ABSTRACT

PENA MARTINEZ, ENRIQUE EDUARDO. Updating Cotton Replanting Recommendations Using a Novel UAV-based Method to Detect Size and Frequency of Skips in Suboptimal Stands. (Under the direction of Dr. Jason Ward).

When suboptimal cotton stands occurs, growers face the decision to accept or reject the stand. Growers know that cotton is a resilient crop, but this property can make the decision difficult. Furthermore, elevated replant prices increase grower's uncertainty in the decision. Traditional methods like visual assessments and manual counts in cotton stands are commonly used to support a replant. Most times, however, suboptimal stands do not provide clear visual evidence of a replant. Moreover, these methods are prone to sampling error and human bias. Multiple recommendations advise replanting based on plant populations, plant uniformity, skip size, and areas occupied with such skips. The recommendation established by Jost et al., (2006) was of particular interest because it provided a clear replanting threshold: replanting is justified when 50% or more of the planted area is occupied by skips greater than or equal to three ft. Recent years have shown studies adopting unoccupied aerial vehicles (UAVs) and their applications to quantify plant populations and skips in suboptimal cotton stands. This thesis focused on quantifying skip size and skip frequency using two methods: a traditional manual method and a novel UAV-based method. First, the agreement of a UAV-based method and a traditional manual method in detecting planted areas occupied by skips greater than or equal to three ft was tested. Methods agreed in the lowest stand treatment, where skips of large sizes are predominant. In contrast, methods disagreed in the higher stand treatments, where skips of large sizes are scarce. Then, the UAV-based method was used to refine previous replanting recommendations while accounting for the economic impact of a replant. Various stand loss treatment, including a replanted treatment, were subjected to regression analyses and analysis of variance (ANOVA).

Each site had an early planted and a late planted trial. Results demonstrated that the recommendations could continue to use 3-ft skips as the “critical skip size”, and that a 30-40% of planted area occupied by skips greater than or equal to three ft could be enough to trigger a replant for NC cotton.

Updating Cotton Replanting Recommendations Using a Novel UAV-based Method to Detect Size and Frequency of Skips in Suboptimal Stands

by
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APPROVED BY:

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DEDICATION

I want to dedicate this thesis to my family. This thesis would not have been possible without the unconditional support my family has given me throughout my career. In particular, I want to thank my grandparents for their mentorship. They helped me discover my passion for agriculture and shaped the man I am today. I am blessed to have all my four grandparents still with me, and it is an honor to share this achievement with them. To them I say, “I love you all”.

BIOGRAPHY

Enrique Eduardo Pena Martinez was born in Miami, Florida on October 23, 1995. He is the first of three sons between Osvaldo Ramon Pena Prieto and Isabella Martinez Ascanio. Although he grew up in urban Santo Domingo, Dominican Republic, Enrique always aspired to become an agricultural engineer. His grandfather, Manuel Arturo Pena Morel, and his grandmother, Consuelo Ascanio Rodriguez, mainly fostered his passion for agriculture. During his teenage years, Enrique enjoyed designing and constructing hydroponic systems and raised garden beds in the roof of his grandfather's house. After graduating from high school, Enrique went to study Biological Engineering at Santo Domingo's Institute of Technology (INTEC) for two years, and transferred to Penn State University as part of a 2+2 program to finish his bachelor degree. During his junior year of college, Enrique interned in Agroempresa BHS in Hato Mayor, Dominican Republic where he was exposed to numerous agricultural machineries used for citrus farming. His time in the company made him realize that novel technologies were necessary to elevate Dominican agriculture and compete with international markets. After returning to the U.S. for his senior year, Enrique and his capstone team designed and constructed a solar-powered enclosed trailer that acted as a cold-storage room for the Penn State student farm during the summer and as a water-storage room during the winter.

In 2019, Enrique moved to North Carolina to pursue a master's degree in Biological and Agricultural Engineering. He collaborated with Dr. Jason Ward to research the potential benefits and drawbacks of unoccupied aerial systems and remote sensing applications in cotton farming. Today, Enrique plans to continue his studies in the discipline of remote sensing, and will pursue a PhD in the Electrical and Computer Engineering department at NC State University. In particular, Enrique wants to research potential applications of hyperspectral sensors in sweet potato farming.

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First, I would like to thank my advisor, Dr. Jason Ward, for all the mentoring, time, and effort he put in the last couple of years. Throughout this time, Dr. Ward was a genuine, honest, and hard-working individual that strived for my success as a master's student. Together we dissected my life goals and drew the path I needed to take to fulfill those goals. He believed in me and my abilities in times where I did not believe in myself. He allowed me to make mistakes and grow from them. Not only was he a great mentor, he was also a great friend. Several times, we discussed about trending topics and shared some laughs. He would ask me about my family and health, and always made sure I was not overloaded with work. I am forever grateful to that fact that Dr. Ward helped me find funds for my studies and cost of living to alleviate many of my financial concerns. Dr. Ward guided my professional development in the remote sensing industry and had a significant influence in my growth. Overall, I was lucky to work with Dr. Ward and I hope we continue to collaborate in the near future.

I would also like to thank my committee members Dr. Guy Collins and Dr. Natalie Nelson. Both acted as if they were my primary advisor, and both attended my needs at my request. Sometimes, Dr. Collins and I would talk for hours on the phone about my research; some of those calls took place after 10:00 PM. Similarly, late night email responses from Dr. Nelson were not uncommon. She also fostered my R programming skills, which I have found extremely useful in my profession. My committee was dedicated to my success, and I cannot be more grateful for their work. It has been an absolute pleasure working with them.

Finally, I would like to thank Dr. Ed Barnes and Cotton Inc. for funding my research. Without your support, this would have not been possible. Thanks to all the station managers: Clyde

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TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

Chapter 1 – Introduction

Overview

Poor cotton stands are common in cotton farming. In many cases, cotton growers decide to replant these stands with intentions of achieving higher yields. However, many growers feel uncertain with their decision because numerous factors influence the yield of replanted cotton. Current methods for evaluating cotton stands are visual assessments and manual measurements. Visual evaluations are subjective, and are conducted by growers or consultants assessing stand loss (the size and frequency of missing plants within a row). Manual measurements are objective calculations consisting of sampling small areas within a field to measure the percentage of a stand loss and extending those results to entire planted areas. Visual evaluations can be conducted rather quickly, but they lack precision. Manual measurements are tedious and time-consuming, but are much more precise. Given how modern growers must make important decisions quickly, this creates an opportunity for growers to implement remote sensing for cotton seedling detections post-emergence, to calculate stand loss (or skipped area), and to replant with precision. The agreement of a remote sensing method and a traditional method in detecting skipped area was tested in Chapter 2. Then, Chapter 3 adopted the novel technique proposed in Chapter 2 and used it to refine previous replanting recommendations. The objectives of Chapter 2 were to: (i) compare the time of skip detection and skipped-area evaluation between a remote sensing method and the manual method described in Jost et al. (2006), (ii) quantify the percentages of planted areas occupied by skips greater than or equal to three ft derived from skips detected with each method, (iii) regress lint yield to the percentage of planted area occupied by skips greater than or equal to three ft calculated with each method, and (iv) test the agreement of both methods in their assessment of percent of planted area occupied by skips greater than or equal to three ft. The objectives for Chapter 3 were to (i) establish a critical skip size that best correlates with lint yield, (ii) determine a critical skipped area based on a critical skip size, and (iii) evaluate the yield potential and economic benefit or penalty of replanted cotton to earlier planted cotton.

Thesis Organization

This thesis is composed of four chapters written in manuscript format. The first chapter (current chapter) provided an overview of the thesis, the background, and a short literature review on remote sensing applications in cotton farming. The second chapter compared a common manual method to a remote sensing method on detecting skips using Bland-Altman plots. A systematic procedure detailed how the remote sensing method was used to evaluate suboptimal stands, and explained the benefits and drawbacks of each method. The third chapter of the manuscript refined replanting recommendations based on empirical percentages of areas occupied by skips greater than or equal to three ft and the climate conditions presented during the growing seasons of 2019 and 2020. The fourth and final chapter of this manuscript summarized the results and discussions from Chapter 2 and Chapter 3.

Background

Cotton seed are known to be very sensitive to cool temperatures, saturated soils, and surface crusting within the first three to five days of planting (Bednarz et al., 2007; Butler et al., 2019; Whitaker et al., 2013). As such, poor stands often result when planting occurs during periods of suboptimal weather or after an intense rainfall event. Depending on the severity of the stand loss, suboptimal stands are often replanted. Decisions to replant are generally based on percent stand loss evaluations (size and frequency of skip assessments). It is common to observe skips, or missing plants, in a section of row of planted cotton post-emergence. However, the size and frequency of skips is generally highly variable across the field. These irregularities can make yield loss predictions difficult. Hasna (1982) recognized that yield reductions are usually not proportional to the size of skips, and that yield losses are compensated to some degree by plants bordering the skip segments. More precisely, yield compensations are dependent on the ability of the bordering plants to utilize extra sunlight, nutrients, and moisture from the skipped areas. Naturally, the ability of plants to compensate for space is also dependent on adequate time and heat units remaining within the season, which allows for maturation of outer-position or vegetative bolls (Herbert et al., 2006). Fields with severe stand loss and a high number of large skips are likely to result in yield losses greater than the cost of replanting. Current methods for evaluating cotton stands are visual assessments and manual measurements. Visual evaluations are subjective, and are conducted by growers or consultants assessing stand loss. Manual measurements are more objective. They consist of sampling small areas within a field to measure the percentage of a stand loss, and then extending those results to entire planted areas. Visual evaluations can be conducted rather quickly, but they lack precision. Manual measurements are tedious and time-consuming, but are much more precise. Therefore, decisions to replant are often difficult to make with precision and in a timely manner.

In recent years, replanting suboptimal stands of cotton has become more costly. Prior to 2012, replanting costed between \$10-15 acre^{-1} in North Carolina (Dodds, 2013; Edmisten & Collins, 2020). Today, producers demand for replanting seed has increased the cost of a replant to an estimated \$35 acre^{-1}. This figure includes cost of seed, labor, equipment and fuel (Boman & Lemon, 2005; Butler et al., 2019; Edmisten & Collins, 2020). Using an average estimated value of \$0.70 lbs^{-1} for cotton lint in Southeastern United States (USDA-AMS, 2020), yield losses exceeding 50 lbs acre^{-1} of lint resulting from poor stands justify replanting. The increased costs associated with replanting may discourage replanting. Still, replanting continues to be a common practice for some farmers, although it remains a challenging and costly decision to make.

Changes in weather patterns bring more uncertainty to replanting decisions. Drastic variations in temperature and soil moisture detrimentally affect cotton emergence. It is crucial for seedlings to have at least five days of increasing growing accumulation days and moderate amounts of rainfall for optimal emergence (Butler et al., 2019; Whitaker et al., 2013). In North Carolina, cotton is typically planted from late April to late May, with crop insurance deadlines occurring on May 25th and again on May 31th. In some years, drastic weather conditions impede planting into early June (Collins & Edmisten, 2018a). This represents a rather narrow planting season. As such, large-acreage growers in NC must usually plant on most days during the planting window when fields are dry enough to allow for equipment passage. Inevitably, it is common for planting to occur when conditions are not ideal for cotton emergence.

