row.getValue(Count) / size_4)
        elif row > size_4:
            row.setValue(Count, row.getValue(Count) / size_4)
        cursor.updateRow(row)

summed_total = 0
with arcpy.da.SearchCursor(output, Count) as cursor:
    for row in cursor:
        summed_total = summed_total + row[0]
```

Part III. Determining Cotton Yield Potential from Planting Date and Population

Abstract

Cotton producers in the U.S. Mid-South often plant early in cool, wet conditions to lengthen the growing season and maximize yield potential. While multiple studies have been conducted to determine optimum planting windows and seeding rates, few studies have evaluated the interaction of these parameters. In order to make the replant decision, the yield potential of the current stand versus the yield potential of the replant must be estimated. Subsequently, the objective of this study was to determine the impact of plant population and planting date on lint yield and fiber quality. Field experiments were conducted in 10 site-years from 2016-2018 in Tennessee, Mississippi, and Missouri. Treatments included 5 seeding rates (0.75, 1.5, 3, 6.75, and 10.5 seeds m-1) and multiple planting dates (typically early May, mid-May, and early June). While yields were lowest at later planting dates and low populations, results suggested a uniform population of 74,000 plants ha-1 will likely not warrant a replant at any date and uniform populations as low as 49,000 plants ha-1 planted after 5-May will also likely not warrant a replant. Fiber quality was impacted by environment and planting date, with micronaire decreasing and length, strength, and uniformity increasing as Julian date increased. This data will assist practitioners with replant decisions by providing estimates of the current stand relative to the yield potential of a successful (or unsuccessful) replant. Furthermore, results suggest producers may be able to reduce seeding rate at later planting dates without reducing yield potential.

Introduction

One of the most difficult decisions we make in various aspects of life is often some form of a commitment. One could argue that this holds true when gauging whether to accept a cotton (*Gossypium hirsutum,* L.) stand or to replant. In order to provide ample time to produce and mature their crop, growers in Tennessee target planting dates between 20-April to 10-May (Craig, 2010).

While early planting lengthens the growing season and shifts flowering and boll-fill into months which historically are cooler and receive greater amounts of rainfall, planting early increases the risk of seedling disease and cold stress (Pettigrew, 2002). Unfortunately, growers along the northern edge of the U.S. Cotton Belt are particularly at risk for inadequate soil temperatures and excessive rainfall during the optimum planting window. If abiotic stressors of cold temperatures and excessive rainfall are severe enough to kill a substantial number of the emerging seedlings, a decision of whether to accept or replant the crop must be made. While cotton seedlings typically emerge within 5 to 12 days after planting under favorable conditions (Wanjura et al., 1969), emergence rate decreases linearly with decreasing temperatures (Reddy et al., 2017). The narrow target planting window and length of time for which it takes a seedling to emerge under abiotic stresses complicates the replant decision; by the time the stand can be assessed, the yield potential of the replant will typically fall outside the optimum planting window. Subsequently, producers must often decide between accepting the reduced yield potential of the current stand relative to the reduced yield potential and expense of the replant.

In Tennessee, uniform plant populations between 74,000 to 148,000 plants ha^{-1} are recommended for optimum yield potential (Main, 2012). Current methodology to assess plant population includes: collecting a minimum of 4 measurements from several representative areas in the field; using the 1/1,000th method to determine required length of row to count plants, based upon planted row spacing; counting the number of plants within this linear distance of row and multiplying by 1,000; and finally averaging these numbers to estimate representative plant population per hectare of the assessed field (Godfrey et al., 2010). It has been demonstrated that a uniform, lower plant population may provide adequate yield potential, especially if seeded earlier in the recommended planting window and environmental conditions are favorable (Siebert et al., 2006; Wrather et al., 2008, Adams et.al., 2019). In studying the effect of reduced seeding rates in narrow (76 cm) row spacing in Tennessee, Gwathmey et. al. (2011) found that yield potential was not significantly reduced until plant populations fell below 30,000 plants ha^{-1}. However, lower populations may result in delayed maturity, increase the risk of poor fiber quality, and must be managed for earliness (Jones and Wells, 1998; Wrather et al. 2008). Limited reports on the effect of stand uniformity and skip length exist today, although it is theoretically assumed to greatly impact yield potential. Jost (2005) suggested yield reductions may be noticed with excessive skip lengths greater than 10.5 m. Boman and Lemon (2007) reported that in the Texas High Plains in the 1980's skips that reduced stands between 25 to 45% but still were in excess of 6 plants m^{-1} lowered yields by 17 to 26%. It is generally recommended, when making a replant decision, to accept stands when densities are uniform and greater than or equal to 3 plants row m^{-1} (Craig, 2010; Supak, 1990).

While plant population and planting date greatly influence growth and development of cotton (Jones and Wells, 1998; Smith et al., 1979; Siebert et al., 2008; Wrather et al., 2008), few studies have been conducted determining the interaction of planting date and plant population on cotton lint yield (Wrather et al., 2008). Galanopoulou-Sendouka et al. (1980) did demonstrate the effect of population density, planting date, and genotype on growth and development of cotton in Greece. Planting date had the strongest influence on maturity and earliness, while density had the strongest impact on morphological characteristics and yield components. No impact amongst the interactions of planting date, population, or selected cultivar on lint yield was observed (Galanopoulou-Sendouka et al., 1980). Wrather et al. (2008) conducted similar work in the Mississippi River Delta Region. The interaction of planting date and plant population was significant and suggested as population decreased and at later dates, lint yield decreased.

Interestingly, lint yield harvested from 17,000 seed ha^{-1} planted in late April was significantly greater than or equal to all plant populations planted in mid-May. While densities greater than or equal to 2.5 plants row m^{-1} did not significantly impact cotton lint yield, fiber color and maturity was negatively affected (Wrather et al., 2008). Although populations between 50,000 and 100,000 plants ha^{-1} have been demonstrated to have no significant differences in lint yield amongst differing varieties (Pettigrew et al., 2013), lint yield progressively increased as year of varietal release increased (Wells and Meredith, 1984). Due to these occurrences, producers have looked to maximize profits by stabilizing yield goals while decreasing seeding rates.

Currently, producers, scouts, and consultants possess minimal tools that will help them decide to accept or replant a stand of cotton outside of personal judgement from past experiences. A model usimg cotton plant population and planting date to predict lint yield potential may greatly assist in the replant decision making process and provide guidance towards management requirements throughout the season. Therefore, the objective of this study was to determine the impact of plant population and planting date on lint yield and fiber quality to provide improved guidance in the replant decision making process.

Materials and Methods

Field trials were established across 10 site-years from 2016 to 2018. During 2016, a pilot study was conducted at Ames Plantation in Grand Junction, TN. During 2017, expanded studies were repeated in Grand Junction, TN; at the West Tennessee and Milan Research and Education Centers in Jackson, TN and Milan, TN, respectively; at the Fisher Delta Research and Extension Center in Portageville, MO; and in Brooksville, MS. During 2018, studies were continued in Grand Junction, Jackson, and Milan, TN as well as Brooksville, MS. Field sites were distanced, latitudinally, at a minimum of 35 km and a maximum of 325 km. Locations provided highly

Table 6. Planting dates for five locations across three years

Location	Year	Soil Type	Planting Date			
			Initial	2nd	3rd	4th
Grand Junction, TN	**2016**	Loring Silt Loam	10-May	-*	-	-
	2017		18-May	30-May	7-Jun	-
	2018		4-May	21-May	30-May	-
Jackson, TN	**2017**	Almo Silt Loam	16-May	1-Jun	7-Jun	-
	2018		20-Apr	3-May	15-May	19-Jun
Milan, TN	**2017**	Falaya Silt Loam	17-May	31-May	7-Jun	-
	2018		15-May	20-Jun	-	-
Brooksville, MS	**2017**	Brooksville Silty Clay	9-May	12-May	21-May	-
	2018		9-May	6-Jun	20-Jun	-
Portageville, MO	**2017**	Dundee Silt Loam	10-May	22-May	1-Jun	-

* (-) Additional planting dates were not evaluated

variable environments across the Mid-South. Five varying seeding rates were selected to be planted at each location and respective date. Seeding rates included: 10.5 seeds m^{-1} (~118,970 seeds ha^{-1}), 6.75 seeds m^{-1} (~76,480 seeds ha^{-1}), 3 seeds m^{-1} (~33,990 seeds ha^{-1}), 1.5 seeds m^{-1} (~17,000 seeds ha^{-1}), and 0.75 seeds m^{-1} (8,500 seeds ha^{-1}). The initial planting date at each location was targeted to fall within range of the recommended planting window for Tennessee of 20-Apr to 10-May (Craig, 2010) (Table 6). In effort to normalize planting dates across the differing environments, the second and third planting dates were triggered approximately 7 and 14 days, respectively, after 50% emergence of the 10.5 seed m^{-1} plots. In 2017, initial planting was delayed until after 15-May in the 3 field sites in Tennessee due to excessive rainfall. Planting dates and soil types are defined in Table 6.

