# PLANT POPULATION DYNAMICS IN COTTON AND REMOTE SENSING APPLICATIONS IN COTTON IRRIGATION MANAGEMENT

A Thesis

by

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Submitted to the Graduate and Professional School of
Texas A&M University
in partial fulfillment of the requirements for the degree of

MASTER OF SCIENCE

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May 2022

Major Subject: Agronomy

## ABSTRACT

The increasing cost of quality cotton seeds, rapidly depleting aquifers used for irrigation, and increasing droughts and extreme weather are making cotton production more expensive and unpredictable in the Texas Rolling Plains and other regions of the world. The research in this thesis explored cotton population density dynamics in irrigated and dryland conditions and tested the utility of a custom remote sensing tool in cotton irrigation management.

The first study was conducted using a replicated split-plot design, with combinations of two irrigation (0 and 90% ET replacement), five population (15,000, 30,000, 60,000, 90,000, and 120,000 plants $ha^{-1}$), and two plant uniformity (even and uneven plant-to-plant spacing) treatments. The focus was to address gaps in our knowledge related to the impact of plant population and stand uniformity on lint yield and quality in low-yielding dryland conditions. Lint yield was unaffected by plant population and stand uniformity in 2020, but there was an interaction between water inputs and plant population in 2021 in which lint yield increased by 25% from 15,000 to 120,000 plants $ha^{-1}$ in irrigated conditions only. There was no consistent effect of stand uniformity on lint yield. Fiber quality parameters were minimally and inconsistently affected by population density and stand uniformity.

In the second study, the utility of an all-inclusive sensor system attached unintrusively to a pivot irrigation system, which calculates the Water Deficit Index (WDI) through NDVI, Tc, and in-field weather data, was tested. An experiment was run with four irrigation treatments (0, 30, 60, and 90% ET replacement), and the system was tested in two production fields. The data collected from pivot-mounted NDVI sensors was linearly related to fraction canopy cover (Fc), but the variability and slope of the relationship was altered relative to purely aerial measurements. The WDI values were generally greater than expected, especially before full canopy closure.

Integration of a mini weather station into the system was effective in representing on-site weather. The results indicate that the system is quite promising, but more study is needed to better establish the relationship between Fc and NDVI and adjustments to the WDI model are needed to better account for soil heat flux.

## ACKNOWLEDGMENTS

I would like to thank my committee chair, Dr. Adams, for his guidance and support throughout the course of this research. I also appreciate the knowledge shared by my committee members, Dr. Rajan and Dr. Ale in this research.

Thanks also go to my friends, colleagues, and mentors at Texas A&M University and AgriLife Research and Extension Center at Vernon for making my time here a great experience.

Most importantly, thanks to my family, Mother, Father, Brother for their patience, encouragement, love and moral support.

# CONTRIBUTORS AND FUNDING SOURCES


## Contributors

This work was supervised by a thesis committee consisting of Dr. Curtis Adams, Dr. Nithya Rajan, and Dr. Srinivasulu Ale. Assistance on data collection and analysis was provided by Emily Harding, Rajan Shrestha, Dr. Philip Hinson, Dr. Qiong Su, Dr. Jasdeep Singh and Tian Zhang. Experiment field sites were maintained by staff of Texas A&M AgriLife Research and Extension station at Chillicothe. Two cotton production fields that were used for data collection in Hardeman County, TX were owned and managed by Aaron Phillips. Dr. Brandon Kelly at the Fiber and Biopolymer Research Institute at Lubbock, TX assisted with analysis of cotton fiber quality data.

## Funding sources

Graduate study was supported by a Graduate Research Assistantship from Dr. Curtis Adams and the Department of Soil and Crop Sciences. This work was also made possible by research grants from Cotton Inc. through the Texas State Support Committee (Project #20-563TX and #17-519TX), and a grant from the Texas Water Resources Institute through their Water Seed Grant Initiative.

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# 1. INTRODUCTION

Cotton (*Gossypium hirsutum* L.) is a crop plant grown in tropical and subtropical regions of the world. Increase in use of cotton fiber for apparel, furnishings, and industrial products have made it a crop with a great value. Cotton in warm conditions can reach the size of a small tree and grow indefinitely, but commercially cultivated cotton is smaller in size and is grown as an annual crop (Percy et al., 2014). The United States is a key producer and exporter of cotton. The U.S. produced about 19.9 million metric tons of cotton in 2019/20, exporting almost 94% of total production (USDA Foreign Agricultural Service, 2021). In producing cotton, plant population and irrigation are two of the most agronomically and economically important factors that U.S. producers manage. High density cropping is often followed to achieve optimum yield, which may not be necessary. Irrigation is often used to supplement the evapotranspiration water loss in the crop. Efficient irrigation water management system can improve the water use efficiency (WUE). The studies included in this proposal focus on yield and fiber quality responses of cotton to plant population dynamics, including uneven stands, and use pivot irrigation system-mounted sensors for efficient irrigation management.

## 1.1. Factors affecting growth, lint yield, and quality of cotton

Cotton growth, fiber yield, and fiber quality are influenced by genetic and environmental factors (Meredith et al., 2012). Genotype is the genetic constitution of the cotton plant, defining inherent characters. Phenotypic and physiological attributes of cotton are affected by the genetics of the plant interacting with the environment. Modern breeding and transgenic approaches to cotton improvement have resulted in greater adaption to different climatic conditions, improved yield and fiber quality, and increased resistance to biotic stressors like insects and diseases

(Constable et al., 2015; Meredith et al., 2012). A 25% improvement in cotton productivity in the U.S. from 1990-2005 can be largely attributed to genetic enhancements in cotton germplasm and better management practices (USDA, 2020). The following paragraphs provide a broad overview of environmental factors that affect cotton production.

Climatic factors influencing the growth and quality of cotton include radiation and photoperiod, temperature, $CO_2$ content in atmosphere, moisture, and relative humidity. These factors also determine the locations where cotton can be grown. Cotton prefers warm temperatures centered around 28°C ± 3°C for its optimum enzyme function, germination, seedling growth, root development, flowering, and int production (Burke and Wanjura, 2010; Snider et al., 2020). Burke et al. (2004) observed decreased pollen germination above 37°C and decreased pollen tube elongation above 32°C, which affected lint formation. The cotton plant becomes inactive below 16°C (Snider et al., 2020). Temperature also affects photosynthesis, stomatal conductance, and transpiration in cotton. DeRidder and Crafts-Brandner (2008) showed substantial reduction in photosynthesis bellow 20°C in cotton seedlings. Temperature above 40°C reduce rubisco activity, which decreases photosynthesis resulting in shorter plants and lower yield (Zahid et al., 2016). Low relative humidity and high temperature increases vapor pressure deficit, which increases transpiration water loss and influences the water balance of the plant, also affecting photosynthesis and growth (Fletcher et al., 2007).

Edaphic factors like pH, salinity, and nutrient availability affect the growth, yield, and quality of cotton. Cotton grows best in soil with pH between 6.3 to 6.9 (Mitchell et al., 2010), though it also tolerates more alkaline soils. Acidic ions like aluminum ($Al^{+3}$) react with phosphoric acid forming insoluble aluminum phosphate which makes phosphorous unavailable for plant uptake (Rao et al., 1993). Excess aluminum in soil modifies the properties of cell wall and plasma membrane, which inhibits water uptake of roots and initiate drought stress (Tamás et al., 2006). Saline soil is also not appropriate for the cotton production. Salt stress impacts on yield and quality of cotton lint due to its effect on cotton germination, emergence, seedling state, root growth, flowering and fiber length, strength, maturity, and fineness (Sharif et al., 2019). Nitrogen, phosphorous, potassium, zinc, and sulfur are often added to supplement the nutritional demand of cotton (Bronson, 2009). Nutrient deficiencies can disturb sink-source relationships in the plant and increase the occurrence of physiological and infectious diseases that negatively impact yield and fiber quality (Xiao and Yin, 2019).