Replanting is not always a clear solution, even when stands from the initial planting are likely to result in yield loss. The replanted cotton must achieve a successful and better stand than the initial planting at the risk of unpredictable variations in rainfall and heat unit accumulation. Multi-year planting date research in NC illustrates that cotton planted from April 29th through June 4th-5th generally has an equal chance of achieving acceptable yields (although cotton planted beyond late May must be managed for earliness and is more sensitive to biotic or abiotic stresses (insects, drought, etc.) that could result in the loss of earlier set bolls). Growers also need to consider the possibility of crop damage caused by hurricanes later in the season that could affect yield of cotton. In 2018, Hurricane Florence caused large-scale crop and livestock losses with an estimated impact of $2.4 billion in the state of North Carolina. The cotton industry had $135 million in direct losses and $124 million in indirect losses (Cooper, 2018). Hurricanes occurring during early to mid-September, and prior to harvest, are likely to reduce yield of early planted cotton more than later planted cotton due to the higher number of opened bolls in early planted cotton. Conversely, hurricanes occurring in mid-October may allow for early planted cotton to be harvested earlier, but can cause greater yield losses in later planted cotton with more opened bolls during that time. As such, there are many factors that could influence the success of replanted cotton compared to the initial planting, which leads to uncertainty of replanting decisions.

Several studies have made replanting recommendations based on planting date, plant population, skip size, skip frequency, and skip uniformity. Hasna, (1982) first recommended replanting at a 40% stand loss threshold. Boman & Lemon (2005) recommended delaying the replanting decision until after two to three days of good growing conditions. Jost et al. (2006) concluded that replanting was justified if at least 50 percent of the planted area was occupied by skips equal to or greater than three ft. Wrather et al. (2008) recommended producers in the Mississippi Delta to not replant cotton after mid-May if the population from a late April planting is greater than 16,988 plants ha-^{1}. Dodds (2016) concluded that stands are acceptable if more than 15,000 plants are counted in one acre and skips of two to three ft are kept to a minimum. All of these recommendations help growers delimit the boundaries for plant population, skip size, skip frequency, and skip uniformity, and defines acceptable (or unacceptable) threshold values based on scientific research.

Utilizing unoccupied aerial vehicles (UAVs) and remote sensing could potentially serve as a tool in making agronomic decisions with precision and timeliness. UAVs have become a widely used technology in modern agriculture. They are compact in size, user-friendly, and bring low operating costs (Ehsani & Maja, 2013). Their advantage over satellite imagery lies in frequency and spatial resolution (Sankaran et al., 2015). They have been used for numerous remote sensing applications in cotton farming such as assessing nitrogen status (Ballester et al., 2017), managing defoliant spray volumes (Xin et al., 2018), detecting the spread of disease infections (Xavier et al., 2019), monitoring furrow irrigation processes (Long et al., 2016), and monitoring plant growth (Papadopoulos et al., 2017).

A few studies have used UAVs to quantify small-sized cotton seedlings. Feng et al. (2020) developed a deep learning model for real-time cotton stand count and canopy size mapping post-emergence. The study was able to quantify seedlings at 15 days after planting with a mean absolute percentage error of 4.4%, and determined that UAV-based hyperspectral sensors were a feasible tool for assessing cotton stand counts. Although hyperspectral sensors are effective, they can be costly to the average cotton farmer. Another study used a multispectral sensor to quantify cotton stand uniformity and understand its relationship with lint yield (Butler et al., 2020). The study observed a moderate correlation between lint yield and stand uniformity (R=0.66), and concluded that reduced spacing between plants produced greater yield potential. The study had various skip arrangement configurations, but observed the largest yield reductions with skips of 1.5 m laid in parallel arrangement (skips in neighboring rows were aligned). This configuration reduced yield by 22%. Both studies provided insight into how replanting decisions could be made. However, they did not incorporate the economic implications of replanting. Moreover, they did not recommend a threshold in terms of stand count or in terms of uniformity to when a replant is justified.

Remote sensing can be used to measure skips or gaps in row crops. De Souza et al. (2017) created skip maps in sugarcane by combining UAV-based, high-resolution images and an object classification process. The model was able to detect skips with a root mean square error (RMSE) of 1.23%. Luna & Lobo (2016) also quantified skips in a sugarcane field using a manual and a

UAV-based method. This study followed the Stolf method for measuring skips in selected row segments. Results clearly showed an upgrade in sampling intensity in favor of their developed UAV-based method. Moreover, their UAV-based method was able to estimate linear gap percentages with an RMSE of 5.04%. The UAV-based methods presented in both studies were effective in quantifying skips in sugarcane. Both studies also indicated that their results would provide valuable insight for establishing a replant. These methods could be extended to cotton farming for the same purpose.

Conclusion

Replanting recommendations need to be adjusted to accommodate current replanting prices and climate variations. Opportunity exists for remote sensing applications to estimate cotton plant populations and skipped areas to make better-informed replanting recommendations. The first goal of this thesis is to test the agreement of a UAV-based method and a traditional method in detecting size and frequency of skips. The second and final goal is to refine previous replanting recommendations by using UAV-based detection methods and accounting for the economic impact of a replant.

Chapter 2 – Comparison of a manual and a UAV-based method on detecting size and frequency of skips in cotton stands

Introduction

Suboptimal plant stands are a common occurrence in cotton farming (Figure 1). Inconsistent cotton emergence has been associated with planting timing, seed vigor or size, seed quality (warm and cold germination), and poor environmental conditions (Collins & Eminsten, 2016; Pettigrew & Johnson, 2005; Pettigrew et al., 2009). In the presence of suboptimal stands, growers need to decide if replanting and the associated costs or risks are justified. The decision to accept or reject a stand has consistently been one of the most challenging tasks for cotton growers in previous years (Butler et al., 2019; Craig, 2010; Jost et al., 2006).

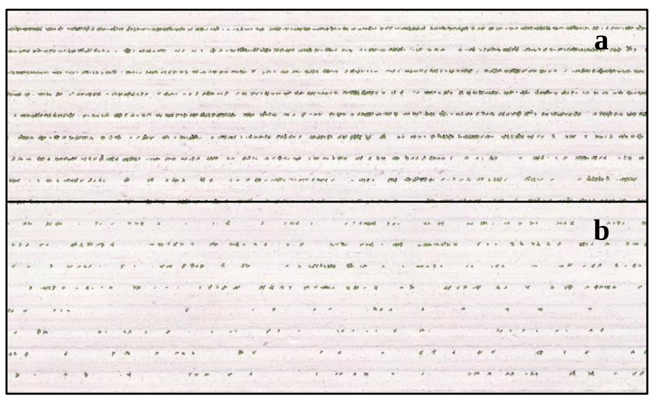

Figure 1. (a) Optimal cotton stand. (b) Suboptimal cotton stand. Peanut Belt Research Station. Lewiston, NC

Conventional methods for assessing stand and skips consisted of manually counting recently emerged cotton plants and determining plant population densities and uniformities. One of the most common methods has been the 1/1000th method. This method involves counting the number of emerged, healthy plants within a pre-determined linear distance of row, and multiplying that number by 1,000, thus providing an estimate of the number of plants ha^{-1} (Godfrey et al., 2010). Manually measuring cotton emergence has been time and effort intensive and prone to human bias (Butler et al., 2019; Liu et al., 2017; Zhao et al., 2018). Manual methods may or may not be representative of the entire fields, and can lead to inaccurate or unnecessary replanting decisions.

Recent studies have proposed using unoccupied aerial vehicles (UAVs) to obtain imagery that can be analyzed for assessing cotton stands. These techniques could potentially replace, and even improve, the data that are already obtained via conventional methods for supporting a replanting decision. Strong correlations in plant detections have already been documented between the 1/1000th method and one novel technique that involves the use of a UAV (Butler et al., 2019). On another study, Chen et al. (2018) used a consumer-grade UAV equipped with a red, green, and blue (RGB) sensor to calculate the average plant size and estimate the number of germinated cotton plants. These estimates were compared to a manual count of the plant population, and the study resulted in an 88.6% identification accuracy. Furthermore, Feng et al. (2019) utilized a UAV equipped with a pushbroom hyperspectral sensor to segment and identify cotton seedlings in the emergence stage. The study successfully detected 98% of the plant population by identifying the geometric characteristics of the seedlings at a meter-scale level. The high accuracy outperformed estimated stands from other studies that did so at a plot-level (18 plots in Zhao et al. (2018), 6 plots in Chen et al. (2018), 90 plots in Jin et al. (2017) and 30 plots in Sankaran et al. (2017). Unfortunately, hyperspectral sensors are costly, complex to integrate and still uncommon in commercial post-processing software like Agisoft Photoscan (Agisoft LLC, St. Petersburg, Russia) and Pix4D (Lausanne, Switzerland).

Another study used a UAV equipped with an optical multispectral sensor to measure plant uniformity and gaps, or skips, between plants. Butler et al. (2019) argued that the identification and quantification of skips is the most important component in deciding whether to replant or not.

The study combined a series of ArcMap tools to quantify the uniformity of emerged cotton plants based upon in-row plant distances, and determined when yield reductions would most likely occur based on uniform skip spacing. The developed model suggested that a uniform population of 74,000 plants ha^{-1} would likely not warrant a replant at any date, and that a uniform population as low as 49,000 plants ha^{-1} planted after 5 May (for Mid-South cotton) would also not warrant a replant. The study reported a positive relationship between the developed uniformity index and lint yield potentials (R^2=0.66), and a clear improvement over conventional methods. Oh et al. (2020) detected cotton seedlings at sub-centimeter resolution and calculated plant population and average spacing between cotton seedlings using deep learning object-detection methods. The study argued that the proposed method could allow farmers to effectively make replanting decisions, but many object-detection tools have been computationally intensive and highly technical. Ultimately, other factors like critical spacing between plants in non-uniform stands and the respective critical time for assessment remain to be determined.

One of the biggest challenges of using UAVs for determining the replanting decision is identifying the seedlings in a period where farmers can still take advantage of optimal planting windows to replant. Another challenge is finding an affordable, consumer-grade sensor with sufficient resolution to detect seedlings during the emergence and germination stage of cotton. Ideally, rapidly emerged cotton seedlings would be identified using a ubiquitous RGB camera. However, some studies have shown that RGB sensors have a limited ability to identify small objects like cotton seedling. One example is given in Feng et al. (2019), where a GoPro HERO 5 RGB camera and a Canon PowerShot SX410 RGB camera were flown at 15 m AGL, 15 days after the cotton was planted. The plants could not be distinguished from the soil in the RGB images. Other studies have had more success using RGB sensors to classify emerged cotton stands and predict yield. In a five-year study, Dodge (2019) suggested that RGB image data collected via UAVs could provide surprisingly accurate and meaningful data, and further be used for stand assessments. This study suggested that an opportunity exists for RGB sensors to displace costlier sensors for stand assessment applications.

Most studies that have used RGB or multispectral sensors for identifying recently emerged seedlings have done so at relatively low altitudes (Table 1). As might be expected, differences in morphological features will vary across crops, so adjustments in flight settings will be conditional to each crop. However, flights conducted at lower altitudes will require longer flight times, multiple flights, and creates much more imagery for processing. Adding complexity could potentially deter users from using UAVs for stand assessment applications.

Table 1. UAV flying altitude of studies that have used RGB or multispectral sensors to detect early-emerged seedlings

Study	Sensor (type of sensor)	Crop	Altitude (m)
Feng et al. (2019)	Canon PowerShot SX410 (RGB)	Cotton	15
Butler et al. (2019)	MicaSense RedEdge (Multispectral)	Cotton	30, 60, 75, and 120
Zhao et al. (2018)	Nikon D800 camera + Nikon 50.0 mm f/1.4 D focal lens (RGB)	Canola	20
Liu et al. (2017)	Sigma SD14 (RGB)	Wheat	1.5
Jin et al. (2017)	Sony ILCE α5100L (RGB)	Wheat	3, 5, and 7

Recently, there has been a push to develop cloud-based platforms that can quantify plant and gap population with UAV-sensed imagery. AgroView (AgroView, Gainsville, FL), Solvi, (Solvi, Sweden) Precision Analytics (Precision Hawk, Raleigh, NC), and Agremo (Agremo, Serbia) are a few commercially available cloud-based platforms. Ampatzidis et al. (2020) explained that AgroView can process and analyze UAV imagery for detecting and georeferencing crop and gap populations, generate plant health maps, and estimate plant height. Although the study was conducted with adult citrus trees, similar algorithms that can estimate plant populations can be found in the market. Opportunity exists for growers to determine the replanting decision with added accuracy and precision based on plant counts provided by these applications.