Trials were established using a double-disc opening planter with a cone seed singulation system, designed specifically from research plot work. Experimental cone planters allow each plot's respective seeding rate to be packaged individually, dumped into each row unit per plot, and dispersed evenly across the planted plot row. Prior to planting, seeds were counted based upon requirement to plant selected seeding rate per 10.7 m plot lengths. Plots were then reduced to 9.1

m lengths by hand trimming to align each replication. Subsequently, in the event seeds were unevenly displaced within the cone system, actual population within plot may have varied slightly from target. Studies were arranged in a randomized complete block design with 4 replications. Plots consisted of four 96.5 cm spaced rows, 9.1 m in length. To standardize in-season management and simulate multiple replant dates within the same field, applications were made to the entire trial area, following respective state extension recommendations for cotton. In each year and location, DP 1522 B2XF (DeltaPine, Bayer CropScience, Raleigh, NC), an early to mid-maturing variety, was selected for its popularity and suitability across differing environments. Prior to harvest, cotton plants within each individual harvest row were hand counted and recorded as actual plant populations. Once plots reached relative maturity, trials were defoliated and the 2 center rows of each plot were harvested with a mechanical spindle picker equipped with a load-cell style weigh basket to generate seed cotton weights. Seed cotton from each plot was sub-sampled to determine turnout (percent lint) and fiber quality. Seed cotton sub-samples were ginned at the UT MicroGin in Jackson, TN. Fiber samples from each plot were shipped to the USDA Cotton Classing Office in Memphis, TN for classification of micronaire, length, strength, and uniformity by high volume instrument (HVI) testing.

In order to normalize yield data across varying environments and years, each plot weight was divided by maximum plot weight within that location and year, resulting in a unit-less measurement of relative yield ranging from 0 to 1. To provide a continuous value for regression modeling, calendar date was converted to Julian date, such that dates ranged from 0 to 365. To characterize the relationship of planting date and plant population on seed cotton yield, lint turnout, and fiber quality, planting dates and actual populations were subjected to response surface regression modeling in SAS (SAS 9.4, SAS Institute, Cary, NC). Response surface regression is a type of multiple regression that uses more than one independent variable (Bas and Boyaci, 2007). The objective of response surface regression modeling is to use values from independent variables to predict the dependent variable. Polynomial equations were obtained by the analysis and were accepted as adequate when tested by the lack of fit and coefficient of determination. Noted differences were considered significant at $P \leq 0.05$. The validity of the models was also verified through use of experimental data. Yield data from planting dates of 20-Apr, 1-May, 10-May, 20-May, 1-Jun, 10- Jun, and 20-Jun and plant populations of 24,000, 49,000, 74,000, 98,000, and 123,000 plants ha^{-1} were selected as benchmarks and subjected to the model and yield potential curves for each interaction were generated to more thoroughly understand the response. Planting date ranges were selected based upon typical times in which cotton planting is initiated and replant decisions are made. Plant populations subjected to the model were selected based upon the uniformity and relevance when selecting a desired seeding rate. Dates and populations subjected to the model were represented by at least one observation within the field studies. The first derivative of this curve was calculated in SAS 9.4 to distinguish rate of change in yield potential across planting date intervals for the five subjected actual plant populations.

Results

Trial location yield environments were variable, with average lint yield for each site year across all planting dates and plant populations ranging from 440 to 1,328 kg ha^{-1}. Average lint yield across all site years equaled 837 kg ha^{-1} (Table 7.). The difference between observed state average yields and average yield observed within these trials can be attributed to the large number of treatments which were either planted outside the target planting date window, were planted below target plant populations, or both. In contrast, lint yields for each site year of treatments within target planting dates and plant populations closely mirrored state average yields (data not

Table 7. Average, maximum and minimum lint yield observed and average turnout, micronaire, length, strength and uniformity observed in each site-year.

Location	Year	Lint Yield[z] ($kg\ ha^{-1}$)			Fiber Quality: Gin Turnout (%)	Micronaire	Length (mm)	Strength ($kN\ m\ kg^{-1}$)	Uniformity (%)
		μ	max	min			μ		
Grand Junction	**2016**	1037	1373	606	40	5.2	27.9	299	81.9
	2017	440	1040	33	39	3.4	29.5	301	83.4
	2018	860	2159	175	39	4.6	29.5	301	83.4
Jackson	**2017**	904	1836	160	36	4.4	29.0	297	82.4
	2018	781	1708	177	35	4.7	28.2	298	81.5
Milan	**2017**	941	1538	169	37	4.2	29.2	299	82.7
	2018	554	1540	26	-[y]	-	-	-	-
Brooksville	**2017**	442	1120	23	-	-	-	-	-
	2018	1328	1909	288	37	5.0	28.2	285	81.8
Portageville	**2017**	1080	1852	283	36	-	-	-	-
Total Site Year (μ)		**837**	**1608**	**194**	**37**	**4.5**	**28.7**	**297**	**82.4**

[Z]Lint yield calculated based upon plot gin turnout

[y]Fiber sample not taken. Lint yield calculated based upon 38% gin turnout

Table 8. Response Surface for Cotton Relative Yield based upon Planting Date and Plant Population

R^2		0.663
Response Mean		0.499
Root MSE		0.151
Coefficient of Variation		30.4
Parameter	**Slope**	**Pr > F**
Intercept	-2.544416	<.0001
Population	0.000018166	<.0001
Date	0.046308	<.0001
Population * Population	-4.7729E-11	<.0001
Date * Date	-0.000185	<.0001
Date * Population	-5.7528E-8	0.0009

shown). Turnout, micronaire, length, strength, and uniformity averaged across all site years equaled 37%, 4.5, 28.8 mm, 297 kN m kg^{-1}, and 82.4%, respectively.

Planting date and actual plant population data collected from 10 site-years was predictive of relative cotton lint yield potential when subjected to response surface regression modeling (Fig. 3A), with a coefficient of determination equal to 0.663 (Table 8). The interactions of planting date, actual plant population, and planting date by plant population were all significant. The linear term of planting date had the greatest effect on relative yield with a slope equal to 0.046308, followed by actual plant population with slope equal to 0.00018166. Mean yield potential of the response surface equaled to 49.9%, conveying an even distribution of yield results across the model. Root mean square error (RMSE) equaled 0.15137 with a coefficient of variation (CV) of 30.3521, suggesting residuals were relatively concentrated close to the response surface (Fig. 3B). Canonical analysis of the response surface model stated that maximum yield may be achieved on 15-April when possessing a germinated plant population stand of 126,774 plants ha^{-1}, however, the model suggested an unrealistic yield potential of 105% at the stationary point.