Cotton yield and fiber quality also depend on the management of the crop. Irrigation and appropriate cropping density are among the most important parameters in crop management. Irrigation replenishes soil moisture used by the crop and lost by evaporation. Plant density influences the light interception, moisture availability, wind movement, and humidity, which affects the canopy height, branching and fruiting behavior, maturity, yield and the quality (Ajayakumar et al., 2017). The following sections cover these topics in greater detail.

## 1.2. Cotton irrigation management

Excess irrigation in cotton, in addition to decreasing water-use efficiency, can induce seedling diseases (Howell, 2002), increase pest infestation (Lytton-Hitchins et al., 2015), and promote leaching of nutrients (McHugh et al., 2008), which negatively impacts the yield and quality. Full yield potential can be achieved with more efficient irrigation management with use of relatively little water. Deficit irrigation is a strategy that limits available soil moisture in a controlled way, with the primary goals of decreasing water use and further increasing irrigation water use efficiency (McHugh et al., 2008). An overarching goal in modern irrigation management is to improve irrigation water-use efficiency.

Flood irrigation using canals and furrows was conventionally practiced in many cotton systems, requiring large volumes of inefficiently used water. Drip and sprinkler irrigation systems are now popular and are more efficient than the conventional systems (Ali et al., 2020; Sorensen et al., 2020). Various types of drip irrigation systems have the capability of frequently supplying water to the root zone. Surface drip irrigation (SDI) is where the drip tubing is placed on the soil surface; deep subsurface irrigation (DSI) is where drip tubing is buried 25 to 30 cm below the soil surface; and shallow subsurface drip irrigation (SSDI) is where drip tubing is buried about 5 cm below the soil surface. Each of these are increasingly used to irrigate cotton (Bronson et al., 2018; Sorensen et al., 2010). Overhead sprinkler irrigation systems (pivots and linears) are being adopted because they are quick to assemble, durable, and relatively easy to operate (Sorensen et al., 2020).

Irrigation management and scheduling in cotton are done in a variety of ways. Some approaches include monitoring soil water potential with tensiometers, soil moisture by electronic sensors, leaf-water potential by various means, crop water stress index (CWSI) using canopy temperature, and ET replacement using meteorological data and crop coefficients (O'Shaughnessy and Evett, 2010; Rajan et al., 2013). Smart irrigation scheduling techniques are emerging that use real-time data from sensors installed in the field and nearby weather data to estimate evapotranspiration (ET) water loss (Rajan et al., 2013; Trimble, 2019; Vellidis et al., 2008; Vories et al., 2020). Peters and Evett (2004) and O'Shaughnessy and Evett (2010) used multiple stationary infrared temperature sensors and nearby weather station data to calculate canopy temperature-based crop water stress index (CWSI) to schedule irrigation in cotton. Vellidis et al. (2008) used multiple soil moisture sensors coupled with a Radio Frequency Identification (RFID) tag transmitting the real-time data to estimate the irrigation water in cotton.

Each of the irrigation management and scheduling approaches just described are still being refined and have various benefits and drawbacks. Common drawbacks include difficulty in implementation, the need for extensive in-field installation of sensors, requirements for extensive manual data collection, high cost, inaccuracy, and inaccessibility to most producers. Another possible approach to irrigation management of cotton, which could overcome many of the drawbacks common in existing systems, is an automated CWSI system in which infrared temperature and NDVI sensors are mounted on a pivot irrigation system.

### 1.3. Water deficit index (WDI) model for irrigation management

Canopy temperature has been long recognized as an indicator of water availability in plants (Jackson et al., 1981; Maes and Steppe, 2012). The difference in canopy temperature (Tc) and air temperature (Ta) has been used to compute the crop water stress index and quantify the crop water status (Colaizzi et al., 2003; Idso et al., 1982; Jackson et al., 1981; Maes and Steppe, 2012; Moran et al., 1994; Sharma and Ritchie, 2015). Hand-held infrared thermometers (IRT) and airborne infrared temperature sensors are usually used to record the canopy temperature. Before the full canopy closure, canopy temperature measurement is often influenced by the temperature of exposed soil in between the canopy because the sensors measure a composite of both the soil and plant temperature (Maes and Steppe, 2012; Moran et al., 2003). Addressing the influence of soil temperature has been the challenge to improve the CWSI based irrigation management approaches. Moran et al. (1994) proposed a theoretical water deficit index (WDI) model, analogous to the CWSI model, which included the influence of soil within the calculation and related it with the reflectance of infrared and near-infrared spectrum to compute the soil adjusted vegetation index (SAVI). Colaizzi et al. (2003) showed that the WDI adequately addresses the water stress in soil. Both estimated the theoretical upper and lower boundary of (Tc-Ta) for well-watered vegetation with full canopy cover, dry vegetation, wet bare soil and dry bare soil using the energy balance equations and computed the water deficit index (WDI). Use of similar moisture deficit index models relating with the percentage canopy coverage to quantify the crop water need and irrigation requirement with the help of autonomously collected senor data from field can help producers to properly manage irrigation and improve yield. The NDVI measurement can be used to estimate the fraction of canopy coverage (Fc). Multispectral images collected from unmanned aircraft system can be used to compute NDVI and canopy coverage in the field, which can be useful in further adjusting the above relationship for the cotton with different irrigation managements (Pix4D, 2018).

### 1.4. Managing plant population in cotton

Plant population in cotton affects plant architecture and maintaining adequate plant density provides better canopy microenvironment (Kaggwa-Asiimwe et al., 2013). Optimizing plant population can reduce evapotranspiration water loss, maximize light interception and photosynthesis, and facilitate the efficient use of applied irrigation and fertilizers, improving cotton yield and fiber quality (Bernarz et al., 2005; Reta-Sánchez, 2002; Yang et al., 2014). Plant populations that are too sparse or dense can have negative agronomic consequences. Lower plant density promotes fruit set on secondary branches and delays overall boll maturation, which affects harvested fiber quality (Bednarz et al., 2000). Extensive branching and thicker stems with lower populations can also decrease the harvesting efficiency. With higher population density, more fruits are produced along the main stem of the plant, which creates more consistency and overall earlier boll maturity and improved fiber quality. High cotton density can also be more effective in suppressing weeds by limiting transmitted photosynthetically active radiation through earlier and more complete canopy coverage (Zhi et al. 2014). However, high populations can also negatively affect harvest efficiency due to reduction in the average boll size, promote fruit shed due to increased canopy shading, and increase foliar and boll diseases due to elevated canopy humidity in humid environments (Adams et al., 2019; Constable et al., 2015; Dong et al., 2006; Khan et al., 2019; Wheeler et al., 2010).

Seeding rate and plant population recommendations for cotton currently vary from area to area, which is largely due to difference in climatic and soil conditions (Collins, 2015; Khan et al., 2019; Kumar et al., 2020; Zhi et al., 2016). To achieve earlier maturity and better fiber quality, producers use higher-density plantings. Liu et al. (2019) recommended 105,000 plants ha$^{-1}$ as the optimum plant population for the semi-wet warm-temperate climate of Henan province in China. Collins (2015) recommended to maintain crop stand of 74,132 plants ha$^{-1}$ in southeast region of the U.S. for the optimum yield. However, after review and quantitative analysis of worldwide data from multiple scientific studies on yield response of cotton to plant population, Adams et al. (2019) found no difference in cotton lint yield above 35,000 plants ha$^{-1}$. This suggests that excessive overseeding is occurring in many cases, resulting in economic losses to producers. The authors noted that little data was available from relatively low yielding dryland production environments, creating uncertainty in plant population dynamics in those conditions.

Another shortcoming of current plant population research in cotton is that few studies reported in the literature have considered uneven crop stands. Imperfect stands are common in actual cotton production systems due to planting equipment errors and seed/plant mortality, which affects both the yield and quality of the cotton fiber. Research addressing cotton lint yield and quality responses to uneven plant stands at different populations is needed to reassess the optimum plant population.