Previous research has suggested that replanting is justified when a field contains skips greater than or equal to three feet in 50 percent or more of the planted area (Jost et al., 2006). This recommendation has been adopted in a few cotton-producing states such as North Carolina and Tennessee (Collins & Edmisten, 2018; Craig, 2010). The proposed recommendation differs from other recommendations because it focuses on size and frequency of cotton skips instead of plant populations. Methods by Jost et al. (2006) assumed that yield reductions would most likely occur in non-uniform stands that contained skips of various frequencies and sizes (a notion that was also alluded to in Butler et al. (2019)).

The goal of this experiment was to test the agreement of a UAV-based method and a traditional manual method in detecting skips greater than or equal to three ft. The objectives of this study were to: (i) compare the time of skip detection and skipped-area evaluation between a UAV-based method and the manual method described in Jost et al. (2006), (ii) quantify the percentages of planted areas occupied by skips greater than or equal to three ft derived from the number of skips detected with each method, (iii) regress lint yield to the percentage of planted area occupied by skips greater than or equal to three ft calculated with each method, and (iv) test the agreement of both methods in their assessment of percent of planted area occupied by skips greater than or equal to three ft. The study hypothesized that the UAV-based method would detect size and frequency of skips with higher accuracy and precision than manual measurements, and provide a better-informed recommendations on the decision to replant suboptimal stands.

Materials and Methods

Experiments were conducted at three sites in North Carolina during 2019: Upper Coastal Plains Research Station, Peanut Belt Research Station, and Tidewater Research Stations located near Rocky Mount, Lewiston, and Plymouth, NC, respectively. At each location, both early and late planted trials were conducted. Within each trial, five treatments were arranged in a randomized complete block, and were replicated four times. Each plot contained four rows that were planted at a rate of 43,560 seeds acre^{-1}. Treatments consisted of varying ratios of transgenic (DP1646 B2XF) and non-transgenic (DP493) cotton seed: 100%, 75%, 50%, and 25% as well as a replanted treatment of 100% transgenic seed. Primary planting for the typical planting date trial across all locations occurred between April 29th, 2019 and May 7th, 2019, and their respective replant treatments were planted between May 24th, 2019 and May 28th, 2019. Primary planting for the late trial occurred between May 23rd, 2019 and May 28th, 2019, and their respective replant treatments were planted between June 4th, 2019 and June 7th, 2019 (Table 2). Following emergence, all treatments except the replant treatment received three weekly sequential applications of glyphosate (32 oz/A) and gluphosinate (42 oz/A) to eliminate the conventional seedlings, and create natural, random, non-systematic skips that varied in size and frequency among adjacent plants in each row.

Table 2. Planting, flying, and harvest dates

Site	Trial	Planting Date	Flying Date (DAP)	Harvest Date
Rocky Mount	Early	April 29, 2019	July 2, 2019 (64)	October 3, 2019
	Late	May 24, 2019	July 2, 2019 (39)	October 18, 2019
Lewiston	Early	May 7, 2019	July 2, 2019 (56)	October 10, 2019
	Late	May 28, 2019	July 2, 2019 (35)	October 23, 2019
Plymouth	Early	May 7, 2019	June 11, 2019 (35)	October 15, 2019
	Late	May 23, 2019	June 11, 2019 (19)	October 24, 2019

Two methods were used for measuring skips in the field: a manual method and a UAV-based method. Manual measurements consisted of randomly subsampling skips in 200 ft sections within the center two rows in each plot. All skips greater than 12 in. within the subsampled distance were recorded using a measuring tape. However, only the skips that were greater than or equal to three ft were used, as suggested by Jost et al. (2006). The UAV-based method collected images over the entire plot area using a DJI Matrice 600 Pro (DJI, Shenzen, China) UAV equipped with a DJI Zenmuse X5 (DJI, Shenzen, China) RGB camera. Autonomous flights were generated using Precision Flight (Precision Hawk, Raleigh, NC). The study areas were flown after all herbicide applications were completed, and after conventional seedlings were terminated (Table 2). The percentage of planted area occupied by skips greater than three ft was derived from equation 1.

$$\%\ of\ planted\ area\ occupied\ by\ skips\ \geq\ 3.0\ ft. = \left(\frac{\sum_{i=1}^{n} S_i}{2L}\right) \times 100 \qquad (1)$$

Where,
S = skips greater than or equal to 3.0 ft
L = length of the plot (L = 200 ft for manual method)
i = index counter for skips greater than or equal to 3.0 ft

The UAV flew over the early and late trials at an altitude of 53 m (175 ft) above ground level and produced imagery with a GSD resolution of 2.3 cm/pixel. The imagery was then stitched and evaluated using Precision Hawk Ag Analytics (Precision Hawk, Raleigh, NC). The Precision Hawk proprietary plant-counting algorithm was applied to the stitched imagery, which returned an orthomosaic of the field and a plant count file with georeferenced point data of the plants. Figure 2 shows a portion of both the plant count file and the orthomosaic map.

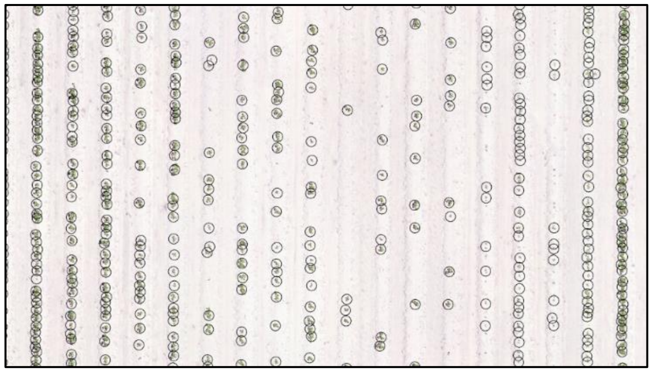

Figure 2. Plant count layer over the orthomosaic map in Lewiston, NC. Seedlings were detected via the UAV-based method. Various frequencies and sizes of skips signal different treatments

Using QGIS 3.8.0 (Quantum GIS Development Team, 2020) and the Distance Matrix function, the linear distances between a reference plant (first plant observed in the center rows of each plot) and the remaining plants in each row were calculated. Similar to the manual method, only the inner two rows for each plot were subjected to this analysis (Figure 3). This time, entire sample rows were analyzed. Two selections were made for each row. The reference plant was selected and saved as a new layer. Similarly, the remaining plants in that same row (target plants) were selected and saved as another layer. For each row, The Distance Matrix tool was used to generate a temporary layer that consisted of the distances between the reference plant and each of the target plants in the row. Each layer was then saved in .csv format and data was stored in a known folder.

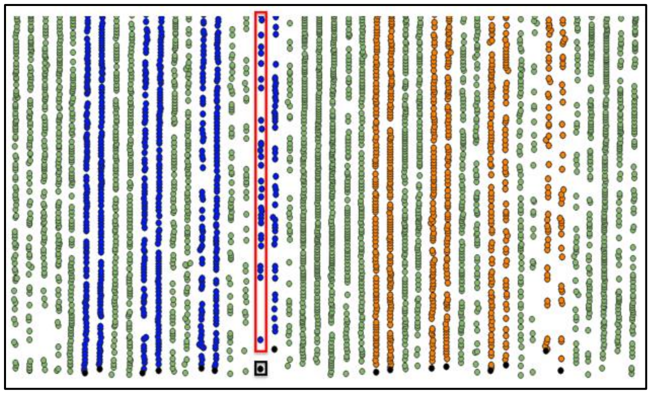

Figure 3. Selection of the reference (square) and target plants (rectangle) in a row of interest in QGIS 3.8.0

The UAV-based method consisted of developing an algorithm in R 4.0.2 (R Core Team, 2020) to transform the linear distances between the reference and target plants into distances between adjacent plants in each row. Similar to the manual method, equation 1 was used to derive the percentage of planted area occupied by skips equal to or greater than three ft for the UAV-based method.

Lint yield was regressed to the percentage of planted area occupied by skips greater than or equal to three ft calculated with each method. Then, a Bland-Altman analysis (Bland & Altman, 1999) was conducted to evaluate the agreement between the manual method and the UAV-based method. The analysis identified systematic differences and possible outliers between both methods. This simple method evaluated bias between mean differences from the two methods and helped establish limits of agreement at a 95% confidence interval (CI) (Giavarina, 2015). More specifically, the plots compared the agreement between the manual and UAV-based method in measuring the percent of planted area occupied by skips greater than or equal to three ft. Differences between methods were calculated using equation 2, and means were calculated using equation 3. The purpose of conducting this analysis was to identify which stand treatment(s), or combination of stand treatments, would capture a difference of zero (or "line of equality" as described by Giavarina (2015)) in the 95% CI of the mean difference. If the interval captures the line of equality then it could be concluded that both methods statistically agree in the mean of their differences.

$$Difference_i = \mu_{manual,i} - \mu_{uav,i} \tag{2}$$

Where,

$\mu_{manual,i}$ is the percent of planted area occupied by skips greater than or equal to three ft detected by the manual method in plot i

$\mu_{uav,i}$ is the percent of planted area occupied by skips greater than or equal to three ft detected by the UAV-based method in plot i

$$Mean_i = \frac{\mu_{manual,i} + \mu_{uav,i}}{2} \tag{3}$$

The 'blandr' package (Datta, 2017) was used in R to evaluate differences between methods. The methods were first compared with all sites and trials together. Then, methods were compared at the site, trial, and treatment levels. QQ-plot p-values, paired t-test p-values, and correlation coefficients were obtained to inform whether both methods agreed in their measurements or not. A significance level of 0.05 was used to measure the strength of the evidence against the null hypothesis (H_{null}) (eq. 4). A QQ-plot p-value higher than 0.05 indicates normality in the response. A paired t-test p-value above 0.05 indicates a lack of evidence against the null hypothesis.

$$H_{null}: \mu_{manual,i} - \mu_{uav,i} = 0 \tag{4}$$

Results and Discussion

Flights were originally flown two weeks after planting when seedlings were in the germination and emergence stage, and non-transgenic seedlings had just been terminated using herbicides. Imagery from these flights resulted in no plant detections (Figure 4). This is consistent with the initial flights conducted by Feng et al. (2019). Inadequate weather conditions, camera settings, and flying altitude were major factors that affected the success of plant detections. The reasoning behind flying as high as 53 m (175 ft) AGL was to do quick flights (<12 min) and assess entire planted areas in just one flight. Consequently, resolution from the images was compromised by using this altitude, which ultimately forced the study to reschedule future flights to dates where the seedlings were more mature. This scenario was problematic for the assessment of stand conditions before the crop insurance deadline on May 25th for NC cotton.

Figure 4. Overhead image of early-emerged cotton taken 15 DAP at 175 ft AGL. May 14, 2019. Rocky Mount, NC. Cotton plants are not visible

Moreover, the UAV-based method was not bereft of sampling error. In some instances, the UAV imagery-based plant counts failed to detect present plants (Figure 5). The frequency and magnitude of this error is unknown. Yet, results from this study are presented under the assumption that this error is insignificant. Because the sampling size from the UAV-based method is a close approximation to the population size, instances where erroneous detections were observed were deemed unimportant. All things being considered, this study recognized their existence and simultaneously acknowledged that the element under study is the usefulness of each method at determining the replanting decision regardless of its intrinsic inaccuracies.