Selected planting dates and actual plant populations were subjected to the response surface model:

$$f(x)=-2.544416 + 0.000018166(x_1) + 0.046308(x_2) - 0.000000057528(x_1*x_2) -0.00000000004772\ ((x_2)^2) - 0.000185\ ((x_1)^2\ )$$

WHERE:
$f(x)$ = Lint yield potential (%)
x_1 = Plant population ha^{-1}
x_2 = Planting date (Julian)

Predicted yield results were plotted and curves were generated for each associated interaction. Interpretations of percent cotton lint yield potential generated from six plant populations suggest yield potential is relatively stable across all populations from 20-Apr until 10-May (Fig. 4). Yield

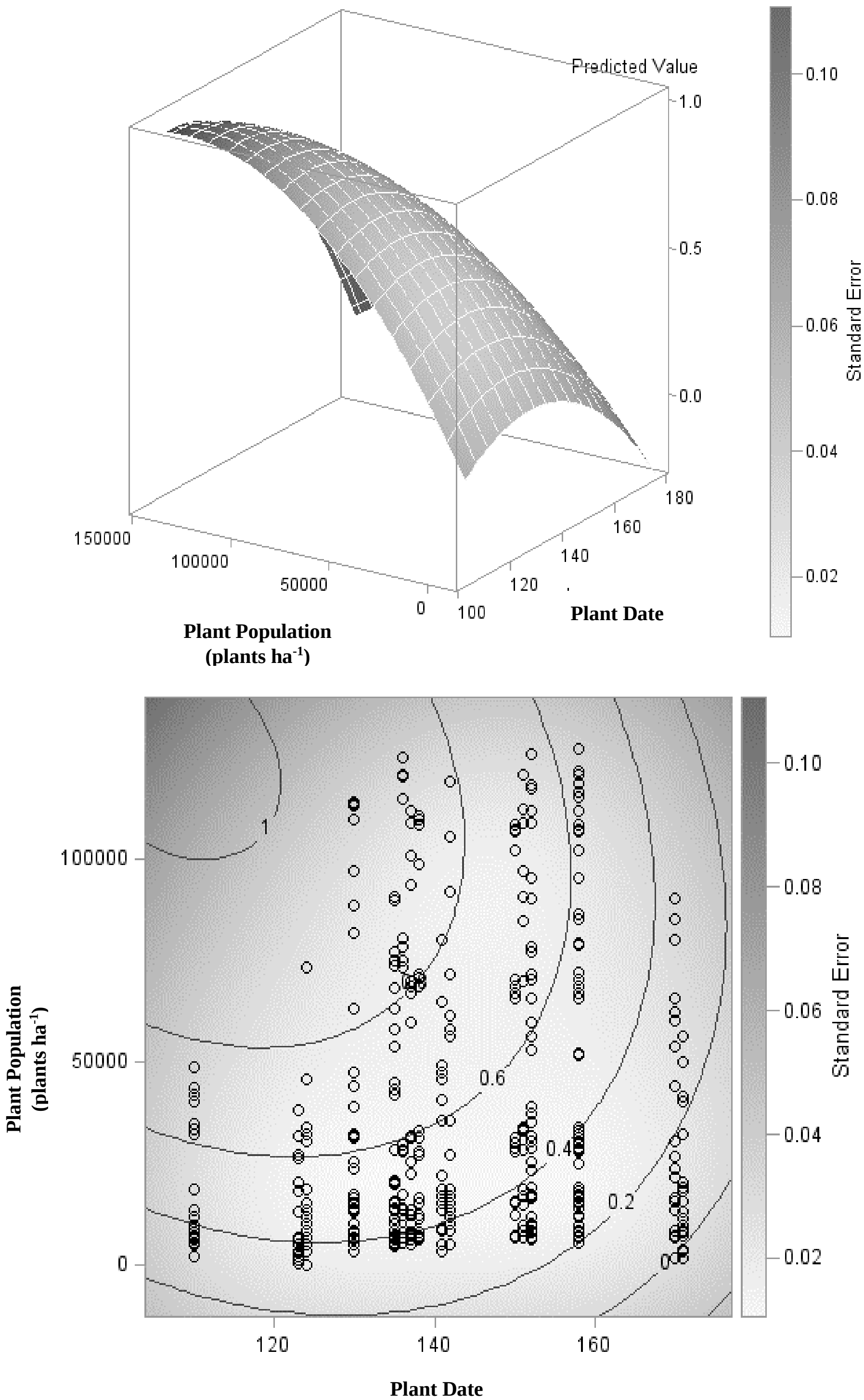

Figure 3a. Response surface model of potential lint yield across planting date and actual plant population. **Figure 3b**. Contour plot response of lint yield potential across planting date and actual plant population**.**

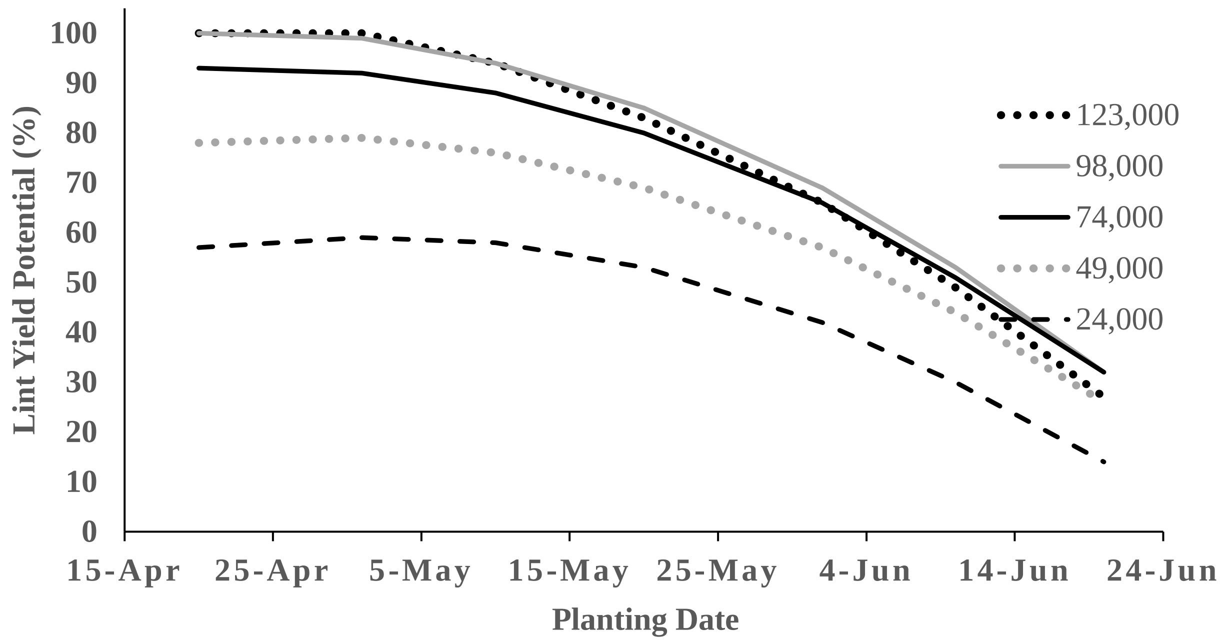

Figure 4. Percent cotton lint yield potential generated from five populations across seven planting dates when subjected to response surface modeling

potentials of actual plant populations from 74,000 to 123,000 plants ha^{-1} varied only slightly, populations of 49,000 plants ha^{-1} possessed drastically lower yield potential within the recommended planting window. While 24,000 plants ha^{-1} followed similar trends across planting dates, the model indicated yield potential of the 24,000 plants ha^{-1} population never exceeded 60%. Interestingly, the plant population of 98,000 plants ha^{-1} provided either equal or greater yield potential than other plant populations across all reported planting dates. Furthermore, after 20-May, populations equal to or greater than 49,000 plants ha^{-1} provided equivalent yield potential to increased plant stands, which suggests target plant stand should decline later in the year and producers will likely be able to utilize lower seed rates if establishing a replant beyond the recommended planting window.