### 1.5. Cotton population density and irrigation management in the Texas Rolling Plains

The Texas Rolling Plains region lies in northcentral Texas. The region has a semi-arid climate with annual rainfall between 46 to 76 cm. In this region, most of the area is rangeland, but major agronomic crops like cotton, winter wheat (*Triticum aestivum* L.) and grain sorghum (*Sorghum bicolor L.*) are also produced (Modala et al., 2017). This region produces about 20% of Texas cotton (Matocha et al., 2009). Imperfect cotton stands are common in this area, primarily due to the challenges of stand establishment in dryland conditions. Despite these challenges, many regional cotton producers are using seeding rates that may be excessive to optimize the yield and quality of cotton fiber.

Water is typically the most limiting factor in production of cotton across the Texas Rolling Plains region. Of the 71,000 ha of crop land in this region, more than 4,000 ha is irrigation dependent (Turner et al., 2011). Climate change studies predict warmer and drier summers in the future that will elevate the demand for irrigation and rapidly deplete the underlying Seymour Aquifer, the primary source of irrigation water in this region (Modala et al., 2017). Innovative water saving irrigation management strategies that result in water saving are critical for sustainable cotton production in this region.

### 1.6. Objectives

There are gaps in our understanding of the effects of plant population on cotton yield and quality in relatively low-yielding dryland cotton systems, especially with uneven plant stands.

There is also a need to develop easier, more reliable, and efficient crop irrigation management systems for cotton. Therefore, this thesis research will focus on following objectives:

a) Expand knowledge on plant population dynamics in dryland systems and with uneven stands through a comprehensive study including population, stand uniformity, and irrigation treatments. Specific aims include:

   i) Evaluating mechanisms of plant adaptation, including boll diameters, boll numbers, and canopy heights.

   ii) Monitoring canopy development through UAS technology.

   iii) Quantify cotton lint yield.

   iv) Characterize fiber quality.

b) Use pivot-based sensors for efficient irrigation management of cotton in experimental and production fields. Specific aims include:

   i) Evaluate the relationship between NDVI determined by pivot-mounted sensors and canopy cover.

   ii) Compare the performance of integrated mini weather stations to a standard weather station at various distances.

   iii) Evaluate use of an existing theoretical Water Deficit Index (WDI) model for irrigation management using pivot mounted sensors that detect canopy and soil.

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# 2. PLANT POPULATION DENSITY IN COTTON: ADDRESSING KNOWLEDGE GAPS IN STAND UNIFORMITY AND LINT QUALITY IN DRYLAND AND IRRIGATED CONDITIONS

## 2.1. Abstract

A recent literature review and data synthesis better defined the yield curve with plant population density in cotton (*Gossypium hirsutum* L.), but it also highlighted gaps in knowledge. Few cotton plant population studies have been conducted in relatively low-yielding dryland conditions; fewer have considered the impact of uneven crop stands, which are common in actual field conditions due to planting equipment errors and seed/plant mortality; and population reports are lacking that include Advanced Fiber Information System (AFIS) testing. To address this, a study was conducted in North Texas with combinations of two irrigation (0 and 90% ET replacement), five population (15,000, 30,000, 60,000, 90,000, and 120,000 plants ha$^{-1}$), and two plant uniformity (even and uneven plant-to-plant spacing) treatments. Canopy development was tracked by unmanned aircraft system (UAS) measurements, late-season measurements were taken of boll density and size, and lint yield and quality measurements were collected at maturity. Lint yield was unaffected by plant population and stand uniformity in 2020, whereas an interaction between irrigation and plant population occurred in 2021. Lint yield was reduced by an average of 14% at 15,000 plants ha$^{-1}$ relative to 30,000 plants ha$^{-1}$ and greater only in irrigated conditions in 2021. There was no apparent or consistent effect of stand uniformity on any response variable. Poor stand quality is often the basis for terminating and replanting troubled cotton crops, but results suggest this is not justified with stand loss in the range tested here. The risk of yield loss is clearly greater when overall plant density decreases below about 30,000 plants ha$^{-1}$, especially in higher-yielding conditions, but the economic tradeoffs of replanting must be considered. Yield

compensation for low plant density and uneven stands was primarily by increased boll number per plant and secondarily by increased boll size. Fiber quality parameters were minimally and inconsistently affected by population density and stand uniformity, suggesting these are not critical factors cotton producers must consider in optimizing the fiber quality of their product.

## 2.2. Introduction

Cotton (*Gossypium hirsutum* L.) is an important natural fiber crop that is used for apparel, furnishings, and many industrial products. About 121 million metric tons of cotton fiber was produced worldwide in 2019/20 (USDA Foreign Agricultural Service, 2021). The U.S. alone produced about 19.9 million metric tons of cotton in 2019/20, exporting almost 94% of production (USDA Foreign Agricultural Service, 2021). In the past 70 years (1951-2020), cotton yield has increased about 122% in the U.S. (Table 2.1), which is due to the use of improved varieties and better crop management practices, including optimizing plant population dynamics (Feng et al., 2017; Meredith et al., 2012; Yang et al, 2020; USDA-NASS, 2021). In addition to impacts on yield, optimizing plant population density has become an increasingly important economic issue to cotton producers due to increased seed costs. In the Southern Great Plains region of the U.S., for example, a seed cost comparison tool provided by the non-profit Plains Cotton Growers, Inc. indicates that cotton seed costs in 2021 ranged from \$29.06 $ha^{-1}$ to \$387.51 $ha^{-1}$, averaging about \$150.14 $ha^{-1}$ at a default seeding rate of about 97,000 seed $ha^{-1}$ (Plains Cotton Growers Inc., 2021). Higher prices for modern cotton seed are typically associated with technology fees.

**Table 2.1.** Average lint yield and change in average yield of cotton in the United States from 1950 to 2020 (USDA National Agricultural Statistical Service 2021).

| **Decade** | **Average Yield ($Kg\ ha^{-1}$)** | **Change in Yield (%)** |
|---|---|---|
| 1951-1960 | 426.0 | |
| 1961-1970 | 534.8 | 25.5 |
| 1971-1980 | 528.6 | -1.15 |
| 1981-1990 | 672.0 | 27.1 |
| 1991-2000 | 722.4 | 7.51 |
| 2001-2010 | 883.2 | 22.3 |
| 2011-2020 | 946.0 | 7.11 |

Cotton seeding rate and plant density recommendations currently vary from area to area (e.g., Collins, 2015; Khan et al., 2019; Kumar et al., 2020). The rationale for the differences is not immediately clear, but could be due to specific cultural systems, risk aversion, or other factors. However, after a review and quantitative analysis of scientific studies on the yield response of cotton to plant population, Adams et al. (2019) found no difference in cotton lint yield above 35,000 plants $ha^{-1}$. Among the studies included in this analysis, yields varied tremendously from approximately 800 to about 2,300 kg $ha^{-1}$, but yield trends with plant density generally similar: yield declined at extremely low densities, then no statistical difference in yield among all higher densities tested. The decline in yield below about 35,000 plants $ha^{-1}$ ranged from moderate to sharp in most cases. For example, Zhi et al. (2015) reported declines in lint yield of about 15 to 38% going from 51,000 to 15,000 plants $ha^{-1}$ in two years of study and Li et al. (2021) reported average decline in lint yield of about 26% going from 33,000 to 15,000 plants $ha^{-1}$ in a decade-long study from 2008 to 2017. But others, like McGinty et al. (2019) and Wrather et al. (2008), reported no decline in lint yield in some years with plant densities lower than the generalized threshold established by Adams et al. (2019). Li et al. (2021) stated that a plant density around 33,000 plants $ha^{-1}$ can produce stable yields across different years and weather conditions, but they found that maximum yield was achieved at 59,000 plants $ha^{-1}$ in their study conditions. The difference between yield at 33,000 and 59,000 plants $ha^{-1}$ was about 165 kg $ha^{-1}$, a difference of about 11%. The results of these studies predictably suggest that the population density threshold for optimizing cotton lint yield varies to some extent with environmental conditions, cotton germplasm, and perhaps other factors, even at the same site. Notably missing from the literature on this topic are reports from lower-yielding dryland environments (Adams et al., 2019). There are other aspects of plant population in cotton that have not been adequately addressed in the scientific literature as well.