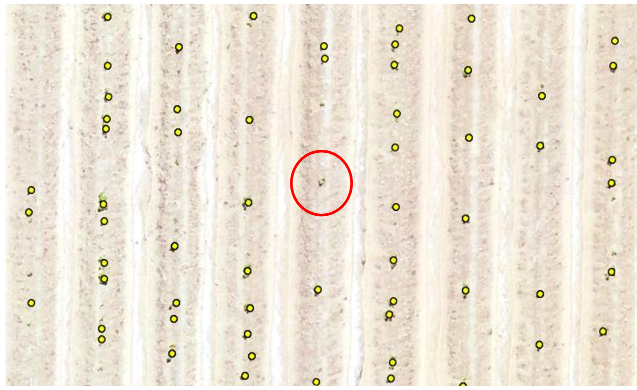

Figure 5. Failed detection of a plant within a row. Rocky Mount, NC.

Size and frequency of skips were successfully detected and analyzed using both methods in every trial within every site when flights were conducted at late emergence growth stage. The UAV-based method was able to assess entire planted areas in approximately 25% of the time required to manually assess 200 ft subsamples per plot. However, the post-processing software took between 24 and 48 hours to return the plant count files and another 24 to 48 hours to conduct QGIS (Quantum GIS Development Team, 2020) and R (R Core Team, 2020) analyses. The manual method also required approximately 24 to 48 hours to calculate the percentage of planted area occupied by skips greater than or equal to three ft. As it currently stands, this is a drawback for both methods because stand assessments continue to be either tedious or time-consuming. However, there is a possibility to automate the proposed UAV-based method and provide a more rapid and user-friendly skip assessment tool to cotton farmers, whereas the manual method will continue to depend on long, cumbersome on-site plant or skip assessments.

The number of skip detections that were greater than or equal to three ft varied across treatments and methods. The manual method detected fewer skips at higher plant stands; almost no skips were detected at the 100% and 75% stand treatment in all trials and sites (Table 3, Table 4, and Table 5). In contrast, the UAV-based method detected a larger number of skips in both of the higher stand treatments in all trials and sites (Table 3, Table 4, and Table 5). Discrepancies between methods may be explained by differences in sampling size. The randomly selected 200 ft of planted row could have been unrepresentative of the entire plot area, whereas the larger sampling size of the UAV-based method could have been more representative.

Table 3. Percentage of planted area occupied by skips greater than or equal to 3.0 ft in Lewiston, NC during 2019

Method	Trial	Treatment	Mean	SD
UAV	Early	100	1.9	0.6
		75	3.2	3.3
		50	4.6	3.0
		25	18.9	10.4
	Late	100	0.1	0.2
		75	2.0	3.4
		50	0.1	0.2
		25	6.5	1.5
Manual	Early	100	0.4	0.4
		75	1.0	1.0
		50	1.7	1.7
		25	33.9	9.5
	Late	100	0.0	0.0
		75	0.0	0.0
		50	3.4	0.9
		25	35.2	6.8

Table 4. Percentage of planted area occupied by skips greater than or equal to 3.0 ft in Rocky Mount, NC during 2019

Method	Trial	Treatment	Mean	SD
UAV	Early	100	3.7	3.0
		75	7.9	4.0
		50	19.4	2.3
		25	59.4	6.5
	Late	100	0.5	0.6
		75	2.7	1.9
		50	10.5	5.3
		25	44.9	5.7
Manual	Early	100	0.0	0.0
		75	1.4	1.5
		50	0.8	1.3
		25	34.0	7.5
	Late	100	0.0	0.0
		75	0.0	0.0
		50	2.2	1.4
		25	35.4	2.2

Table 5. Percentage of planted area occupied by skips greater than or equal to 3.0 ft in Plymouth, NC during 2019

Method	Trial	Treatment	Mean	SD
UAV	Early	100	1.4	1.6
		75	6.2	2.6
		50	17.4	5.4
		25	55.7	6.3
	Late	100	4.0	2.2
		75	15.9	8.2
		50	41.7	6.4
		25	77.7	4.1
Manual	Early	100	0.8	1.4
		75	4.1	3.4
		50	9.5	7.7
		25	66.3	6.9
	Late	100	0.0	0.0
		75	1.0	1.0
		50	5.4	4.7
		25	36.5	9.2

Yield, expressed in pounds acre^{-1}, was regressed to the percentage of planted area occupied by skips greater than or equal to three ft across all trials and sites (Figure 6). A linear fit was plotted for each method. The failure of manual measurements in detecting skips at higher stands was evident with the multiple zero or null values in the horizontal axis. This increased the leverage towards manual observations in the lower stand treatments, which may lead to a flawed replanting decision.

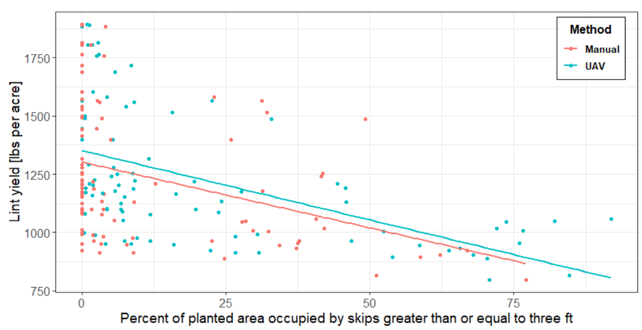

Figure 6. Yield vs Percent of planted area occupied by skips greater than or equal to three ft across all trials and sites

A statistical summary of QQ-plot and t-test p-values and correlation coefficient values are shown in Table 6. A non-Gaussian distribution was observed across all treatments combined. A paired t-test found the means of both methods to be significantly different from each other across all treatments combined. A correlation coefficient of 0.73 indicated a strong linear relationship between both methods in their ability to detect plots with varying skip sizes. Results from plots in all treatments combined suggested that both methods differ in their measurements of areas occupied by skips greater than or equal to three ft.

Table 6. Q-Q plot and t-test p-values and correlation coefficient results between the UAV-based method and manual method across all treatments combined

Parameter	Combined Treatments	Individual Treatment			
		100%	75%	50%	25%
Q-Q plot p-value[a]	>0.001*	>0.001*	0.002*	0.329	0.109
t-test p-value	>0.001*	0.002*	>0.001*	>0.001*	0.101
Corr. coefficient	0.73	0.102	0.167	0.189	0.276

* Statistically significant at an alpha level of 0.05
[a] Significance in the Q-Q plot indicates non-Gaussian distribution

Both methods were also compared at each individual treatment level. Normality in the distribution increased as the treatment-imposed stand decreased. T-test results indicated that methods did not agree in the mean of the percent of area occupied by skips greater than or equal to three ft in the 100%, 75% and 50% treatments. These results can be problematic to farmers who are trying to assess stands that have suffered up to 50% stand losses because it suggests that post-emergence assessments that use the UAV-based method will most likely disagree in the mean of the area (occupied by skips greater than or equal to three ft) with those obtained with the manual method.

The Bland-Altman plot comparing both methods across all treatments is shown in Figure 7. The plot revealed a mean difference of -7.65 and a -40.94 to 25.62 range of agreement. The 95% CI of the mean difference did not capture the line of equality. Therefore, both methods were statistically different in the mean of their differences when treatments were compared altogether. The v-shaped scatter plot indicated agreement in the random relative error between methods when comparing treatments altogether, and suggested that larger measurements of skips output larger errors between measurements. Moreover, the large number of observations with a small percentage of planted areas occupied by skips greater than or equal to three ft contributed to a shortening of the limits of agreement, which could explain why several 25% treatment observations were outliers.

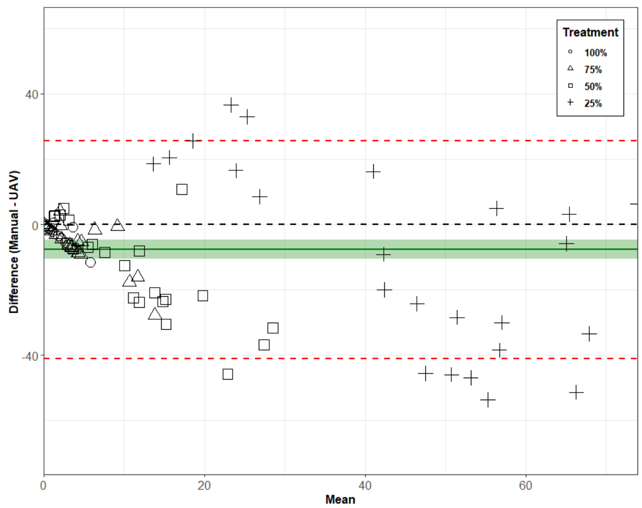

Figure 7. Bland-Altman plot comparison of UAV-based and manual methods at the 100%, 75%, 50%, and 25% treatment levels

A cluster of points belonging to the 100%, 75%, and 50% was distinguished in the left-most portion of Figure 7. Figure 8 shows the Bland-Altman test for the combined 100%, 75%, and 50% treatments excluding the 25% treatment. A mean difference of -6.81 was observed in this plot, and, similar to Figure 7, the 95% CI of the mean difference did not capture the line of equality. A negative trend was observed as the mean increased in magnitude, which suggests a proportional constant error between both methods and clear statistical evidence of a disagreement. This was expected, considering that the UAV-based method detected a larger number of skips greater than or equal to three ft than the manual method. This also implicated that, for denser stands where large skips are scarce, the detected percentage of planted area occupied by skips greater than or equal to three ft will likely vary by method.

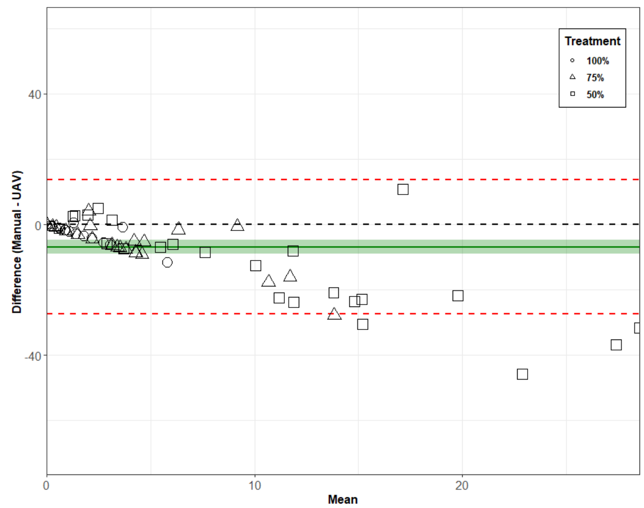

Figure 8. Bland-Altman plot comparison of UAV-based and manual methods at the 100%, 75%, and 50% treatment levels

A mean difference of -10.10 was observed when comparing both methods at the 25% treatment only (Figure 9). In this case, the 95% CI (-20.24, 0.03) of the mean difference captured the line of equality, and provided evidence of agreement between both methods. No outliers were observed.