Graphical representation of the slope for the five selected plant populations over planting date captures this varied rate of change (Fig. 5). Yield potential from the lowest comparative

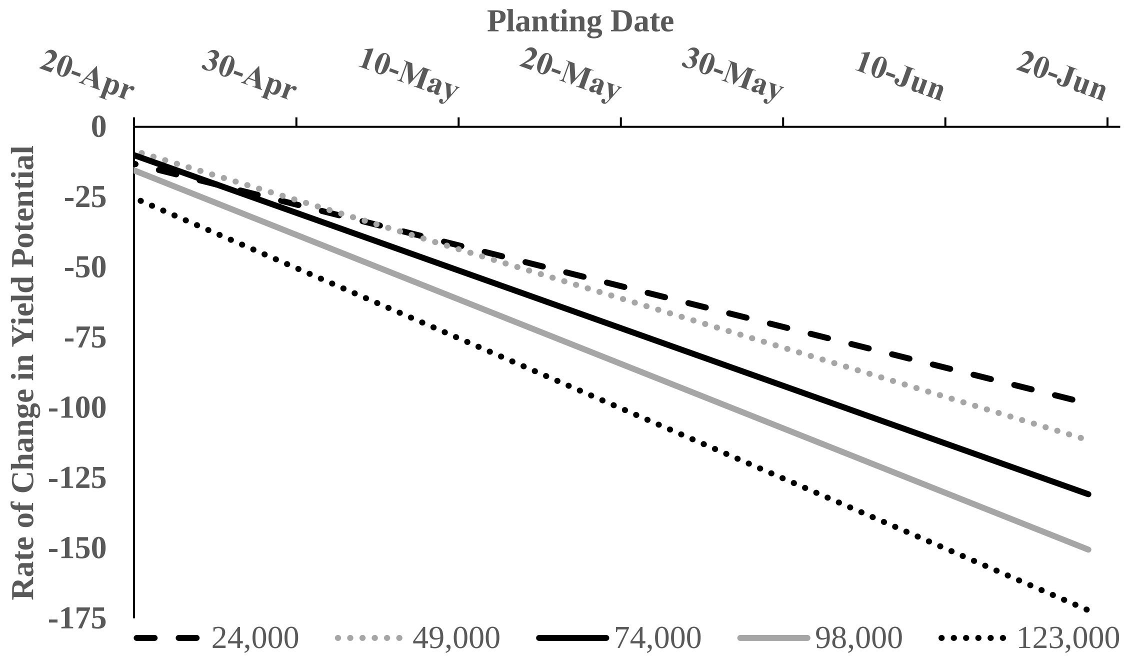

Figure 5. First derivative of percent cotton lint yield potential from five actual plant populations across planting date.

population of 24,000 plants ha^{-1}, (Table 9) decreased at the slowest rate as planting date increased. As plant population is increased, yield potential decreases at a greater rate at later planting dates, with the rate of decline in yield potential becoming greatest at the plant population of 123,000 plants ha^{-1}. It is likely the rate of change in yield potential is lowest at less dense populations due to the low yield potential which characterizes these populations across the entire planting window; maximum yield potential across planting dates within the 24,000 plants ha^{-1} population only varies from ~15% to 60%. At greater populations, yield potential is maximized early in the planting window but decreases at the greatest rate. It is hypothesized dense plant stands may compete with neighboring plants for water, nutrients, and sunlight when planted later. Increases in vegetative growth may be the result of reduced sunlight interception and heat accumulation required to progress growth stages of each individual cotton plant (Hutmacher et. al., 2002).

Table 9. First derivative parameters generated from yield potential generated from response surface regression modeling for five increasing plant populations

Plant Population (plants ha^{-1})	Linear Equation
24,000	y = -0.71177 (Plant Date) + 144.870
49,000	y = -0.85879 (Plant Date) + 182.129
74,000	y = -1.00625 (Plant Date) + 213.308
98,000	y = -1.12557 (Plant Date) + 234.383
123,000	y = -1.22363 (Plant Date) + 246.325

Table 10. Linear regression interaction effect of environment and planting date on fiber quality parameters

Fiber Quality Parameter	Significance (Pr > F)		R^2	Optimized Equation
	Environment	Plant Date		
Micronaire	< 0.0001	0.0004	0.700	y = -0.0046 (Plant Date) + 5.2152
Length	< 0.0001	0.0017	0.500	y = 0.0003 (Plant Date) + 1.0801
Strength	< 0.0001	< 0.0001	0.330	y = 0.0238 (Plant Date) + 26.6854
Uniformity	< 0.0001	< 0.0001	0.330	y = 0.0225 (Plant Date) + 79.0786

The effect of planting date, actual plant population, and environment interactions on fiber quality parameters of micronaire, length, strength, and uniformity were assessed using response surface regression modeling. The effect of actual plant population was not significant for any fiber quality parameters. The effect of both environment and planting date were significant; environment dominated realized micronaire and length, while planting date and environment played similar roles on realized strength and uniformity (Table 10.). As planting date increased, micronaire decreased and length, strength, and uniformity all increased. The model was most predictive of micronaire (r^2 = 0.7), followed by length (r^2 = 0.5), with minimal correlation between strength and uniformity within the interaction of environment and actual plant date (r^2 = 0.33) (Table 10).

Discussion

Few studies have concurrently examined the impact of calendar date and plant population on parameters of cotton lint yield and fiber quality. Similar to early studies conducted by Galanopoulou-Sendouka et al. (1980), increasing plant population resulted in positive significant effects on lint yield, however, Galanopoulou-Sendouka et al. noted no interaction of planting date and population. In contrast, our results more closely mirror the significant interaction of plant date and population captured by Wrather et al. (2008); however, in contrast to the findings by Wrather et al. (2008), the greatest rate of decline in yield potential as planting date increased was associated with the greater plant populations, not the lowest. It is suspected the limited number of site-years, different environmental conditions, and improved varieties could explain some of the discrepancies noted between our findings and those of Wrather et al. (2008) and Galanopoulou-Sendouka et al. (1980).

When assessing the effect of planting date and plant population on fiber quality parameters of micronaire, fiber length, strength, and uniformity, planting date influenced some quality parameters while population had no impact. These results are consistent with reports by Siebert (2006) and Wrather (2008). Environment had the greatest impact on fiber quality parameters, as growing conditions, soil type, and management dominate the generation and development of cotton fibers (Campbell & Jones, 2005). Fiber harvested from later planting dates was less mature, resulting in reduced micronaire and potential discounts. Conversely, cotton planted later produced fiber with increased length, strength, and uniformity, which may lead to premiums. Wrather et al. (2008) also noted an increase in length and strength and a decrease in micronaire at later planting dates but did not note increases in uniformity. While understanding planting date in managing for fiber quality could be important in securing premiums or avoiding penalties, the small parameter estimates will likely limit the power of fiber quality parameters to ultimately determine when to plant since previous evaluations of planting date on fiber quality have indicated slight changes in fiber quality parameters will often not impact lint value (Wrather et al., 2008). Similarly, impacts observed within these studies also indicate the role of fiber quality on selecting planting date will be minor in comparison to lint yield.

While data suggests both calendar date and plant population must be considered when gauging whether to accept or replant cotton stands, additional expenses associated with seed cost, preemergence herbicides, planting costs, logistics, and labor must also be considered. Since these vary substantially by operation and the incorporation of those expenses is beyond the current scope of the project, it is difficult to make sweeping statements concerning the plant populations and dates which would warrant replants. However, based upon these data, a few trends should be noted. First, assuming it will take 15 days to determine if a stand should be replanted, a uniform population of 74,000 plants ha^{-1} will likely not warrant a replant at any date. Furthermore, assuming it will take 15 days to determine if a stand should be replanted, uniform populations of 49,000 plants ha^{-1} established after 5-May will likely not warrant a replant since greater populations established on 20-May were characterized by equal or reduced yield potential in comparison to 5-May, 49,000 plants ha^{-1} observations. These data are consistent with reports developing seeding rate recommendations from Georgia and Tennessee in the early 2000’s (Bednarz et. al., 2005; Gwathmey et. al., 2011). Similar studies by Wrather et al. (2008) in the MS Delta Region suggested plant population does not affect yield potential at densities as low as 34,000 plants ha^{-1}, however, 24,000 plants ha^{-1} significantly decreased yield in one evaluated site year. In a recent study from the Texas High Plains, a breakpoint threshold for seeding rates was established as 35,000 plants ha^{-1} when planting into optimum germination conditions (Adams et.

al., 2019). While producers possess the luxury of accepting a wide range of populations, full seeding rates up to 123,000 plants ha^{-1} demonstrated the greatest yield potential when planted earliest but demonstrated the greatest rate of change as planting date became later.