There is inadequate understanding of the impact of stand uniformity or quality (i.e., evenness of plant-to-plant spacing within rows) on cotton yield. Plant population studies are usually conducted with uniform plant-to-plant spacing within rows, which makes comparisons among treatments easier. But in actual production fields, uneven plant stands are common due to seed and plant loss, as well as due to planter errors, such as seed placement skips and doubles. Causes of poor seedling emergence and plant loss can include soil crusting, low seed viability (i.e., poor seed quality), suboptimal temperatures, sand blasting, disease and pests, among other reasons (Bradow and Bauer, 2010; Reddy et al., 2017). In ideal planting conditions (i.e., optimal soil temperature, moisture, texture), 80% or more of planted cotton seeds will emerge and grow, maintaining a uniform stand. But seedling emergence can be far less than ideal in poor conditions (Collins, 2015; Hand et al., 2021; Smith and Varvil, 1984). For example, Virk et al. (2021) reported seedling emergence of 70, 48, and 40% in three growing seasons, with differences in emergence attributed to differences in local weather conditions. Recent research has focused on developing high-throughput and unbiased characterization of cotton stand quality by UAS (Butler, 2020; Penna Martinez 2021), but there are few studies on the effects of uneven stands on cotton lint yield.

The results from the studies by Hansa (1982), McGinty et al (2019), and Penna Martinez (2021), which are described in greater detail in the Discussion section, show small or no negative effects of uneven stands within the bounds of their treatments. There are also research results mentioned in Extension materials (e.g. Hake et al., 1991; Supak and Bonan, 1999) and conference abstracts (e.g. Jost, 2005), but the primary peer-reviewed sources for these reports could not be found.

More knowledge is also needed on the effects of plant population density on lint fiber quality. At least several studies have reported variation in fiber quality with differences in plant population density, including differences in fiber length, fineness, strength, and maturity (Darawsheh et al., 2009; Pinnamaneni et al., 2021; Zhi et al., 2016). Fiber quality results from most plant population studies come from bulk samples using High Volume Instrument (HVI) testing, which is still a standard test used for cotton fiber sales in the U.S. However, cotton breeders and modern spinning mills are also interested in more detailed measurement of fiber quality utilizing single-fiber measurements, such as Advanced Fiber Information System (AFIS). The AFIS test can better predict spinning performance and yarn quality by characterizing within-sample distribution of the fiber length (Kelly et al., 2015; Delhom et al., 2018).

Cotton seeding rate recommendations vary among regions, with very high rates recommended in some cases. This may be the result of the needs of specific cultural systems, risk aversion, or other factors. Poor germination and stand loss following planting can be difficult to predict, but cotton producers have an economic incentive to optimize their seeding rates due to the high cost of cotton seed. This requires having an excellent understanding of the yield and fiber quality responses of cotton to plant population density. There is, however, uncertainty regarding effects of plant density on lint yield and quality in dryland cotton production settings and effects of stand uniformity on these parameters in all production settings. We hypothesized that the relationship between plant density and lint yield and quality in lower-yielding dryland settings would follow a similar trend as found in higher-yielding environments. We also hypothesized that there would be negative yield and fiber quality impacts of uneven stands at low seeding rates, as the average gap between plants widened, but not at higher rates. Thus, the objectives of this study were to assess cotton lint yield and fiber quality in a two-year study comprising a wide range in plant population density, with even and uneven crop stands, in both irrigated and dryland conditions.

## 2.3. Materials and Methods

### 2.3.1. Experimental Design and Site Description

A two-year study was conducted at the Texas A&M AgriLife Chillicothe Research Station near Chillicothe, TX, USA (34°11'39"N, 99°31'07" W) in the 2020 and 2021 summer growing seasons. The climate of the area is semi-arid, with high rates of evapotranspiration (ET) relative to precipitation (DeLaune, 2012). Annual average rainfall is about 635 mm, occurring in a bi-modal pattern with peaks in the spring and fall, with limited summer and winter rainfall. Two different fields equipped with subsurface drip irrigation systems were utilized for this study. The fields were within 500 m of each other, with identically designed irrigation systems (two parts of a larger irrigation system encompassing six total fields). The field sites have an Abilene clay loam soil (Taxonomic class: fine, mixed, superactive, thermic Pachic Argiustolls). The study included two irrigation treatments and 10 plant population/stand uniformity treatments, arranged in a split-plot design with irrigation as the main plot factor and plant population/stand uniformity as the subplot factor. Irrigation treatments included no irrigation (dryland) and 90% ET replacement. The population/stand uniformity treatments included 15,000, 30,000, 60,000, 90,000, and 120,000 plants $ha^{-1}$, arranged with even and uneven plant-to-plant spacing at each population level. With four replications per treatment factor combination, there were 80 total plots per year. The plots were 14 m long and 4.04 m wide, each including four rows with 1.01 m spacing.

### 2.3.2. Experimental Procedures

Plots were planted on 20 May in 2020 and on 27 May in 2021. All plots were sown with 'Phytogen 480 W3FE' cotton, a mid-maturing cotton variety, using a precision vacuum planter. The seeding rate was set to a consistent rate of 161,450 seeds $ha^{-1}$ in 2020 and 194,900 seeds $ha^{-1}$ in 2021, both greater than the highest population to be tested of 120,000 plants $ha^{-1}$. In 2020, only six out of 16 plots expected to have 120,000 plants $ha^{-1}$ actually achieved that density. One dryland plot with 30,000 plants $ha^{-1}$ with uneven stand uniformity was also lost in 2020. After the plants were established each year, about 15 days after sowing, the stands were thinned by hand to the target treatment densities and uniformities. Spacing between plants within rows was consistent in the even plant spacing treatments. In uneven spacing treatments, a Microsoft Excel-based randomizer was used to generate uneven plant spacing patterns specific to each population treatment, which were referenced as a guide to select plants for removal. Gaps between plants within rows ranged from about 1 to 238 cm at 15,000 plants $ha^{-1}$, 1 to 195 cm at 30,000 plants $ha^{-1}$, 1 to 118 cm at 60,000 plants $ha^{-1}$, 1 to 68 cm at 90,000 plants $ha^{-1}$, and 1 to 46 cm at 120,000 plants $ha^{-1}$.

The weekly irrigation rate in the 90% ET replacement treatment was determined using reference ET output by an on-site weather station (Campbell Scientific, Logan, UT) and the growth stage-specific ET coefficients for cotton published by Ko et al. (2009). The dryland plots were never irrigated. Crop management practices followed regional recommendations for weed and pest control. Ethephon (2.92-liter $ha^{-1}$) + Folex (1.17-liter $ha^{-1}$) was applied on 20 October 2020 and Super Boll (2.92-liter $ha^{-1}$) + Folex (1.17-liter $ha^{-1}$) was applied on 11 October 2021 for boll opening and defoliation. No plant growth regulators were applied in the trial.