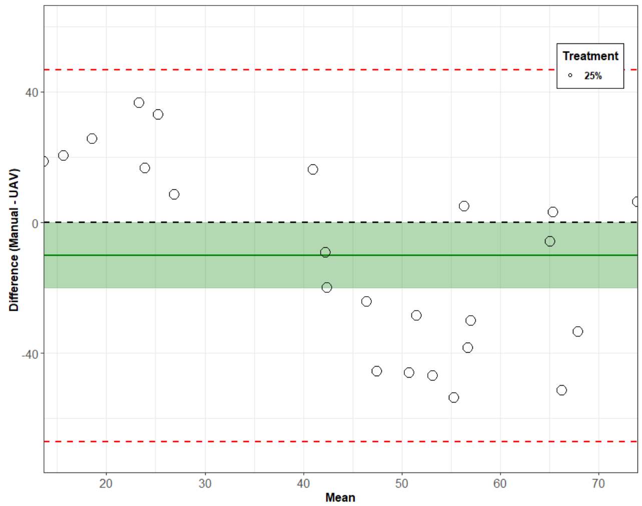

Figure 9. Bland-Altman plot comparison of UAV-based and manual methods at the 25% treatment levels

Figure 10, Figure 11, and Figure 12 correspond to the Bland Altman method bias comparison for the 100%, 75%, and 50% treatments. As the treatments increase from 50% to 100%, the volume of skips greater than or equal to three ft. detected by the manual method decreases faster than the UAV-based method.

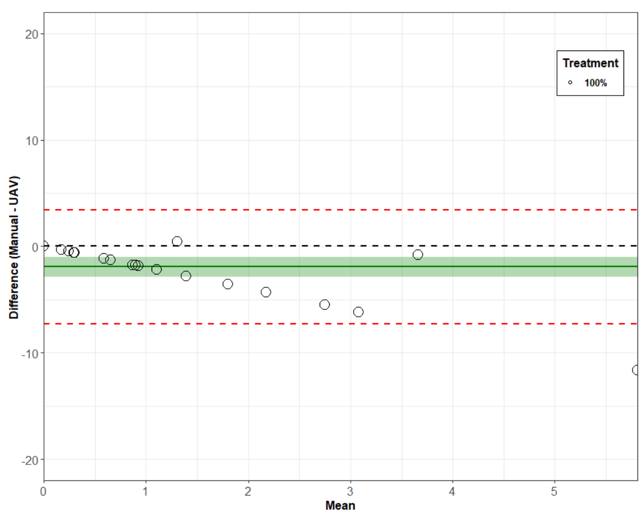

Figure 10. Bland-Altman plot comparison of UAV-based and manual methods at the 100% treatment level

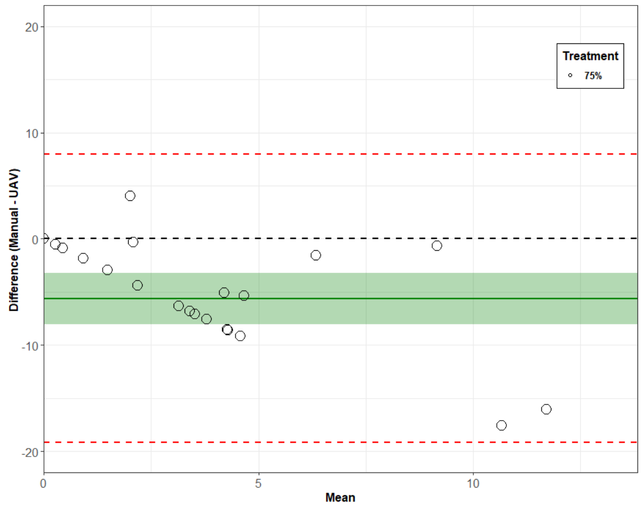

Figure 11. Bland-Altman plot comparison of UAV-based and manual methods at the 75% treatment level

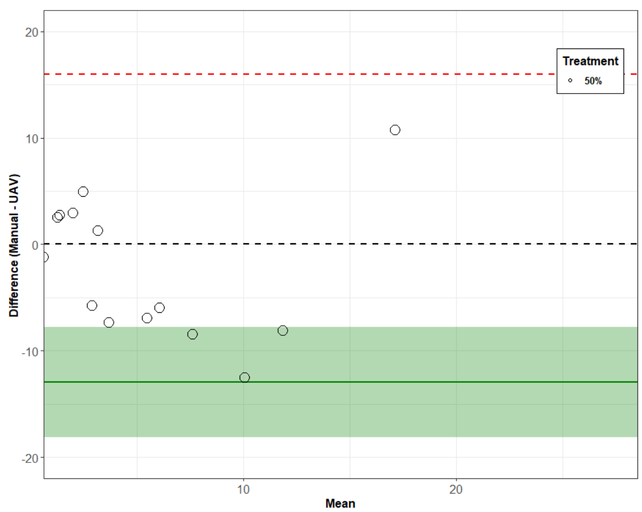

Figure 12. Bland-Altman plot comparison of UAV-based and manual methods at the 50% treatment level

Table 7 shows the Bland-Altman bias estimates and the 95% CI of the mean differences for each treatment as well as a various treatment combinations. Only at the 25% treatment was the 95% CI of the mean differences observed to capture the zero mean bias. No treatments and treatment combinations captured the line of equality. This indicates that data at each of these tests were not consistent with equal population means and that a significant difference between the UAV-based and manual method was observed.

Table 7. Bland-Altman bias estimates and 95% confidence intervals for each treatment and various treatment combinations

Treatment	Mean Difference	95% CI	Limits of Agreement
100% (n=24)	-1.93	(-3.09, -0.78)	(-7.30, 3.43)
75% (n=24)	-5.62	(-8.55, -2.69)	(-19.20, 7.95)
50% (n=24)	-12.96	(-19.20, -6.72)	(-41.92, 16.00)
25% (n=24)	-10.11	(-22.36, 2.15)	(-67.00, 46.79)
75% + 50% (n=48)	-9.29	(-12.78, -5.81)	(-32.82, 14.23)
100% + 75% + 50% (n=72)	-6.81	(-9.31, -4.38)	(-27.40, -13.72)
100% + 75% + 50% +25% (n=96)	-7.66	(-11.10 , -4.22)	(-40.94, 25.62)

Conclusion

Overall, results from the Bland-Altman test suggest that, in the presence of severely poor cotton stands, methods will most likely agree in the mean difference of the percentages of area occupied by skips greater than or equal to three ft. Results from this study also suggest that undetermined stands will generate a poor agreement between methods. Farmers who wish to measure the percent of area occupied by three ft skips in a field with an undetermined stand will have to choose between the manual and the UAV-based method recongnizing that results may differ between them. This raises a question: which method is most appropriate for detecting size and frequency of cotton skips in fields where stand losses are not clearly visible? It can be argued that if a stand cannot be visibly determined to be suboptimal then there is no need to perform manual or remote sensing assessments, and, consequently, neither is to replant. The UAV-based method demonstrated a superior ability to sample skips in treatments with denser stands. However, cotton farmers have been manually counting skips for decades to assess the severity of a suboptimal stand, and, today, manual methods like the 1/1000th method and the method proposed by Jost et al. (2006) are still accepted methods in industry and academia. It may be true that for stands containing skips that are small in size, finding skipped-area percentages similar to how it was done in this study will not be needed. However, in the case that it is needed, results suggest that the proposed UAV-based method is a more suitable method for this application.

Limitations

The spatial accuracy of UAV measurements was limited to the spatial accuracy of the onboard GPS in the Matrice 600 Pro for the 2019 growing season.

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Chapter 3 – Redefining Cotton Replanting Recommendations

Introduction

Previously, seed needed for replanting was provided by seed companies at no charge. By 2013, the cost of replanting soared to \$15-20 acre^{-1} (Dodds, 2013). Initially, the major seed companies charged 50% of the seed cost plus, in some cases, an additional technology fee (Dodds, 2013). More currently, there is not a clear distinction between the seed or germplasm costs, and technology fees. Therefore, most seed companies are charging 25% of suggested retail price per bag of replanting seed. Today, the total cost of replanting has increased to approximately \$35 acre^{-1}, which includes fuel, labor, and equipment usage for a seeding rate of 43,560 sd acre^{-1} (Edmisten & Collins, 2020). Large acreage producers often do not have the luxury of time or the labor resources needed to determine if replanting is justified. The additional cost of replanting warrant methods that can determine the need for replanting in a precise and timely fashion.

Several studies have made replanting recommendations based on planting date, plant population, skip size, and skipped area (Butler, 2019; Hasna, 1982; Jost et al., 2006; Pettigrew et al., 2009). However, many studies have disregarded the economic impact of a replant. Although some studies do mention that the cost of replanting is important in making a replanting decision (Hasna, 1982; James McQuigg et al., 1965), many have excluded the economic implications of a replant in their analyses. For this reason, it is plausible that inaccurate replanting recommendations have been reported. Modern unoccupied aerial vehicles (UAVs) equipped with advanced sensing technologies are capable of generating high-resolution images of entire planted areas, which can be used to make well-informed agronomic decisions. Previous studies have demonstrated that UAVs can assist in cotton yield estimations (Feng et al., 2020), manage spraying volumes of cotton defoliants (Xin et al., 2018), and detect spreading of cotton disease infections (Xavier et al., 2019).

Certainly, it was worth exploring UAVs as a prospective tool for detecting cotton seedlings and skips in cotton farming. Leveraging modern sensing technologies, ensuring that the correct metrics are applied, and updating recommendations to reflect current economic and climatic changes should provide better guidance for justifying the replanting decision.

Full lint yield potential observed in late-planted cotton have demonstrated that replanting may be beneficial if planting conditions are appropriate (Craig, 2010; Edmisten & Collins, 2020). Warm temperatures during late planting increase the likelihood of rapid seedling emergence and the potential to produce larger leaves and stems that can sustain boll development (Collins & Edmisten, 2015; Quinn, 2015). Craig (2010) determined that a replant is likely to be successful on a warmer day in late May than on a colder day in early May. However, other studies have shown that planting too late reduces yield due to limited flower and boll development (Abd-El-Gawad et al., 1986; Darrin Dodds, 2016; Killi & Bolek, 2006; Saroya et al., 1980). This often results from reduced heat unit accumulation during the latter part of the season, which is needed to fully develop younger, less mature bolls. Data collected in a two-year study revealed a 15% seed yield increase from earlier-planted cotton and a 28% seed yield decrease from later-planted cotton when compared to cotton planted on May 1st (Killi & Bolek, 2006). Collins & Edmisten (2015) recommended increasing the seeding rate in order to avoid late maturity and reliance on outer position vegetative bolls for optimal yield. Despite the risk associated with overextending the planting date, higher market values for cotton lint motivate growers to consider late planting. Yet, results from the aforementioned studies were variable and dependent on local conditions, and supported the idea that objective measures will provide more localized results.

The optimal planting date will ultimately depend on numerous production variables including length of growing season and the associated heat unit accumulation, matching rainfall and temperature patterns with cotton growth stages, reducing pressure from pests, and avoiding unfavorable weather conditions during crop termination and harvest (Boman & Lemon, 2005). Optimal planting dates will also vary among regions in the United States. In Southeastern United States, the optimal planting date occurs between April 29th and June 10th. Cotton planted from late April through late May generally has an equal chance of achieving optimal yields, whereas lint yield decreases to below early-planted levels after early June 10th (Edmisten & Collins, 2020). However, it is generally advised that cotton planted after late May must be irrigated and managed with growth regulators and insecticides in a very timely manner given the shortened season for late-planted cotton. Growers in Tennessee target planting between April 20th and May 10th (Craig, 2010). The optimal planting window in mid-South United States occurs in mid-April (Boquet & Clawson, 2009). These studies highlight the importance of understanding local climate patterns and its effect on planting date to avoid a replanting situation.