Yield potential was relatively stable across all populations during the recommended planting window (20-Apr until 10-May). These results are consistent with recommendations for cotton planting date windows across the Mid-South (Main, 2012; Robertson et. al., 2018). Wrather et al. (2008) suggested lower plant populations seeded in early May have the potential to outperform greater plant populations seeded in late May; their results are consistent with this study. However, when evaluating the effect of plant population on yield potential when seeding in late May or early June, the time in which most replant decisions are made, yield potential decreases at a slower pace amongst decreased plant populations, suggesting growers making a replant decision may be able to achieve optimum yield potential with reduced seeding rates of approximately 49,000 plants ha^{-1}, similar to reports by Pettigrew et al. (2013).

The proposed yield potential model allows for a producer or consultant to subject initial planting date and observed plant population to determine current crop yield potential. Consecutively, the user may be able to subject expected plant population ranges with the current calendar date to observe if yield potential is equal to or greater than the current stand, or if accepting the current stand is economically beneficial. As expected, the current data suggests that greater cotton populations planted earlier have ample time to fully grow and mature to the level of optimum yield, however, as planting date becomes later, these greater populations begin to outcompete with neighboring in row plants for sunlight (Pettigrew and Meredith, 2012), ultimately reducing yield potential. Conversely, lower seeding rates, particularly with more determinate varieties, planted earlier are limited by the yield potential of the reduced number of plants within the field, however, with minimal impacts as planting date becomes later, especially if strictly managing for earliness, reducing vegetative growth.

This study generated data on uniform stands without skips and does not quantify stand uniformity and the impacts of uniformity on yield potential or fiber quality; still, uniformity must be considered when accepting reduced plant stands. The method of establishing population treatments within these experiments generally resulted in a consistent distance between plants which may not capture variability noted within-field. Until studies quantifying uniformity are conducted and incorporated into the replant decision matrix, the potential yield penalty from large skips should be considered severe. Also, the direct impact of environmental conditions was not directly considered. Yields were normalized by location to eliminate differences within a location, however, environmental impacts on maturity resulting in yield impacts were not determined causing some uncertainty in the response surface and overall rate of change. Managing treatments individually based on response to the environment could reduce some uncertainty within the model, however, the scope of this study was to determine impacts on lint yield on reduced populations or later emergence dates in comparison to desired.

Conclusion

The significant interaction of planting date and plant population suggests producers in the Mid-South must consider both calendar date and plant population when gauging whether to accept or replant cotton stands. While additional expenses associated with seed cost, preemergence herbicides, planting costs, logistics, delayed harvest and labor must be included within the decision matrix, the developed model suggests a uniform population of 74,000 plants ha^{-1} will likely not warrant a replant at any date and uniform populations as low as 49,000 plants ha^{-1} planted after 5-May will also likely not warrant a replant. Furthermore, stronger reductions in the yield potential of greater plant populations were noted as planting date shifted to later within the year. These trends suggest reduced seeding rates may be more cost effective later in the year. Although additional research must be conducted to incorporate some measure of stand uniformity and operation-specific expenses, the developed relationship between plant population, planting date and yield potential provides insight into the yield potential of a replant relative to the yield potential of a current stand.

Page IV. Making the Cotton Replant Decision: A Novel and Simplistic Method to Estimate Cotton Plant Stand Uniformity Using UAS Imagery

Abstract

Unmanned aerial systems (UAS) allow the user to quickly obtain overhead images of an entire field, providing new avenues of determining crop status and making in-season assessments, and allowing for management strategies to deployed in very precise areas of the field. One benefit from UAS imagery is the ability to evaluate cotton (*Gossypium hirsutum*, L.) stands after emergence. The objective of this research was develop and test the ability of a UAS to accurately determine the uniformity of plant stands across a wide range of plant populations, and plant skip arrangements. Treatments included five populations ranging from 8,500 to 118,970 seeds ha^{-1} and three skip arrangements consisting of 1) parallel skips 1.5 m in length, 2) staggered skips 1.5 in length, and 3) a ramp skip treatment, with skips increasing from 0.3048 m to 2.4384 m. A method was developed for classifying, thresholding, and determining distances to nearest neighboring plant to quantify uniformity. Cotton stands possessing greater than 90% stand uniformity lead to optimum yield, while, stands possessing greater than 75% uniformity may provide adequate yield if plant populations are great enough. The developed UAS methodology to understand emerged plant population and uniformity has the potential to improve both spatial and temporal efficiency of generating quantifiable data to support cotton replant decision making.

Introduction

When producers, scouts, and consultants look to evaluate the emergence of cotton (*Gossypium hirsutum,* L) stands, they will climb out of their vehicle, walk out to a few randomized areas in the field, usually of known, poor history, and perform the 1/1000th stand assessment method (Godfrey et al., 2010). To perform this method, assessors would count the number of emerged, healthy plants within a pre-determined linear distance of row, and multiply this number by 1,000 to provide an estimate of the number of plants per hectare. Generally, outside of visual appearance, this is the only physical methodology supporting the decision of whether to accept or replant a stand of emerged cotton. Along with only providing an estimation of plant population both highly influenced by human bias and heavily reliant on a minute spatial area, it has frequently been hypothesized that uniformity of cotton plant stands provide the greatest significant impacts on lint yield (Adams et al., 2019; Boman and Lemon, 2007; Craig, 2010; Dong et al., 2006; Galanopoulou-Sendouka et al.,1980; Main, 2012; Jost, 2005; Siebert et al., 2006; Smith et al., 1979; Wanjura, 1980; Wrather et al., 2008). A UAS approach to assessing cotton plant stand uniformity could both eliminate human bias and provide spatially dense information across the entire area of interest rapidly. A UAS approach could also provide a novel and simplistic method to quantifying the uniformity of cotton plant stands.

Few studies have been published defining the impact of uniformity of cotton lint yield, subsequently, specialists and consultants have limited resources to determine if stands possessing increased numbers of areas in which cotton plants have not emerged, commonly referred to as a "skip", will cause yield reductions significant enough to warrant a replant. In studies from East Georgia and South Louisiana, Jost concluded skip lengths of 0.61 and 1.07 m within a row length 80 m could cause yield losses of 5.27 and 8.97 kg ha^{-1}, respectively (Jost, 2005). In an Extension article on making the cotton replant decision in the Rio Grande Valley of Texas and Texas High Plains, at stands greater than 6.56 plants m row^{-1}, skips which reduced populations by 25 – 40 % and 26 – 45 %, reduced yields 17 – 23 % and 13 – 26 %, respectively (Boman and Lemon, 2007). Authors stated the data was collected in the late 1980's. In studies from the mid 1970's, lint yields were not negatively impacted until reaching a 30.cm spacing between plants (Smith et al., 1979). A final study suggested that plants stands outside of a ± 12.5 % range of 10.2 cm seed spacing may cause yield limitations, and that seeding technology of the time could not consistently achieve this accuracy (Wanjura, 1980).

To our knowledge, no reports of a method to quantify cotton stand uniformity using unmanned aerial system (UAS) imagery is currently available. Pérez-Ortiz developed a method of distinguishing and differentiating sunflower and maize rows in efforts to identify weeds species using Object Based Image Analysis (OBIA) and the Hough Transform (HT) methodology (Pérez-Ortiz et al., 2016). A final study determined skip rates using OBIA procedures to extract information of UAS imaged sugarcane rows (de Souza et al., 2017). Consecutive phases of identifying the sugarcane planting rows, identifying existent sugarcane within the crop rows, and skip extraction were utilized to determine skip rates.

A simplistic method to determine the uniformity of emerged cotton plants based upon in-row plant distance could provide a quick approach to determining if the current stand is acceptable or if the frequency and length of skips within an area has reached a level in which yield potential may be negatively impacted. Therefore, the objective of this study was to develop a novel method utilizing UAS imagery to quantify uniformity based upon distance of plant spacing and determine at what skip spacing yield reductions may occur.