An unmanned aircraft system or UAS equipped with a MicaSense RedEdge-MX multispectral sensor (MicaSense, Seattle, WA, USA) was deployed over the plots to assess cotton growth and development dynamics across different growth stages. Flights were made on 28 July (69 days after planting or DAP), 26 August (98 DAP), and 16 September (119 DAP) in 2020 and on 16 July (51 DAP), 12 August (78 DAP), and 26 August (92 DAP) in 2021. All flights were made within two hours of solar noon at 30 m height to collect plot-wide multispectral images. The imagery was processed using Pix4D Mapper (Pix4D S.A., Prilly) to produce dense point clouds and Orthomosaic to be used for further analysis in ArcMap 10.8.1 (ESRI, 2011). The middle two rows of each plot were selected to estimate average normalized difference vegetative index (NDVI). Also using the middle two plot rows, the binary thresholding function in ArcMap, which uses the Otsu method in combination with Zonal statistics tool, was used to estimate the average canopy cover percentage (Otsu, 1979; ESRI, 2011).

Near the end of each season, at approximately the first boll open stage (26 August 2020 or 98 DAP and 25 August 2021 or 90 DAP), three representative plants were selected from each plot to measure yield attributes: plant height, boll number per plant, and average boll diameter. Canopy height was measured as the distance from the ground to the natural canopy foliage envelope, then averaged among plants. For boll numbers per plant, every boll on the three plants were counted and recorded, then averaged among plants. For boll diameter, three representative bolls were selected for measurement from each plant and averaged. The plots were mechanically harvested when mature using a two-row cotton stripper equipped with an on-board weigh system on 19

November 2020 and 11 November 2021. The samples were ginned to remove trash and seed to determine lint turnout, which was applied to the total plot sample weight to determine lint yield.

Fiber quality measurements were made on the lint samples using the High-Volume Instrument (HVI 4-4-10) and Advanced Fiber Information System (AFIS 3X3,000) tests at the Fiber and Biopolymer Research Institute, Lubbock, TX. The HVI fiber test has been extensively used to estimate fiber quality on basis of fiber weight, whereas AFIS utilizes length distribution measurements based on number of fibers per length to estimate fiber quality that affects the yarn spin. Micronaire, fiber strength, uniformity, upper half mean length (UHML), reflectance (rd), yellowness (+b), and elongation were recorded from HVI. Upper quartile length by weight (UQLw), mean length by number (Ln), short fiber content by number (SFCn %), fineness, maturity ratio, and standardized fineness (Hs) were recorded form AFIS measurements.

**2.3.3. Statistical Analysis**

In statistical analysis, irrigation, stand uniformity, and population density were considered as fixed effect in the statistical model, while replication (blocks) was considered a random effect. Initially, overall analysis was done including year as the fixed effect, but multiple interactions of year and the response variables were observed. Thus, the analysis for each year was conducted separately. The data was analyzed by ANOVA using the PROC MIXED procedure in the SAS 9.4 software (SAS Institute, Cary, NC). Post-hoc means comparisons were made using the Tukey method with a statistical threshold of $P \leq 0.05$. The data for all response variables were checked for the assumption of normality and equal variances using histograms, Q-Q Plots, and plots of residuals. The PROC REG procedure was used to test for polynomial relationships (linear and quadratic) on the response variables. The simplest model that adequately fit the data, judged by significance of the *P*-value and coefficient of determination, was chosen for presentation of regression results.

## 2.4. Results

### 2.4.1. Yield

Cotton lint yield was affected by irrigation in 2020 and 2021, whereas stand uniformity had no significant effects in either year (Table 2.2). Population density had no effect on lint yield in 2020, but there was an interaction between plant population and irrigation in 2021. The nature of the interaction was such that lint yield decreased at 15,000 plants $ha^{-1}$ relative to all greater densities with irrigation, but there was no difference in yield among plant densities in dryland conditions. The change in lint yield in irrigated cotton in 2021 ranged from 1432 to 1775 kg $ha^{-1}$ at 15,000 to 120,000 plants $ha^{-1}$, respectively. The lint yield, averaged across population and stand uniformity treatments, was 473.4 kg $ha^{-1}$ in 2020 and 641.3 kg $ha^{-1}$ in 2021 in dryland conditions, and average lint yield was 1499 kg $ha^{-1}$ in 2020 and 1625 kg $ha^{-1}$ in 2021 with irrigation.

**Table 2.2.** Summary of yield, yield attributes, and statistical significance of cotton in response to plant population density, stand uniformity, and irrigation treatments in the 2020 and 2021 growing seasons.

| Variables | Year 2020 Yield (kg ha$^{-1}$) | Bolls (# plant$^{-1}$) | Boll Diameter (mm) | Height (cm) | Year 2021 Yield (kg ha$^{-1}$) | Bolls (# plant$^{-1}$) | Boll diameter (mm) | Height (cm) |
|---|---|---|---|---|---|---|---|---|
| *Irrigation (I)* | | | | | | | | |
| Dryland | 473.4b[+] | 4.9b | 29.1b | 59.1b | 641.3b | 10.3b | 30.9b | 79.6b |
| Irrigated | 1499a | 7.3a | 32.3a | 86.4a | 1625a | 16.1a | 33.6a | 84.8a |
| *Stand uniformity (U)* | | | | | | | | |
| Even | 973.0a | 6.2a | 30.7a | 71.9a | 1146a | 13.6a | 32.4a | 82.1a |
| Uneven | 999.0a | 6.0a | 30.8a | 73.5a | 1120a | 12.8b | 32.1a | 82.4a |
| *Plant Population (P)* | | | | | | | | |
| 15,000[#] | 966.6a | 11.0a | 32.5a | 77.5a | 1032b | 26.4a | 34.3a | 90.4a |
| 30,000 | 964.4a | 8.0b | 31.6a | 73.4b | 1122ab | 16.5b | 33.0b | 84.2b |
| 60,000 | 947.0a | 4.4c | 30.5b | 72.0bc | 1132ab | 10.4c | 32.0c | 80.8c |
| 90,000 | 986.6a | 3.9c | 29.8b | 71.0bc | 1169ab | 6.92d | 31.2d | 79.2c |
| 120,000 | 1066a | 2.9c | 29.2b | 69.8c | 1209a | 5.73d | 30.7d | 76.6d |
| | | | | | | | | |
| *Source of Variation* | | | | | | | | |
| I | *** | *** | *** | *** | *** | ** | *** | ** |
| U | NS | NS | NS | NS | NS | * | NS | NS |
| P | NS | *** | *** | *** | ** | *** | *** | *** |
| I x U | NS | NS | NS | NS | NS | NS | NS | NS |
| I x P | NS | NS | NS | NS | ** | *** | *** | ** |
| U x P | NS | NS | NS | NS | NS | ** | NS | NS |
| I x U x P | NS | NS | NS | NS | NS | NS | NS | NS |
| CV | 54 | 58 | 7.1 | 21 | 47 | 66 | 6.3 | 7.1 |
| *n* | 69 | 69 | 69 | 69 | 80 | 80 | 80 | 80 |

[+]Means within the table column followed by the same letter are not significantly different according to ($P \leq 0.05$).
*Significant at the .05 probability level, ** Significant at the .01 probability level, ***Significant at the .001 probability level, NS - not significant, CV - Coefficient of Variation, [#]Unit of plant population: plants ha$^{-1}$.
Note: Boll number, boll diameter and plant height were collected on 98 DAP and 90 DAP on 2020 and 2021, respectively.