Temperature, precipitation, and soil moisture are factors that affect germination, emergence, and early season vigor (Bradow & Davidonis, 2000). Morphological and physiological effects of low temperatures during these stages negatively affected lint yield in some studies (Bauer & Bradow, 1996; Kittock et al., 1987). Furthermore, cotton seedlings are highly sensitive to excessively wet soils, especially when cooler temperatures prevail. Whitaker et al., (2013) reported sheer amounts of rainfall caused detrimental conditions in emerged cotton in Georgia. Pettigrew et al. (2009) concluded that cooler and wetter conditions associated with early planting were contributing factors toward a 16% stand reduction. Heat units in degree days may explain and predict occurrence of events in cotton development (Kerby et al., 1987; Landivar & Benedict, 1996; Oosterhuis, 1999). Degree-Day 60s (DD60s, Equation 1) are an estimation of the accumulated temperature effect during a day, based on the average of the maximum and minimum daily temperatures in degrees Fahrenheit (Main, 2012). A 5-day post-planting period with heat unit accumulation relates to a rapid, uniform emergence and early growth indicators of strong and resilient plants (Boman & Lemon, 2005). Edmisten & Collins (2020) suggested that emergence was optimal after 50 DD60s had accumulated and advised not to plant when temperatures were below 50°F in the seed zone to avoid injuring the seed. Furthermore, Reddy et al. (2017) reported that cotton emergence rate decreased linearly with decreasing temperatures. Planting forecasts that use DD60 as an indicator for stand establishments can be beneficial for farmers making planting decisions.

$$DD60s = \frac{(°F_{max} + °F_{\min})}{2} - 60 \tag{1}$$

Plant population is highly correlated to lint yield. Lower plant populations, especially those with uneven plant spacing, are known to reduce yields. Evaluating plant populations helps growers quantify the success rate of emerged plants as compared to the target population and determine if a replant is necessary. Numerous studies have focused on studying the differences between plant populations and deriving recommendations that can establish optimal yield results (Table 8). It can be inferred from these studies that plant populations between 15,000 and 30,000 plants ha^{-1} do not achieve full yield potential. Butler (2019) observed no differences in yield between 49,000 plants ha^{-1} and 123,000 plants ha^{-1}. All other studies using a minimum population size greater than 49,000 plants ha^{-1} observed similar, non-significant differences from higher plant populations. This suggested that plant populations greater than 49,000 plants ha^{-1} were unlikely to result in significant yield increases or losses. Boman & Lemon (2005) found a population size as low as 32,500 plants ha^{-1} to be no different from a population of 65,000 plants ha^{-1}. This however, was inconsistent with Bednarz et al. (2005) who established a difference between 36,000 plants ha^{-1}

and populations of larger size. Adams et al. (2019) normalized most of the studies shown in Table 8 and established that 35,000 plants ha^{-1} are the minimum population density at which yield can be optimized. Even with inconsistent findings in previous research, the disagreement in results suggested that additional measures were needed to characterize cotton plant performance.

Table 8. Reported significant and non-significant differences in lint yield between various plant population sizes

Study	Plant Population (plants ha^{-1})	Difference in Lint Yield
Zhi et al. (2016)	15,000 - 87,000	Significant
Dai et al. (2015)	15,000 - 105,000	Significant
Wrather et al. (2008)	24,000 - 136,000	Significant (2 out of 4 years)
Gwathmey et al. (2011)	30,000 - 114,000	Significant
Boman & Lemon (2005)	32,500 - 65,000	Not Significant
Bednarz et al. (2005)	36,000 - 126,000	Significant
Butler (2019)	49,000 - 123,000	Not Significant
Pettigrew et al. (2013)	50,000 - 100,000	Not Significant
Craig (2010)	50,000 - 175,000	Not Significant
Pettigrew & Johnson (2005)	70,000 - 130,000	Not Significant
Edmisten & Collins (2020)	70,000 - 137,500	Not Significant
Main (2012)	75,000 - 150,000	Not Significant
Feng et al. (2014)	75,300 - 226,000	Not Significant

Other studies have focused on quantifying skip size and skip population instead of plant population to predict lint yield. Boman & Lemon (2005) specified skip size and skip frequency as critical parameters that affect yield loss. Ray (1975) reported rapid declines in yield after the intra-row spacing of plants increased over 0.67 ft. Kerby (1989) suggested that six ft skips with plants on adjacent rows would result in a 13% yield loss potential for the portion of the field with such skips. The study also concluded that yield losses tend to decline when three ft skips were found on adjacent rows rather than longer skips within a row. Furthermore, Bonner (1989) suggested that stand losses as large as 30% can occur without suffering significant yield losses, but only if skips are bordered by rows with no skips. Chambers (1986) established an index based on skip size; skips of 12 to 18 inches long were assigned a value of one, and the index value increased by one for each additional six inches. Yield reductions were mainly observed when the index reached values between 40 and 60. Results from the aforementioned studies provided useful insight on the impact of size and frequency of cotton skips in lint yield and underlined the importance of uniform spacing within and in adjacent rows. However, most of these studies were conducted over 30 years ago and base their results on obsolete varieties with lower yield potentials than modern varieties. In a more recent study, Butler et al. (2019) reported a 45% lint yield reduction on stands of less than 1.5 seeds m^{-1}. Growers were advised to consider large skips as a factor that severely affects the potential yield, and called for further studies to build on the effect that non-uniform stands have on yield. Opportunity exists for researchers to implement modern remote sensing technologies on cotton skip detections, and to revise replanting recommendations accordingly.

As previously mentioned, many of the current replanting recommendations are based on planting date, plant population, skip size, skip frequency, and skip uniformity. Understanding the effect of these factors on lint yield and the influence they have over a farmers' decision-making process is paramount for establishing replanting recommendations. Boman & Lemon (2005) recommended delaying the replanting decision until after 2-3 days of good growing conditions. Dodds (2016) concluded that yield potentials are acceptable if more than 15,000 plants are counted in one acre, and skips of two to three ft remain minimal. The study also concluded that replanting during the month of June is risky and should be avoided. Wrather et al. (2008) recommended producers in the Mississippi Delta to not replant cotton after mid-May if the population from a late April planting is greater than 16,988 plants ha^{-1}. Moreover, Hasna (1982) justified a replant when 40% of the planted area was occupied by skips of any given size. Jost et al. (2006) later refined the replanting threshold at 50% of the planted area occupied by skips equal to or greater than three ft. This last recommendation was compelling because it provided a threshold to the allowable skipped area and defined a skip as a portion of a row with no plants that is at least three ft in length. Although recommendations varied between studies, all studies agreed that if there is still doubt in the replanting decision, then it is generally safe to not replant.

Growers make agronomic decisions based on their experiences and knowledge on cotton's response to the environment. Some of these decisions like determining the optimal planting date and seeding rate have been heavily studied, and numerous recommendations have been refined. Other decisions, like replanting decisions, continue to be an enigma due to the numerous environmental, agronomic and economic factors involved. Furthermore, there is no guarantee that a replant will emerge satisfactorily. Experienced growers will attempt to work with a suboptimal stand rather than undergo a replant. Edmisten & Collins (2020) suggested replanting only the areas that are unacceptable, but reminded growers that suboptimal stands often appear less severe later in the season when plants are more mature. The decision to save or replant an existing crop requires the integration of the best available field and research data (Boman & Lemon, 2005). New advances in remote sensing technologies now provide farmers the necessary data to make better-informed decisions. Remote sensing technologies like unoccupied aerial vehicles (UAVs) allow farmers to quickly detect a larger number of plants and measure a larger number of skips. The goal of this study was to refine recommendations established by Jost et al. (2006) using remotely sensed data. The objectives were to: (i) establish a critical skip size that best correlates with lint yield, (ii) determine the critical skipped area based on the critical skip size, and (iii) evaluate the yield potential and economic benefit or drawback of replanted cotton to earlier planted cotton.

Methods and Materials

Experiments were conducted over a two-year period (2019-2020) in eastern North Carolina at the Upper Coastal Research Station in Rocky Mount, NC, The Tidewater Research Station in

Plymouth, NC, and the Peanut Belt Research Station in Lewiston, NC. Each site included both an early-planted and a late-planted trial. Within each trial, five treatments were arranged in a randomized complete block design with four replications. Individual plot units were composed of four rows. The treatments consisted of varying ratios of transgenic (DP1646) to non-transgenic cotton seed (DP493): 100%, 75%, 50%, 25%, and a 100% replant treatment. In 2020, a 10% treatment was added to each trial. In 2019, early planted trials were planted between April 29th and May 7th for all locations, and replanted treatments were planted between May 24th and May 28th (Table 9). Late-planted trials were planted between May 23rd and May 28th, with the replanted treatment planted between June 4th and June 7th. In 2020, early trials were planted between April 29th and May 12th for all locations, and the replanted treatment was planted on May 26th. Late-planted trials were planted on May 26th, with the replanted treatment planted between June 4th and June 5th. All trials were planted with a seeding rate of 43,500 seeds acre^{-1}. After emergence, non-transgenic seedlings were terminated with three weekly sequential applications of 43 oz/A of glyphosate and glufosinate to terminate conventional seedings and create random, non-systematic skips.

Table 9. Planting, flying, and harvest dates (2019-2020)

Site	Trial	Planting Date	Flying Date (DAP)	Harvest Date
Rocky Mount	Early	April 29, 2019	July 2, 2019 (64)	October 3, 2019
	Late	May 24, 2019	July 2, 2019 (39)	October 18, 2019
Lewiston	Early	May 7, 2019	July 2, 2019 (56)	October 10, 2019
	Late	May 28, 2019	July 2, 2019 (35)	October 23, 2019
Plymouth	Early	May 7, 2019	June 11, 2019 (35)	October 15, 2019
	Late	May 23, 2019	June 11, 2019 (19)	October 24, 2019
Rocky Mount	Early	April 29, 2020	June 18, 2020 (49)	October 15, 2020
	Late	May 26, 2020	June 18, 2020 (25)	October 28, 2020
Lewiston	Early	April 29, 2020	June 26, 2020 (57)	October 14, 2020
	Late	May 26, 2020	June 26, 2020 (31)	October 27, 2020
Plymouth	Early	May 12, 2020	July 3, 2020 (46)	October 19, 2020
	Late	May 26, 2020	July 3, 2020 (38)	October 21, 2020

A Zenmuse X5 RGB sensor mounted to a DJI Matrice 600 Pro was used to collect images over each site after all non-transgenic plants were terminated. Flights were carried out at an altitude of 175 ft AGL during 2019 and 100 ft AGL during 2020. Two post-processing software were used to generate plant count files: Precision Hawk Ag Analytics (Precision Hawk, Raleigh, N.C.) and Solvi (Solvi, Gothenburg, Sweden). Precision Hawk Ag Analytics (Precision Hawk, Raleigh, N.C.) was used during 2019 trials, and Solvi (Solvi, Gothenburg, Sweden) was used during 2020 trials. Both software adopted the same post-processing algorithm for generating RGB and multispectral orthomosaics and plant counts. Only the inner two rows were analyzed for each plot. The first plant from each plot was selected as the reference plant during 2019. Similarly, each row ended with the last plant within the center two rows. Conversely, dummy plants were placed at the start and end of each row during 2020 to account for skips that occurred in the plot edges Figure . Distances between the reference plant and all other plants were measured using the Distance

Matrix tool in QGIS 3.8.0 (Quantum GIS Development Team, 2020) for all 2019 trials and the Near tool in ArcGIS Pro (Esri Inc., 2020) for all 2020 trials.