Materials and Methods

Field trials were established in 4 site years during the 2016 and 2017 growing seasons in 3 varying locations including Ames Plantation in Grand Junction, TN; the West Tennessee Research and Education Center (WTREC) in Jackson, TN; and the Milan Research and Education Center (MREC) in Milan, TN. In effort to understand uniformity across multiple plant populations and arrangements, 7 treatments were selected, including: seeding rates of 10.5 seeds m^{-1} (~118,970

Table 11. Planting dates for five locations across three years

Location	Year	Soil Type	Planting Date
Grand Junction, TN	**2016**	Loring Silt Loam	10-May
	2017		18-May
Jackson, TN	**2017**	Almo Silt Loam	16-May
Milan, TN	**2017**	Falaya Silt Loam	17-May

*** (-) Additional planting dates were not evaluated**

seeds ha^{-1}), 6.75 seeds m^{-1} (~76,480 seeds ha^{-1}), 3 seeds m^{-1} (~33,990 seeds ha^{-1}), 1.5 seeds m^{-1} (~17,000 seeds ha^{-1}), and 0.75 seeds m^{-1} (8,500 seeds ha^{-1}) along with differing arrangements of skips parallel to one another, staggered amongst each other, or increasing size skips ranging from 0.3048 to 2.4384 m row^{-1} (Figure 6.). Each treatment consisted of a 4 row plot, spaced 96.5 cm apart, at a length of 9.1 m. Treatments were arranged using a randomized complete block design. Each location was planted from 10-May to 18-May (Table 11), falling up to a week past the recommended date range for cotton in Tennessee (Main, 2012).

Trials were established into no-till soils using a double-disc opener planter with an experimental-style cone seed singulation system. These types of planters allow each plot's respective seeding rate to be pre-counted and packaged individually. Each packet is dumped into each row unit per plot and evenly dispersed across the planted plot row. Seeds fall into cells within the rotating cone, and once reaching the seed tube opening, fall to the furrow. Seed spacing is highly dependent on the ground speed of the tractor, in which an average 4 km hr^{-1} was utilized. To create skip patterns, plots were seeded at a rate of 10.5 seeds m^{-1}, and upon full emergence, patterns were created by hand removal of cotyledon cotton plants. For the parallel treatments, each of the 4 plot rows contained, 1.5 m of plant row, followed by 1.5 m of skip, repeated through the length of the plot. For the staggered treatment, each of the 4 plot rows contained alternating patterns of 1.5 m of plant row, followed by 1.5 m of skip, with its adjacent possessing 1.5 m of skip, followed by 1.5 of plant row, with these patterns continuing throughout the remainder of the

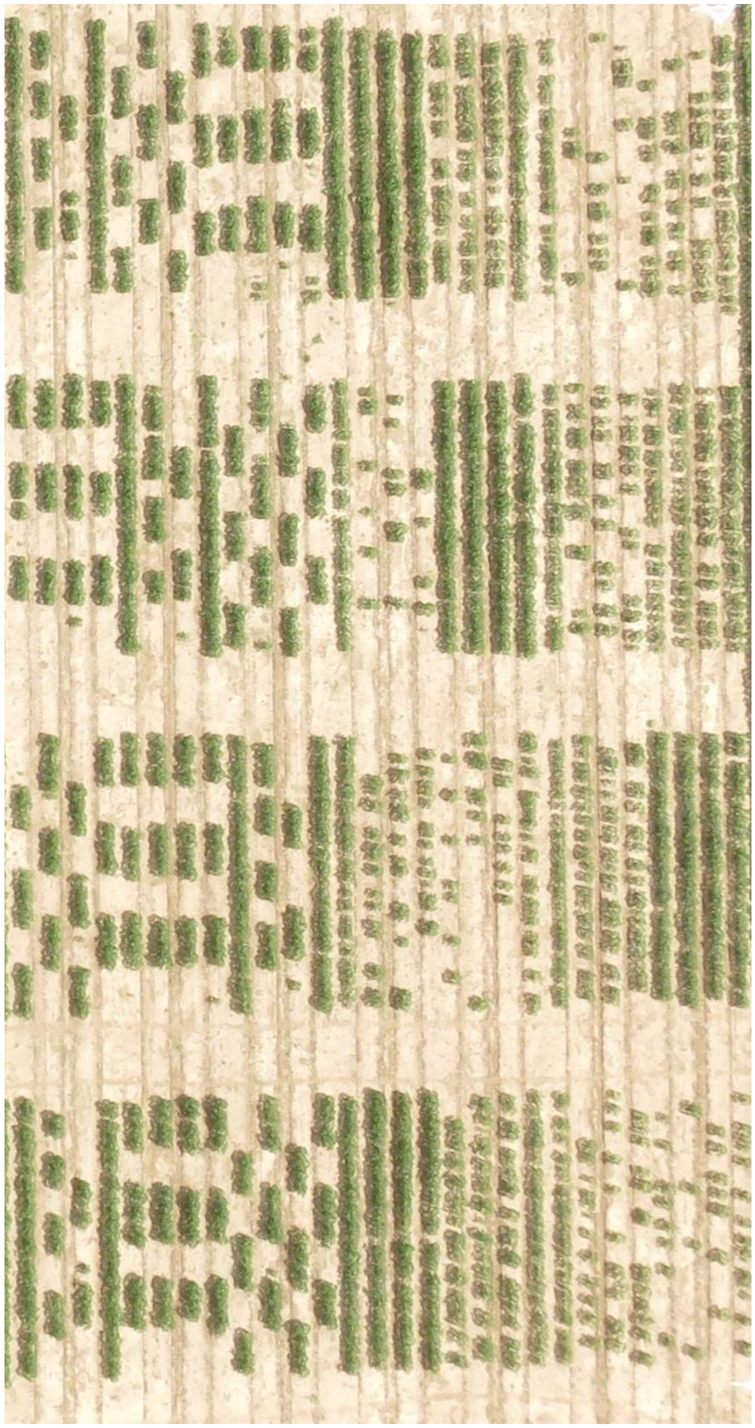

Figure 6. In-season aerial image of five different plant populations and three varying plant arrangements. Treatments included: (1) 10.5 seed m^{-1}, (2) 6.75 seed m^{-1}, (3) 3 seed m^{-1}, (4) 1.5 seed m^{-1}, (5) 0.75 seed m^{-1}, (6) Ramp Skip, (7) parallel skip, (8) staggered skip.

length of the plot. The ramp strip treatment, contained in the 2nd row, skips of 0.3048, 0.6096, 0.9144, 1.2192, and 1.5 m with 0.762 m of plant row between each skip, and in the 3rd row, skips of 1.8288, 2.1336, and 2.4384 m with 0.6858 m of plant row between each skip. Each arrangement represented potential skips patterns equal to 1.5 m in length amongst desired plant populations. In each site year, DP 1522 B2XF (DeltaPine, Bayer CropScience, Raleigh, NC), an early to mid-maturing variety, was seeded based upon its suitability across multiple environments in West TN. All plots were managed based upon UT Extension recommendations for cotton production, and once reaching 60% open boll, all plots were defoliated for harvest. The center 2 rows of each plot were harvested using a mechanical spindle picker equipped with a load-cell style weigh basket to generate seed cotton weights. Seed cotton weights were adjusted to lint yield assuming a 38% turnout of lint following the gin process. To normalize lint yield potential across site years, normalized yield was calculated by dividing each plot weight by maximum plot weight within that location and year, resulting in a unit less measurement of yield ranging from 0 to 1. These values were multiplied by 100 to represent lint yield potential, or relative yield.