**Table 2.3.** Post-hoc mean comparison for significant interactions between irrigation and plant population density, and stand uniformity and plant population density in several response variables in 2021.

| Irrigation X Population | | | | | Uniformity X Population | |
|---|---|---|---|---|---|---|
| **Variables** | **Bolls (# plant$^{-1}$)** | **Boll diameter (mm)** | **Plant height (cm)** | **Yield (kg ha$^{-1}$)** | **Variables** | **Boll diameter (mm)** |
| Irrigated - 15,000# | 30.2a+ | 35.9a | 94.2a | 1432b | Even - 15,000 | 28.4a |
| Dryland -15,000 | 22.5b | 32.7cd | 86.5b | 632.8c | Uneven -15,000 | 24.4b |
| Irrigated - 30,000 | 23.3b | 34.9b | 86.9b | 1583ab | Even - 30,000 | 17.1c |
| Dryland - 30,000 | 9.75cd | 31.1e | 81.4cd | 660.7c | Uneven - 30,000 | 15.9c |
| Irrigated - 60,000 | 11.7c | 33.0c | 84.1bc | 1648ab | Even - 60,000 | 10.1d |
| Dryland -60,000 | 9.04cd | 31.0ef | 77.5ef | 690.2c | Uneven -60,000 | 10.6d |
| Irrigated - 90,000 | 8.45de | 32.3cd | 81.2ce | 1684ab | Even - 90,000 | 6.75e |
| Dryland - 90,000 | 5.38ef | 30.1fg | 77.3f | 579.5c | Uneven - 90,000 | 7.08e |
| Irrigated - 120,000 | 6.7def | 31.8de | 77.9df | 1775a | Even - 120,000 | 5.54e |
| Dryland -120,000 | 4.79f | 29.6g | 77.3f | 643.3c | Uneven -120,000 | 5.92e |

+Means within the table column followed by the same letter are not significantly different according to ($P \leq 0.05$).
#Unit of plant population: plants ha$^{-1}$.

**Table 2.4.** Regression analysis of yield and yield attribute data with plant population in 2020 and 2021, including dryland and irrigated conditions.

| **Variable** | **Irrigation** | **Relationship** | **Intercept** | **Coefficient (a,b)** | **$R^2$** | **P-value** |
|---|---|---|---|---|---|---|
| *2020 Season* | | | | | | |
| Boll number (# plant$^{-1}$) | Irrigated | Quadratic | 15.77 | $-2.15\text{x } 10^{-4}$, $9.51 \text{ x } 10^{-10}$ | 0.96 | 0.0173* |
| | Dryland | Quadratic | 12.01 | $-2.11 \text{ x } 10^{-4}$, $1.14 \text{ x } 10^{-9}$ | 0.92 | 0.0362* |
| Boll diameter (mm) | Irrigated | Linear | 33.88 | $-2.45 \text{ x } 10^{-5}$ | 0.79 | 0.0266* |
| | Dryland | Linear | 31.41 | $-3.65 \text{ x } 10^{-5}$ | 0.98 | 0.0005** |
| Height (cm) | Irrigated | Linear | 90.41 | $-6.08 \text{ x } 10^{-5}$ | 0.74 | 0.0397* |
| | Dryland | Linear | 61.92 | $-5.37 \text{ x } 10^{-5}$ | 0.30 | 0.2005 |
| *2021 Season* | | | | | | |
| Boll number (# plant$^{-1}$) | Irrigated | Quadratic | 38.45 | $-5.97\text{x } 10^{-4}$, $2.79 \text{ x } 10^{-9}$ | 0.98 | 0.0059* |
| | Dryland | Quadratic | 25.72 | $-4.41 \text{ x } 10^{-4}$, $2.27 \text{ x } 10^{-9}$ | 0.66 | 0.1717 |
| Boll diameter (mm) | Irrigated | Linear | 36.04 | $-3.89 \text{ x } 10^{-5}$ | 0.89 | 0.0103* |
| | Dryland | Linear | 32.55 | $-2.59 \text{ x } 10^{-5}$ | 0.81 | 0.0241* |
| Height (cm) | Irrigated | Linear | 93.49 | $-1.37\text{x } 10^{-4}$ | 0.87 | 0.0139* |
| | Dryland | Linear | 85.55 | $-9.43 \text{ x } 10^{-5}$ | 0.76 | 0.0336* |

*Significant at the .05 probability level, ** Significant at the .01 probability level,
***Significant at the .001probability level.
Note: Boll number, boll diameter and plant height were collected on 98 DAP and 90 DAP on 2020 and 2021, respectively.

**Table 2.5.** Summary of cotton canopy cover percentage and statistical significance in response to plant population density, stand uniformity, and irrigation treatments in the 2020 and 2021 growing seasons. (DAP, days after planting)

| | Year 2020 | | | Year 2021 | | |
|---|---|---|---|---|---|---|
| **Variables** | **69 DAP** | **98** | **119** | **51** | **78** | **92** |
| | | | **Canopy Cover (%)** | | | |
| *Irrigation (I)* | | | | | | |
| Dryland | 16.9a[+] | 35.9b | 43.9b | 48.0a | 58.7b | 61.1b |
| Irrigated | 17.2a | 58.2a | 85.1a | 46.7a | 67.1a | 88.3a |
| *Stand uniformity (U)* | | | | | | |
| Even | 16.6a | 47.2a | 71.9a | 48.0a | 63.2a | 74.9a |
| Uneven | 17.4a | 46.9a | 73.5a | 46.7a | 62.6a | 74.5a |
| *Plant Population (P)* | | | | | | |
| 15,000[#] | 6.84c | 41.2b | 54.4c | 32.6c | 57.2b | 65.1c |
| 30,000 | 13.6b | 47.6a | 63.4b | 43.3b | 63.0ab | 73.0b |
| 60,000 | 19.8a | 48.9a | 68.0a | 51.0a | 65.6a | 77.4ab |
| 90,000 | 22.0a | 48.3a | 68.0a | 54.2a | 64.7a | 78.6ab |
| 120,000 | 22.9a | 48.4a | 68.1a | 55.6a | 63.9a | 79.2a |
| | | | | | | |
| *Source of Variation* | | | | | | |
| I | NS | ** | *** | NS | *** | *** |
| U | NS | NS | NS | NS | NS | NS |
| P | *** | *** | *** | *** | ** | *** |
| I x U | NS | NS | NS | NS | NS | NS |
| I x P | ** | NS | NS | NS | NS | NS |
| U x P | ** | NS | NS | NS | NS | NS |
| I x U x P | NS | NS | NS | NS | NS | NS |
| CV | 43 | 28 | 39 | 21 | 13 | 49 |
| *n* | 69 | 69 | 69 | 80 | 80 | 80 |

[+]Means within the table column followed by the same letter are not significantly different according to ($P \leq 0.05$).
*Significant at the .05 probability level, ** Significant at the .01 probability level, ***Significant at the .001probability level, NS – not significant, CV – Coefficient of Variation, [#]Unit of plant population: plants $ha^{-1}$.

**Table 2.6.** Post-hoc mean comparison for significant interactions between irrigation and plant population, and stand uniformity and plant population for percent canopy cover at 69 days after planting in 2020.

| **Irrigation X Population** | | **Uniformity X Population** | |
|---|---|---|---|
| **Variables** | **Canopy Cover (%)** | **Variables** | **Canopy Cover (%)** |
| Irrigated - 15,000[#] | 6.96e[+] | Even - 15,000 | 6.56e |
| Dryland -15,000 | 6.73e | Uneven -15,000 | 7.12de |
| Irrigated - 30,000 | 16.2c | Even - 30,000 | 10.2d |
| Dryland - 30,000 | 11.0d | Uneven - 30,000 | 17.0c |
| Irrigated - 60,000 | 20.7ab | Even - 60,000 | 20.8ab |
| Dryland -60,000 | 18.8bc | Uneven -60,000 | 18.6bc |
| Irrigated - 90,000 | 23.2a | Even - 90,000 | 22.6a |
| Dryland - 90,000 | 20.9ab | Uneven - 90,000 | 21.5ab |
| Irrigated - 120,000 | 22.3ab | Even - 120,000 | 23.1ab |
| Dryland -120,000 | 23.5ab | Uneven -120,000 | 22.7abc |

[+]Means within the table column followed by the same letter are not significantly different according to ($P \leq 0.05$).
[#]Unit of plant population: plants $ha^{-1}$.