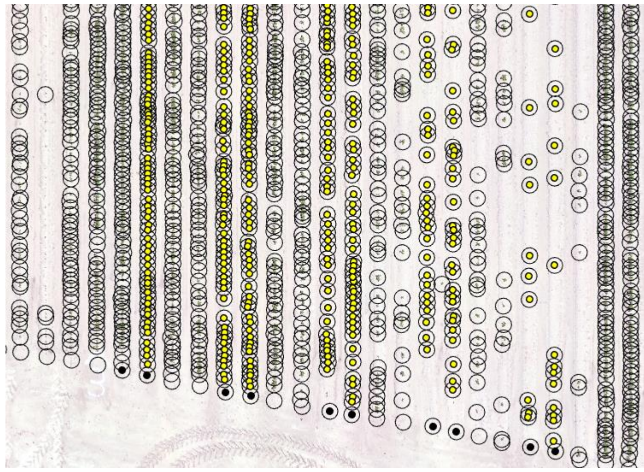

Figure 13. Reference (black) and target (yellow) plant detections in Lewiston Early 2020

Next, the distances between subsequent plants were calculated via a coded algorithm written in RStudio (R Core Team, 2020). The code also categorized each of the measured distances as size skips that were greater than or equal to 2.0, 2.5, 3.0, 3.5, and 4.0 ft. For example, all measurements that were greater than or equal to 2.0 ft fell under the 2.0 ft category, and all measurements greater than or equal to 3.5 ft fell under the 2.0, 2.5, 3.0, and 3.5 ft category. Therefore, the smaller skip size categories contained more data than the larger skip size categories. The skipped area percentage was calculated for each plot using equation 1.

$$Skipped\ Area\ Percentage \ = \left(\frac{\sum_{i=1}^{n} S_i}{2L}\right) \times 100 \tag{1}$$

Where,
S = skips greater than or equal to 2.0, 2.5, 3.0, 3.5, or 4.0 ft
L = length of the plot
i = index counter for skips greater than or equal to 2.0, 2.5, 3.0, or 4.0 ft

After harvest, lint yield was recorded for each plot, and subsamples of cotton seed were sent to the University of Tennessee Microgin for ginning and subsequent High Volume Instrumentation (HVI) analysis of fiber quality. Harvest dates are shown in Table 9. A multiple linear regression that included site, trial, and treatment as categorical variables was used to model the response of lint yield during each year. An analysis of variance (ANOVA) tested the differences between all group means. Additionally, all treatments within all trials were subjected to Tukey's Honest Significant Difference (HSD) and means were separated at $p \leq 0.1$. Linear regression was subsequently used to model the effect of skipped area on lint yield for each skip size category. Pearson correlation coefficient values were obtained using the ggpairs() function in the GGally R package (Schloerke et al., 2020) to indicate the critical skip size that best predicted lint yield.

Next, based on the critical skip size, the skipped area threshold was calculated for each trial. The threshold accounted for the economic cost that presumes a replant. The estimated cost of replanting, \$35 acre^{-1}, divided by the value of lint as of 2020 in the USDA-AMS report, \$0.70 lbs^{-1}, established the economic threshold that justified a replant. Therefore, a 50 lbs acre^{-1} penalty was subtracted to the replant lint yield to account for the estimated cost of a replant. Then, for each replication, each plot's lint yield was divided by the replant lint yield. The newly calculated ratio was regressed to the skipped area percentage for each trial. Finally, the fitted skipped area percentage that matched a 1:1 lint yield to replanted lint yield ratio was calculated for each trial. The purpose of this was to identify the plots that yielded higher and lower than the corresponding replant in the replication. Moreover, the fit provided an estimated guess to the threshold of the replanting decision based on empirical data from the two-year study. Finally, accumulated precipitation and DD60 was recorded at each research station throughout both growing seasons.

These parameters helped this study explain some of the events that occurred post-emergence and throughout each growing season.

Results and Discussion

Blending transgenic and non-transgenic seeds at known ratios was effective at simulating non-systematic skips of various sizes. Cotton seedlings were successfully detected using UAV-based imagery. Flights conducted at 100 ft AGL during 2020 provided better image resolution than flights at 175 ft AGL during 2019. Some trials had to be revisited on later dates to detect more mature, larger plants within the germination stage. Table 9 shows the flying date at which the seedlings were successfully detected and the days after planting (DAP) when they occurred. The earliest plant detections occurred in Plymouth Late at 19 DAP. However, other trials were more inconsistent and required over 30 DAP. Detections this late may cause producers to miss optimal planting date windows or surpass crop insurance deadlines. Although 19 days is outside the ideal time frame, there is still a chance to assess the replanting decision and achieve optimal yields if the original planting occurred at an early date.

Means for yield of each treatment are illustrated in Table 10. Most trials over both years exhibited no significant differences among yields for the 100%, 75% and 50% stand treatments, suggesting that a uniform stand loss as large as 50% in any given planted area would most likely not justify replanting. Although the 100% stand was planted at 43,560 sd ac^{-1}, these results were similar to that described by Pettigrew et al. (2013), where no significant differences were observed between populations of 100,000 plants ha^{-1} (100% stand) and 50,000 plants ha^{-1} (50% stand). As expected, the 10% stand treatment in the 2020 trials yielded poorly compared to the treatments with higher plant stands. This suggested that a planted area with an extreme 90% stand loss would likely require a replant.

Table 10. Within treatment yield ANOVA test and Tukey's HSD. P-value = 0.1. Study year: 2019

Treatment	Trial					
	Lew Early	Ply Early	RM Early	Lew Late	Ply Late[(a)]	RM Late
100%	1756.8 a	1062.2 a	1212.7 a	1502.6 a	1248.7	1207.7 a
75%	1813.8 a	1055.5 a	1059.4 b	1504.7 a	1173.4	1126.7 b
50%	1723.2 a	1014.5 a	977.4 cd	1474.9 a	.	1136.5 b
25%	1537.0 b	879.0 b	1003.1 bc	1267.4 b	.	960.3 c
Replant	1464.8 b	1083.0 a	922.6 d	1321.7 b	.	981.5 c
LSD, P = 0.1	91.4	105.7	77.2	64.5	.	44.8
SD	72.5	83.9	61.2	51.2	.	35.6

(a) Could not calculate LSD (% mean diff) because error mean square = 0

Although it was determined that a 50% stand loss would most likely not warrant a replant, uncertainty remains if the same conclusion can be extended to a 75% stand loss. Differing yields in the 25% treatment and the replant treatments were observed throughout the study (Figure 13). The replanted treatment yielded virtually equal or lower than the 25% treatment in most early and late trials during 2019, suggesting that late-planted or replanted cotton may not always result in optimal yields. These results aligned with recommendations established by Wrather et al. (2008), which discouraged replanting after mid-May if populations from early planting were greater than 16,988 plants ha^{-1}. One exception occurred in the early planted trial at Plymouth in 2019, where the replant treatment was statistically indifferent than the 100% treatment. The 2020 replant treatment yielded virtually the same as all the 100% treatment in the early-planted trials, and in two of the three of the late-planted trials (Table 11). Inconsistencies with late trial replants also suggested that it is best to avoid replanting in June unless more than 75% of the planted area has been lost. Butler et al. (2019) also observed significant yield reductions after planting ocurred during the month of June.

Figure 13. Treatment yield bar chart for the early and late trial at each site (2019-2020)

Table 11. Within treatment yield ANOVA test and Tukey's HSD. P-value = 0.1. Study year: 2020

Treatment	Trial					
	Lew Early	Ply Early[(a)]	RM Early	Lew Late	Ply Late	RM Late
100%	875.2 ab	628.5 ab	706.1 b	1069.0 a	589.9 a	853.6 ab
75%	860.8 ab	598.0 ab	687.1 b	987.9 b	591.5 a	846.2 ab
50%	825.5 b	535.7 b	661.3 bc	984.8 b	560.6 a	875.3 a
25%	745.1 c	388.7 c	537.8 c	902.0 c	494.8 a	774.6 c
10%	443.4 d	199.8 d	239.6 d	578.2 e	288.5 b	556.9 d
Replant	905.5 a	673.9 a	942.0 a	747.7 d	554.2 a	798.9 bc
LSD, P = 0.1	64.3	110.0	135.9	79.3	108.1	57.1
SD	51.9	74.3	109.6	64.0	87.2	46.1

(a) 3rd replicate was discarded due to water ponding

Differences between early and late trial yields of stand loss treatments and their respective replanted treatments can be attributed to the evident discrepancies in DD60s and precipitation observed throughout the two-year study (Figure 14 and Figure 15). Warmer temperatures and wetter soils during the late month of April and throughout the month of May 2019 allowed for uniform and rapid emergence similar to the described in Boman & Lemon (2005). The optimal growing conditions continued throughout late planting and produced exceptional stands and lint yields, even at the 25% treatment level. The ANOVA results clearly illustrated statistical similarities within the trial levels (Table 12). Conversely, cooler temperatures and wetter soils detrimentally affected germination in early-planted stands and lint yield in 2020. Temperatures improved by the time the late-planted trials were planted and contributed to the production of superior stands, as compared to the earlier planted trials during 2020. Clear statistical evidence showing the difference between trials is presented in Table 13. Results in 2020 were consistent with Edmisten & Collins (2020), which supported late planting when conditions were favorable. The clear distinction between both experimental years indicated that planting yields were highly dependent on the weather conditions. Results further underlined the importance of generating recommendations that were more specific to local weather patterns.

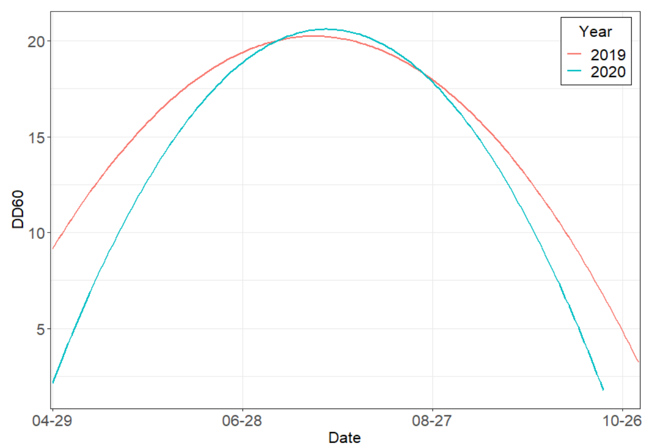

Figure 14. Fitted DD60 during the typical NC cotton growing period

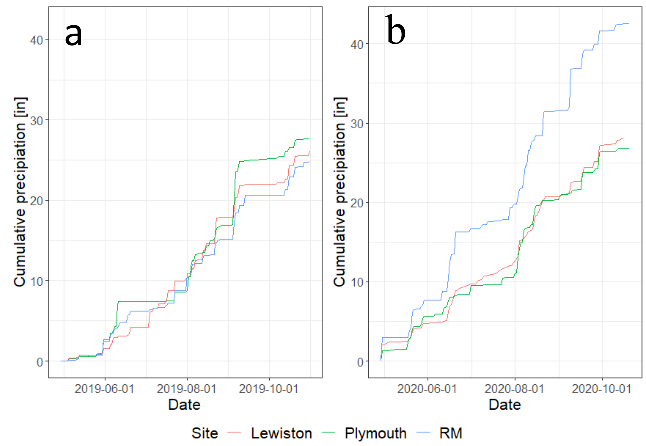

Figure 15. (a) Cumulative precipitation during the typical growing period for NC cotton in 2019. (b) Cumulative precipitation during the typical NC cotton growing period in 2020

Table 12. Between-subject ANOVA type II test. Study year: 2019

	Sum Sq	df	F value	Pr(>F)
Site	1644611	2	70.0	2.90E-10
Trial	29698	1	2.5	0.12611
Treatment	291652	4	6.2	0.00168
Residuals	258446	22	NA	NA

Table 13. Between-subject ANOVA type II test. Study year: 2020

	Sum Sq	df	F value	Pr(>F)
Site	611126	2	42.8	4.26E-09
Trial	66885	1	9.4	0.00496
Treatment	1542069	5	43.2	4.77E-12
Residuals	192851	27	NA	NA

Correlation values between the percentage of planted area occupied by skips and lint yield varied between 0.40 and 0.80 across all skip sizes and between both years. Each of the skip sizes had a moderate correlation with lint yield in 2019 (Table 14). In 2019, linear variations in lint yield were best explained by skips of 2.0 ft or greater with a correlation value of 0.555. Correlation between the percent skipped area and yield decreased slightly as the skip size increased. This is reasonable because the smaller the skip size, the larger the resolution of the skipped area will be. Nevertheless, that was not the case the following year. Lint yield in 2020 was best explained by

4.0 ft skips with a correlation of 0.778, and correlation values decreased slightly as skip size decreased (Table 14). One possible explanation to this anomaly is that there was not a sufficient number of larger-sized skips (e.g. 3.0 ft and 4.0 ft skip sizes) during 2019. Most skips of these larger sizes were observed in the 25% treatment, and few were found in the higher stand treatments. This can be evidenced with the clustering of points in the left-most portion of Figure 16. Since a 10% treatment was added during 2020, it is plausible that the better linear agreement observed in 2020 was due to the increased amount of larger skips detected.