Aerial imagery was captured using a MicaSense RedEdge (MicaSense, Seattle, WA) multispectral sensor (Table 12). The sensor was fixed to a custom built quad-copter by a motorized gimbal mount, with camera orientation always directly perpendicular to the target, regardless of pitch or roll of the unmanned aerial vehicle (UAV). Autonomous flight patterns were generated using Mission Planner (ArduPilot, Indianapolis, IN), arranged in a serpentine “lawn-mower” pattern running perpendicular to the planted rows at an altitude of 30 m above ground level (AGL) with designated 80% image overlap and sidelap. Upon shutter, each imager saved its representative band image to a microUSB drive from the respective georeferenced location. Upon programmed mission completion, images were downloaded from the microUSB to computer internal hard drive

Table 12. UAS multispectral sensor specifications

Sensor	Ground Sampling Distance (cm/pixel)	Sensor Width (mm)	Focal Length (mm)	Image Width (pixels)	Image Height (pixels)	Spectral Resolution			
						Red Band (nm)		Near-Infrared Band (nm)	
						Center Wavelength	Bandwidth	Center Wavelength	Bandwidth
RedEdge	2.1	4.8	5.4	1280	960	668	10	840	40

for further analysis. Images were subjected to Pix4Dmapper (Pix4D Inc., San Francisco, CA) and orthomosaics were generated, resulting in a 16-bit geotiff file (.tif) containing each of 5 spectral band layers including: blue (475 nm), green (560 nm), red (668 nm), red edge (717 nm), and near infrared (NIR) (840 nm), and embedded metadata.

Uniformity analyses were conducted within ArcMap 10.6 (ESRI, Redland, CA). For thresholding and reclassification of cotton plants from the soil and other residue, procedures followed those used by Butler (2018), in efforts to estimate plant populations. The normalized difference vegetation index (NDVI) was first generated using the Raster Calculator following the formula:

$$\mathbf{NDVI} = \frac{\mathbf{NIR - Red}}{\mathbf{NIR + Red}}$$

Values within the resulting rasters were classified as either cotton plants, soil, or residue using the Reclassify tool in the Spatial Analyst toolbox (Table 13). Threshold values were developed by identifying the range of each parameter, through manual selection until reaching maximum and minimum values. Values outside of the identified ranges were excluded and means were calculated for each parameter. The reclassified raster was subjected to the Raster to Polygon tool within the Conversion toolbox, producing a polygon for each identified cotton plant or string of

Table 13. NDVI Plant Thresholding Parameters

Sensor	NDVI		
	Cotton	Residue	Soil
	Value Range		
RedEdge	0.24 - 0.76	0.06 - 0.2	-0.05 - 0.1
	Mean Value		
RedEdge	0.55	0.11	0.08

plants. Individual polygons were generated for each individual plot and the resulting Raster to Polygon layer was joined to each respective plot using the Clip tool in the Analysis toolbox. The Generate Near Table tool was then used to determine the distance to the nearest polygon feature. The search radius was set to 1.524 m using the planar method. Average distance to the nearest plant polygon for each respective plot was calculated. The number of polygons within each plot was also counted. To quantify singulation, average distance to the nearest cotton plant within each plot was estimated. Once determining if over or under estimating expected distance, values were compared to expected average distance between plants based upon selected seeding rate, referred to as the normalized plant singulation index (NPSI) ranging from -0 – 100, with 0 equaling very poor singulation and 100 equaling optimum singulation, using the formula:

$$\mathbf{NPSI = 100\ (1\ \pm \frac{(x1 - x2)}{(x1 + x2)})}$$

WHERE
x1 = observed average distance within row between plants (cm)
x2 = expected distance within row between plants (cm)

To eliminate the requirement of determining total plant population, normalized plant population was calculated by identifying the maximum number of polygons within one plot at each site year, and the number of polygons for each plot was divided by this value, resulting in a unit-less range of 0 – 1. This normalization is based upon the assumption that a plant population is acceptable within at least one area of interest. This range was multiplied by 100 to provide a normalized stand, ranging from 0 to 100. The impact of number of polygons within each plot, and the average distance between cotton plants were thus combined to generate stand uniformity, by adding NPSI to normalized plant population multiplied by 2, and dividing the sum by 3, providing a percentage of stand uniformity ranging from 0 to 100, with 0 equaling very poor uniformity and 100 equaling optimum uniformity.

$$\textbf{Stand Uniformity} = \left(\frac{(\mathbf{x1}) + (\mathbf{x2})}{(\mathbf{2})}\right)$$

WHERE
x1 = NPSI
x2 = Normalized Plant Population

Lint yield potential and distance observed between plants within each plot were subjected to analysis of variance (ANOVA) in JMP 14 (SAS Institute, Cary, NC), with means separated using Tukey's Honest Significant Difference (HSD) test at an alpha level equal to 0.05. Site year, replication, and all interactions within were considered to be random effects within the model. To understand the relationship of normalized plant population, NPSI, and stand uniformity to lint yield potential, a quadratic regression model was fit using yield data of the five plant population treatments, removing pattern arrangement treatments.

Results

Site year average lint yield was equal to 815 kg ha^{-1}, and ranged from 0 to 1807 kg ha^{-1}, consistent with state averages for the state of Tennessee (USDA, 2019). Yield potential was significantly greatest amongst seeding rates of 6.75 and 10.5 seed m^{-1} (Table 14.). Yield was significantly reduced at populations of 3 seed m^{-1}. The skips created in the staggered, ramp, and parallel arrangement treatment plots significantly reduced yield by 10, 18, and 22%, respectively. Stands produced from less than 1.5 seed m^{-1} provided less than 55 % lint yield potential.

Table 14. Lint yield potential, stand uniformity, normalized plant singulation index (NPSI), and normalized plant population for 5 different seeding rates and 3 different plant arrangements

Treatment (seed m^{-1})	Lint Yield Potential		Stand Uniformity		NPSI		Normalized Plant Population	
	%	HSD*	%	HSD	%	HSD	%	HSD
10.5	85.404	A	85.810	A	66.277	BC	95.440	A
6.75	79.369	B	79.796	B	68.237	A	85.797	B
Staggered	75.050	C	56.281	D	64.434	D	52.703	D
3	72.757	D	50.614	F	61.438	E	45.140	F
Ramp	67.367	E	67.125	C	66.567	B	67.750	C
Parallel	63.298	F	54.300	E	65.148	CD	49.406	E
1.5	54.771	G	33.960	G	49.076	F	26.733	G
0.75	40.461	H	18.825	H	33.268	G	11.537	H

***Treatments followed by different letter groupings are significantly different at an alpha-level = 0.05**

Utilizing the described calculations eliminated the need to identify the planted rows, their orientation, and the exact number and size of skips, which could potentially represent computational burdens. The average of plant stand uniformity across all treatments was equal to 55.849%. The only two seeding rates producing significantly greater than 75% stand uniformity were 6.75 and 10.5 seed m^{-1}, with 6.75 seed m^{-1} seeding rate possessing the significantly greatest stand uniformity, at 85.81%. The only other treatment producing greater than 60% stand uniformity was generated by the ramp skip arrangement treatment, equaling 67.125%, however, this value was heavily influenced by the solid planted stands in rows 1 and 4 of the respective plots.

Stand uniformity was predictive of lint yield potential (R^2 = 0.66) (Figure 7.). Treatments possessing greater overall plant uniformity typically resulted in greater lint yield potential. Of the two parameters used to determine stand uniformity, NPSI was more highly predictive of lint yield potential (R^2 = 0.66) in comparison to normalized plant population (R^2 = 0.64). These results suggest that if enough plants exist, reduced spacing between these plants will produce greater yield potential.

Discussion

To our knowledge, there are no current studies published on a defined method of determining stand uniformity and comparing to in field yield data, although many have stated yield differences amongst differing plant populations when making the assumption of uniform cotton plant stands (Adams et al., 2019; Boman and Lemon, 2007; Craig, 2010; Dong et al., 2006; Galanopoulou-Sendouka et al.,1980; Main, 2012; Jost, 2005; Siebert et al., 2006; Smith et al., 1979; Wanjura, 1980; Wrather et al., 2008). Yield results were consistent with previous work suggesting penalties would occur at less than 3 seed m^{-1} (Smith et al., 1979). Contradicting other work, stand uniformity within a ± 12.5 % range of 10.2 cm seed spacing was able to be achieved with current planter technology, and seed spacing greater than 10.2 cm between seed was able to generated significantly equivalent yield potential (Wanjura, 1980). Repetitive 1.5 m skips that reduced plant stands by 50% caused up to 18% yield loss, similar to results reported by Boman and Lemon (2007).