### 2.4.2. Yield Attributes and Canopy Cover

Overall, bolls per plant, boll diameter, and canopy height decreased as the plant population density increased, and these parameters were reduced in dryland relative to irrigated conditions (Table 2.4). Stand uniformity had limited effect, as described below. The number of bolls per plant decreased quadratically in both irrigated and dryland conditions with increasing plant density in both years (Table 2.4). The bolls per plant were greatest at 15,000 plants $ha^{-1}$, decreased at 30,000 and 60,000 plants $ha^{-1}$, and plateaued at that population in 2020. Bolls per plant decreased up to 90,000 plants $ha^{-1}$ and plateaued at that population in 2021 (Table 2.2). Stand uniformity and an interaction between stand uniformity and plant population density affected only the number of bolls per plant in 2021. The number of bolls per plant with even stand uniformity was greater by about 6.18% than in uneven stands (Table 2.2). The average boll diameter and canopy height decreased linearly with increasing plant density in both irrigated and dryland conditions in both study years (Table 2.2; Table 2.4). Compared to dryland conditions, irrigated cotton had an average across all plant densities of 51% more bolls per plant, 11% bigger boll diameter, and 46% taller plants in 2020 and about 56% more bolls per plant, 9% bigger boll diameter, and 6% taller plants in 2021 (Table 2.2).

In 2020, three observations of canopy cover percentage were made at 69, 98, and 119 DAP to represent the first bloom, maximum bloom, and first open boll stages, respectively. Similarly, the three observations in 2021 at 51, 78, and 92 DAP represented first bloom, maximum bloom, and first open boll stages, respectively. The canopy coverage differed among the growth stages in both years, increasing with time (Table 2.5). Except at the first observation in both years, canopy coverage differed between irrigation treatments, with 90% ET replacement having greater coverage than dryland. The canopy coverage also consistently differed with plant population density over time in both years. In general, percent canopy cover was the least at 15,000 and 30,000 plants $ha^{-1}$, and plateaued at 60,000 plants $ha^{-1}$ and above, though sometimes canopy coverage did not increase above 30,000 plants $ha^{-1}$ (Table 2.5). There were interactions between irrigation and plant population and stand uniformity and plant population on canopy coverage at the earliest observation in 2020, but these did not persist over time (Tables 2.5 and 2.6). There were no effects of stand uniformity observed in either year (Table 2.5).

### 2.4.3. Fiber quality

Population density had no effect on fiber quality parameters, except strength and +b in 2020, whereas most fiber quality parameters were affected by irrigation in both 2020 and 2021. Stand uniformity only affected fiber elongation in 2020 (Table 2.7; Table 2.8).

Comparing the HVI measurements, UHML, uniformity, fiber strength, and $R_d$ were consistently lower in dryland compared to irrigated conditions in both years (Table 2.7). +b was greater in dryland conditions than with irrigation in 2020, but it was greater in irrigated conditions in 2021 (Table 2.7). Micronaire in 2020 was greater in dryland compared to the irrigated conditions, but was unaffected in 2021. Fiber strength was greatest at 15,000 plants $ha^{-1}$ and least at the highest population densities (90,000 and 120,000 plants $ha^{-1}$). There was no consistent change in +b with the change in plant density (Table 2.7).

Comparing the AFIS measurements, SFCn, Fineness, and Hs were not affected by irrigation in either year of the study. However, UQLw, and mean fiber length by number (Ln) were consistently lower in dryland compared to irrigated conditions in both years (Table 2.8). Maturity ratio was lower in dryland compared to irrigated conditions in 2021. Stand uniformity did not affect any AFIS measured parameters in either year. Plant population density affected Ln, SFCn, and Hs in 2020, but only maturity ratio in 2021. Ln in 2020 was greatest at 15,000 plants $ha^{-1}$ and least at 120,000 plants $ha^{-1}$. SFCn in 2020 was least at 15,000 plants $ha^{-1}$ and greatest at 120,000 plants $ha^{-1}$. Plant density affected Hs in 2020 and Maturity ratio in 2021, but the effect was not consistent with increase/decrease in plant population (Table 2.8).

**Table 2.7**. Summary of HVI measured cotton fiber quality and statistical significance of cotton in response to plant population, stand uniformity, and irrigation treatments in 2020 and 2021 growing seasons.

| | Year 2020 | | | | | | | Year 2021 | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **Variables** | **Micronaire** | **UHML (mm)** | **Uniformity (%)** | **Strength (g tex$^{-1}$)** | **Yellowness (+b)** | **Reflectance ($R_d$)** | **Elongation (%)** | **Micronaire** | **UHML (mm)** | **Uniformity (%)** | **Strength (g tex$^{-1}$)** | **Yellowness (+b)** | **Reflectance ($R_d$)** | **Elongation (%)** |
| *Irrigation (I)* | | | | | | | | | | | | | | |
| Dryland | 4.60a | 27.8b | 82.1b | 30.2b | 9.76b | 74.9b | 6.96 | 3.96 | 26.4b | 81.5b | 29.0b | 9.08a | 76.0b | 6.57b |
| Irrigated | 4.14b | 30.1a | 84.0a | 31.6a | 10.3a | 75.4a | 6.79 | 4.16 | 27.9a | 82.7a | 30.9a | 8.88b | 77.4a | 6.74a |
| *Stand uniformity (U)* | | | | | | | | | | | | | | |
| Even | 4.39 | 28.9 | 83.1 | 30.9 | 9.99 | 75.1 | 6.80a | 4.05 | 27.2 | 82.2 | 30.0 | 9.96 | 76.7 | 6.66 |
| Uneven | 4.34 | 28.9 | 83.0 | 30.9 | 10.0 | 75.0 | 6.68b | 4.07 | 26.9 | 82.0 | 29.9 | 9.00 | 76.6 | 6.66 |
| *Plant Population (P)* | | | | | | | | | | | | | | |
| 15,000[#] | 4.31 | 29.2 | 83.5 | 31.6a | 10.3a | 74.6 | 6.78 | 4.01 | 27.2 | 82.1 | 30.0 | 8.99 | 76.6 | 6.66 |
| 30,000 | 4.43 | 29.1 | 83.2 | 31.0ab | 10.1ab | 75.2 | 6.77 | 4.12 | 27.0 | 82.0 | 29.7 | 8.98 | 76.7 | 6.68 |
| 60,000 | 4.42 | 29.0 | 83.1 | 30.7ab | 10.0ab | 75.4 | 6.76 | 4.09 | 26.9 | 81.9 | 29.6 | 8.98 | 76.5 | 6.66 |
| 90,000 | 4.47 | 28.9 | 83.0 | 31.1b | 9.89b | 75.2 | 6.78 | 4.07 | 27.3 | 82.3 | 30.4 | 8.99 | 76.9 | 6.65 |
| 120,000 | 4.23 | 28.2 | 82.4 | 30.1b | 9.84ab | 75.2 | 6.66 | 4.02 | 27.1 | 82.2 | 29.9 | 8.95 | 76.7 | 6.65 |
| *Source of Variation* | | | | | | | | | | | | | | |
| I | * | ** | ** | ** | ** | * | NS | NS | ** | ** | * | ** | *** | * |
| U | NS | NS | NS | NS | NS | NS | ** | NS | NS | NS | NS | NS | NS | NS |
| P | NS | NS | NS | ** | ** | NS | NS | NS | NS | NS | NS | NS | NS | NS |
| I x U | NS | NS | NS | NS | NS | NS | NS | NS | NS | NS | NS | NS | NS | ** |
| I x P | ** | NS | NS | ** | NS | * | NS | NS | NS | NS | NS | NS | NS | * |
| U x P | NS | NS | NS | NS | NS | NS | NS | NS | NS | NS | NS | NS | NS | NS |
| I x U x P | NS | NS | NS | NS | NS | NS | NS | NS | NS | NS | NS | NS | NS | NS |
| CV | 8.5 | 4.5 | 1.6 | 3.7 | 4.1 | 1.1 | 2.1 | 6.1 | 4.4 | 1.2 | 5.1 | 3.0 | 1.6 | 2.2 |
| *n* | 69 | 69 | 69 | 69 | 69 | 69 | 69 | 80 | 80 | 80 | 80 | 80 | 80 | 80 |

[+]Means within the table column followed by the same letter are not significantly different according to ($P \leq 0.05$).
*Significant at the .05 probability level, ** Significant at the .01 probability level, ***Significant at the .001 probability level, NS - not significant, CV - Coefficient of Variation, [#]Unit of plant population: plants ha$^{-1}$.