Table 14. Correlation (R^2) values between lint yield and skip size

	Skip Size				
Year	2.0 ft	2.5 ft	3.0 ft	3.5 ft	4.0 ft
2019	0.56	0.55	0.52	0.49	0.46
2020	0.73	0.75	0.76	0.77	0.78

Combined results suggest that no particular skip size is critical for measuring percent of skipped area. It is plausible that too many smaller skips (e.g. 2.0 ft skips) can have the same detrimental effect in lint yield potential as fewer, larger skips. Due to the lack of agreement in correlation trends between both study years, the 3.0 ft skip level was chosen as the explanatory variable in Figure 16 and Figure 17 because it has been the most commonly recommended measure in the past.

As alluded earlier, replanting was generally not recommended during 2019 trials by virtue of the optimal conditions that were present during early and late planting, which resulted in higher yields across all treatments compared to replanted treatment. Most plots within each trial yielded over the 1:1 yield to replant yield ratio. The 2019 late-planted trial at Plymouth had the largest yield to replant yield ratio due to the poor performance in the late replanted yield (Figure 16). The lack of plots that yielded below the 1:1 ratio and the clustering of points in the left-portion of Figure 16 hindered the predictions of skipped area percentage thresholds. To the latter point, it is plausible that the observed clustering may have leveraged the regression. Still, predictions were carried out to provide a notion on replanting thresholds for each trial.

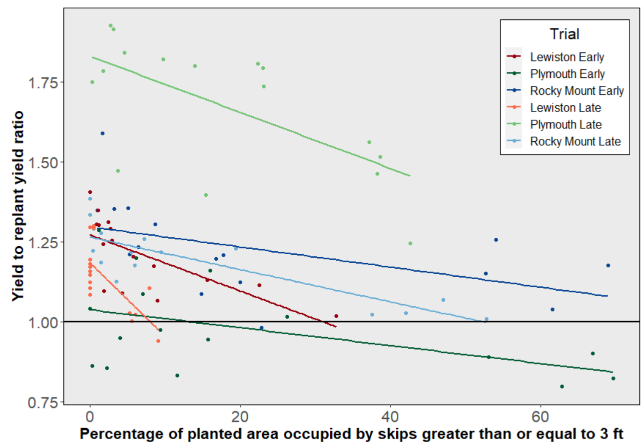

Figure 16. Relationship between the ratio of yield to replant yield and the percentage of planted area occupied by skips greater than or equal to three ft. Study year: 2019

Most of the threshold values were estimated to be in the 40 to 50% range for 3.0 ft skips in 2019 (Table 15). This is consistent with Jost et al. (2006) who recommended a replant if 50% of the planted area was occupied by skips greater than or equal to 3.0 ft. Considering that the former study was conducted over 15 years ago using manual measurements, these percentages are surprisingly similar. However, results from this study suggest that this recommendation should remain true for seasons where warm temperatures prevail throughout the months of April and May; it is plausible that Jost et al. (2006) also observed similar conditions throughout the study. The conservative nature of the recommendation frames the replant as a very unlikely scenario. Unless an external factor occurs, such as poor quality seed, replanting will most likely not be necessary under optimal weather conditions. The decision gets more complicated by the fact that long-term weather is difficult to predict and usually unknown at the time of planting.

Table 15. Percentage of planted area that would justify a replant based on 2019 experimental results

Site	Trial	Skip Size (ft)				
		2.0	2.5	3.0	3.5	4.0
Rocky Mount	Early	59.9	48.3	40.4	33.3	26.3
	Late	64.2	52.3	41.5	33.3	26.8
Plymouth	Early	31.8	24.5	19.9	16.2	13.1
	Late	78.1	63.7	49.7	38.3	30.3
Lewiston	Early	40.9	26.8	18.9	14.6	11.9
	Late	16.5	8.9	5.2	3.2	2.2

A larger number of plots yielded below the 1:1 yield to replant yield ratio in 2020 (Figure 17). This suggests that a decision to replant would have probably resulted in increased yields for treatments that yielded below this threshold. The addition of the 10% stand treatment in 2020 helped explain part of the variation that occurred at higher skipped area percentages, eliminated any concerns in regards to clustering, and contributed to increasing the linear correlation from 0.50 to 0.70. Most skipped area percentages ranged between 30 to 40% (Table 16), suggesting that the replanting threshold should be established within that range. This threshold is less conservative than the recommended threshold by Jost et al. (2006). Because weather patterns observed during 2020 were more consistent with years before the observed in 2019, 30 to 40% appears to be the true replanting threshold that is applicable during most years for NC cotton. Nevertheless, variations in atypical weather conditions have shown to skew the threshold over and under the 30 to 40% range.

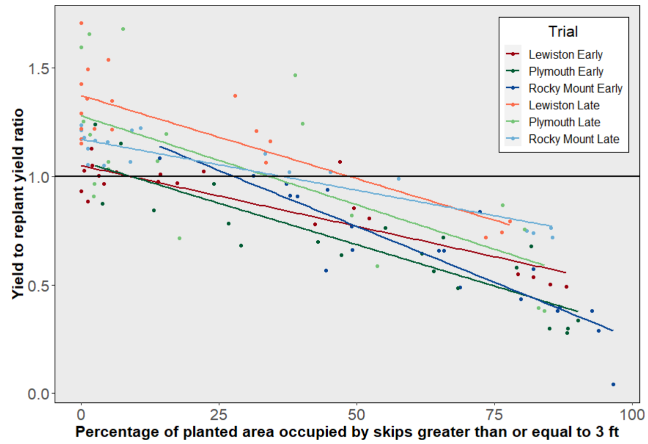

Figure 17. Relationship between the ratio of yield to replant yield and the percentage of planted area occupied by skips greater than or equal to three ft. Study year: 2020

Table 16. Percentage of planted area that would justify a replant based on 2020 experimental results

Site	Trial	Skip Size (ft)				
		2.0	2.5	3.0	3.5	4.0
Rocky Mount	Early	51.1	41.9	34.4	28.0	22.0
	Late	45.3	39.3	35.1	31.7	28.3
Plymouth	Early	32.8	24.4	18.3	14.6	11.7
	Late	42.7	36.1	30.8	27.3	24.0
Lewiston	Early	26.8	18.7	13.7	10.3	7.6
	Late	53.1	46.6	41.2	36.9	32.8

Conclusion

Replanting decisions have become more important in recent years, now that the costs associated with replanting are considerable. The cost of a replant is now the equivalent of losing an estimated 50 lbs acre^{-1} lint or more, due to poor stands. Given the tedious and cumbersome nature of manual measurements of stand loss, many growers make replanting decisions based on visual assessments of stand loss. While previous studies provide a good baseline to when a replant may be justified, concerns remain regarding the conservative nature of those recommendations. The rise of remote sensing technologies in agriculture now allow for quicker and precise plant and skip detections to be conducted. It was of interest to explore the validity from these recommendations, particularly the established by Jost et al. (2006), and improve the accuracy and precision of those recommendations. More specifically, the focus of this study was to refine the critical skip size and the critical skipped area that may justify replanting.

This research suggested that no meaningful yield loss was likely until stand loss exceeded 50 percent in most cases. The addition of the 10% stand treatment in 2020 provided a clearer understanding of the relationship between yield loss and the size and frequency of skips. No particular skip size was found to be more predictive of yield loss in this study. The correlation between skip size and lint yield decreased as skip size increased in 2019, but increased as skip size increased in 2020. Since no clear pattern was observed between both years, 3.0 ft skips was chosen to be the “critical skip size” based on the findings of previous research (Jost et al., 2006). As such, replanting was justified when 30 to 40% of planted area was occupied by 3-ft skips or greater in most trials during 2020. Cold and wet conditions during the typical early planting dates detrimentally affected emergence rates in all early trials during 2020. Favorable weather conditions occurred at later planting dates, and ultimately resulted in higher lint yields than many earlier planted cotton.

Further research is needed to explain the relationship between crop maturities, flying altitude, DAP, and successful plant detections using available and economic sensors. Cotton growers that have access to UAVs could benefit from guidelines that detail when to assess a given field based on these parameters. Future research should also continue to build on the effect of varying climatic patterns on current replanting recommendations.

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Chapter 4 – Conclusions

The agreement between the manual and UAV-based methods in detecting size and frequency of cotton skips was discussed in Chapter 2. The manual method consisted of measuring plant distances with a measuring tape in 200-ft subsamples of the inner-two rows of each plot. The UAV-based method consisted of flying entire planted areas at 175 ft AGL and 100 ft AGL and remotely sensing the seedlings using an RGB sensor. This method was quicker than the manual method in on-site evaluations. The manual method took approximately three hours for each trial, whereas the UAV-based method assessed an entire site in less than 12 minutes. However, the methodology described in this chapter was not bereft of computational intensity. The post-processing software took a day or two to return the plant count files, and an additional day or two was required to measure the skip sizes and skipped areas for each trial. This delay can put a timing constraint to the replanting decision before the end of the optimal planting window.

Although the timing was not ideal, both method successfully calculated the percentage of area occupied by skips greater than or equal to three ft. Bland-Altman Analysis showed that the 25% treatments promoted the best agreement between methods. It was determined that both methods were statistically interchangeable at very poor stands where large skips are more frequent and prone to exist. However, in undetermined stands, where skips of various sizes exist, the UAV-based method provided a better prognostic of the stand severity.

Replanting recommendations were refined in Chapter 3. All of the detected skips were classified as 2.0, 2.5, 3.0 3.5 and 4.0 ft skips; each skip classification included all of the skips greater than or equal to their respective size and excluded the smaller skips. It was of particular interest to identify the skip size that best correlated with lint yield. Inconsistent results in both years led to the conclusion that none of the skip sizes best-predicted lint yield. Therefore, the study was continued using three ft skips to provide comparable results to those reported in Jost et al. (2006). In 2019, most studies justified a replant at 50% of planted area occupied by skips greater than or equal to three ft. The warm temperatures extended the planting window and allowed for optimal yield potentials. These results closely mirror findings from Jost et al. (2006). In contrast, the 2020 planting window was narrower due to colder temperatures and increased precipitations. Even though conditions were detrimental, replanting was not justified in most trials until a 30-40% of skipped area was detected.

Advances in remote sensing allowed this study to assess the severity of entire planted areas with increased accuracy and precision. This study was a testament of cotton's resiliency; it build on the idea that growers who are unsure of a replant will most likely not need to replant. The agreement of a novel UAV-based method was compared to a traditional manual method for scouting skips. Replanting recommendations were successfully refined by incorporating the current economic impact of a replant and by using a novel UAV-based detection method. Finally, the recommendations in this study were based on two dissimilar climatic seasons, which should provide growers a good notion on plausible courses of action.