This is the first report of cotton plant stand uniformity being quantified through a simplistic series of ArcMap tools. The described method effectively differentiated cotton plants from soil and residue and allowed distance to nearest neighboring plant to be measured and calculated. In attempting to make replant decisions, a user could quickly assess an orthomosaic of a field using the described methodology of determining plant stand uniformity and methods of determining plant population (Butler, 2018). In determining whether to replant, the user would determine the size of an area in which they would be willing to travel to the field to make an economically beneficial replant. Grids would be constructed based upon these areas, and results from the described method could be merged to the grids, for both visual and numerical representation of areas that require replants. In comparison to methods described by de Souza et al (2017), OBIA

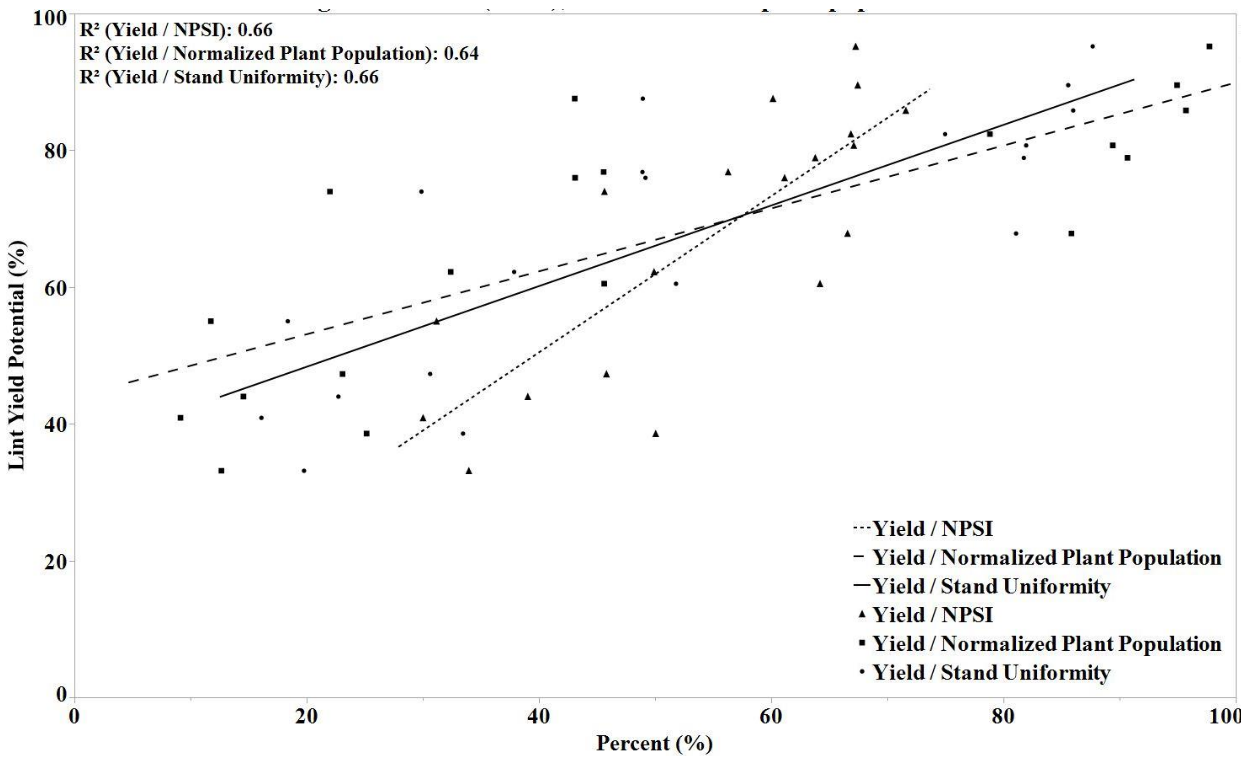

Figure 7. Linear relationship of lint yield potential explained by stand uniformity, normalized plant singulation index (NPSI), and normalized plant population

procedures and extensive phases of identifying and extracting skips was not required in the described method, providing a temporally beneficial process to understanding plant stand uniformity.

Conclusion

In studies examining the impacts of cotton plant stands, the most commonly made assumption is that plant stands evaluated are uniform: however, a value of uniformness is almost never reported. While plant population is a very valuable parameter in predicting lint yield potential, it is hypothesized plant stand uniformity is as equal, if not of greater importance. The described demonstrates a novel and simplistic method to quantify plant stand uniformity which will be crucial in determining when and where cotton plant stands require replanting. Strong relationships ($R^2 = 0.66$) observed between the developed uniformity index and lint yield potentials support the effectiveness of the developed index. While user inputs of grid size and adjustments between weight of normalized population and stand singulation may be capable of strengthening relationship between the developed uniformity index and lint yield potential, the developed uniformity index clearly represents an improvement over the currently utilized method of stand assessment. The various parameters causing significant impacts on yield potential will more efficiently become exposed from various interpretations made available through the utilization of the described method.

Part V. Conclusion

Cotton producers have a very short time frame to plant and assess their crop to insure an adequate plant stand is achieved to provide optimum yield potential for the remainder of the growing season. The previous chapters describe methods for estimating plant population and plant stand uniformity along with providing quantitative values of each of these parameters and their impacts on lint yield potential. For cotton producers in the mid-south, 74,000 plants ha^{-1} will likely not warrant a replant at any date and uniform populations as low as 49,000 plants ha^{-1} may provide an adequate number of plants to achieve optimum yields. Utilizing the described methodology to determine the range of plant populations and uniformness of these plant stands will help to both improve efficiency in stand evaluation while insuring maximum return on investment in each field through a more accurate estimation of areas that should be accepted or replanted.

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Vita

Shawn Alan Butler was born June 26, 1988, in Jackson, TN. He is the son of Jimmy Butler and Debbie Myrick of Jackson, TN. He is married to Lacey, also of Jackson, TN, and they have two fury children, Rhett and Gray, brother and sister goldendoodles. Shawn attended North Side High School where he lettered in football, baseball, and cross country, graduating in May of 2006. He then continued his education at Jackson State Community College, majoring in Pre-Engineering, in the fall of 2006. After his first semester, Shawn was forced to go back to work, where he held positions in car audio and video installation, as well as Engineering Lab Technician with Black and Decker for 3 years. During this time, Shawn got into production agriculture, growing corn, cotton, soybean, and wheat with his uncle. Shawn later landed a student assistantship working for Dr. Larry Steckel, University of Tennessee Extension Weed Specialist, at the West Tennessee Research and Education Center in Jackson, TN. Shawn held this position for four years. In the fall of 2010, Shawn began working on his education again, re-enrolling at Jackson State Community College, majoring in Agriculture Sciences. Shawn completed his Associate of Science in the spring of 2012, and in that same semester also began working on his Bachelor of Science at the University of Tennessee at Martin. In the summer of 2013, while continuing research projects with Dr. Steckel, Shawn held a Sales internship with Sanders Inc. in Ripley, TN. He completed his degree in the spring of 2014, majoring in Agricultural Sciences with a concentration in Row Crop Production. Upon graduation, Shawn continued his education at the University of Tennessee at Knoxville, joining Dr. Heather Kelly's program to pursue his Master of Science degree in Plant Pathology. In the spring of 2015, Shawn formed Farm Specific Technology, LLC., a company started to create innovative solutions to improve food production systems, in which he serves as President and CEO, looking to license his patented technology, the flex roller crimper. Shawn has been honored with numerous awards during his undergraduate and graduate career, including Outstanding Agricultural Science Student, Elmer Counce Memorial Award, and Ed and Gladys Seigel Agriculture Award at the University of Tennessee at Martin, and Jimmy and Illeen Cheek Medal of Excellence Nominee, Charles Wheeler Outstanding M.S. Student Award, GSS Graduate Research Award and Glyn and Lynda Newton Research and Development Award at the University of Tennessee at Knoxville, and recognized as a Future Leader in Science by the American Society of Agronomy, to list a few. He has also presented at numerous professional and extension meetings and won awards at the Southern Weed Science Society, Beltwide Cotton Conference, and American Society of Agronomy annual meetings. Following the completion of his Ph.D. degree, Shawn will be moving to Darien, GA, where he will begin work as a Cotton Development Specialist for Corteva-Phytogen, covering East Georgia.