**Table 2.8.** Summary of AFIS measured cotton fiber quality and statistical significance of cotton in response to plant population, stand uniformity, and irrigation treatments in 2020 and 2021 growing seasons.

| | Year 2020 | | | | | | Year 2021 | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **Variables** | **UQLw (mm)** | **Ln (mm)** | **SFCn (%)** | **Fineness (mTex)** | **Maturity** | **Hs (mTex)** | **UQLw (mm)** | **Ln (mm)** | **SFCn (%)** | **Fineness (mTex)** | **Maturity** | **Hs (mTex)** |
| *Irrigation (I)* | | | | | | | | | | | | |
| Dryland | 28.3b | 19.2b | 25.8 | 171 | 0.89 | 190 | 27.6b | 18.8b | 26.1 | 160 | 0.86b | 185 |
| Irrigated | 30.7a | 20.2a | 25.8 | 164 | 0.87 | 188 | 29.4a | 19.7a | 25.5 | 165 | 0.88a | 187 |
| *Stand uniformity (U)* | | | | | | | | | | | | |
| Even | 29.6 | 19.8 | 25.7 | 168 | 0.88 | 189 | 28.5 | 19.2 | 26.1 | 162 | 0.87 | 186 |
| Uneven | 29.5 | 19.7 | 25.9 | 167 | 0.88 | 188 | 28.5 | 19.3 | 25.5 | 162 | 0.87 | 186 |
| *Plant Population (P)* | | | | | | | | | | | | |
| 15,000# | 29.9 | 20.2a | 24.3b | 167 | 0.88 | 189ab | 28.8 | 19.5 | 25.2 | 162 | 0.87ab | 185. |
| 30,000 | 29.4 | 19.8ab | 25.1b | 169 | 0.89 | 190ab | 28.4 | 19.4 | 25.0 | 164 | 0.87a | 187 |
| 60,000 | 29.5 | 19.7ab | 26.0ab | 167 | 0.88 | 189ab | 28.3 | 19.2 | 25.6 | 163 | 0.87ab | 187 |
| 90,000 | 29.6 | 20.0a | 24.6b | 169 | 0.88 | 190a | 28.7 | 19.2 | 26.7 | 161 | 0.86ab | 186 |
| 120,000 | 29.3 | 18.9b | 29.0a | 163 | 0.87 | 186b | 28.5 | 19.1 | 26.4 | 160 | 0.86b | 185 |
| *Source of Variation* | | | | | | | | | | | | |
| I | *** | * | NS | NS | NS | NS | ** | ** | NS | NS | * | NS |
| U | NS | NS | NS | NS | NS | NS | NS | NS | NS | NS | NS | NS |
| P | NS | ** | ** | NS | NS | * | NS | NS | NS | NS | * | NS |
| I x U | NS | NS | NS | NS | NS | NS | NS | NS | NS | NS | NS | NS |
| I x P | NS | NS | NS | NS | NS | * | NS | NS | NS | NS | NS | NS |
| U x P | NS | NS | NS | NS | NS | NS | NS | NS | NS | NS | NS | NS |
| I x U x P | NS | NS | NS | NS | NS | NS | NS | NS | NS | NS | NS | NS |
| CV | 4.4 | 4.9 | 11.0 | 4.3 | 3.3 | 1.9 | 4.9 | 4.1 | 8.1 | 2.9 | 1.7 | 1.5 |
| *n* | 69 | 69 | 69 | 69 | 69 | 69 | 80 | 80 | 80 | 80 | 80 | 80 |

+Means within the table column followed by the same letter are not significantly different according to ($P \leq 0.05$).
*Significant at the .05 probability level, ** Significant at the .01 probability level, ***Significant at the .001 probability level, NS - not significant, CV - Coefficient of Variation, #Unit of plant population: plants $ha^{-1}$.

## 2.5. Discussion

*Lint Yield*

There was no difference in cotton lint yield with plant density ranging from 30,000 to 120,000 plants $ha^{-1}$ in the current two-year study. At 15,000 plants $ha^{-1}$, the lowest population density tested, yield was reduced only in irrigated conditions and only in 2021. At the lowest population densities tested, the outcomes of this study are similar to some other studies reported in the literature. Wrather et al. (2008) reported no difference in yield among plant densities ranging from 23,782 to 135,904 plants $ha^{-1}$ in two years of a four-year study and only minor differences in the other two years. McGinty et al. (2019) reported no loss in lint yield when population density was reduced to 19,631 plant $ha^{-1}$ in dryland conditions and 14,003 to 34,961 plants $ha^{-1}$ in irrigated conditions, depending on the year in a three-year study. In a one-year study, Galadima et al. (2002) observed no difference in lint yield among plant densities ranging from 15,000 to 75,000 plants $ha^{-1}$. But the general trend is for yield to decline moderately or greatly below a population of about 35,000 plants $ha^{-1}$, as shown by Adams et al. (2019) and Li et al. (2021). The lack of lint yield decline at very low population densities in the current study and other studies could be due to several factors.

One of the factors that could mitigate yield decline at low plant populations is the choice of cotton variety. Cotton germplasm differs in physiological adaptations that enable crop canopy adjustment to system, enviroment, and available resources (Iqbal and Khan, 2011). The shorter bush-type cotton varieties, such as used in the current study, have been shown to have greater growth plasticity, adjusting to a broder range of plant desities than the taller stature columnar-type varieties (Kaggwa-Asiimwe, 2013). Weather factors, such as temperature, sunshine hours, and precipitation may also have contributed, as these factors were shown to account for up to 30% of yield variability in a plant population trial where plant density itself accounted for about 46% of the variability in yield (Li et al., 2021). As an example of this, crop maturity could be delayed by secondary branch growth in lower density cotton stands and, if low temperatures further slow development or terminate the season early (i.e. frost), yield could be negatively impacted (Lokhande and Reddy, 2014; Li et al., 2021). In the conditions of the present study, factors such as temperature and growing season length would not have been expected to limit growth and development, which likely contributed to the lack of difference in yield, even at the lowest population densities.

At higher populations, the results of this study are consistent with the vast majority of related studies (e.g. Liu et al., 2019; Zhi et al., 2016; Dai et al., 2015; and Feng et al., 2014), observing no gain in lint yield above a population of about 35,000 plants $ha^{-1}$ (Adams et al., 2019). Some have suggested that extremely high plant populations, even greater than the 120,000 plants $ha^{-1}$ tested in this study, would negatively impact lint yield in relatively low-yielding dryland environments (e.g., Hake et al., 1991; Deltapine, 2020). The mechanism for this would be intense plant competition for limited moisture, which induces earlier or more intense plant drought stress. Both Bednars et al. (2005) and Feng et al. (2014) tested extreme plant populations—up to 215,000 and 226,000 plants $ha^{-1}$, respectively—and reported no negative impacts on yield. But moisture availability and lint yield [~1300 kg $ha^{-1}$ for Bednars et al. (2005) and ~1200 to 1700 kg $ha^{-1}$ for Feng et al. (2014)] in these studies was greater than typically observed in some dryland cotton production environments. In the Texas Rolling Plains region (i.e., the current study site), for example, dryland yields are typically between 0 and 1000 kg $ha^{-1}$, with the lowest yields in drought years (Kimura et al., 2020; Kimura et al., 2021). No known plant population study has addressed extremely high densities in such an environment, but using extreme seeding rates has no practical purpose and is economically disadvantageous to cotton producers in these cases.

Plant density interacted with irrigation level or moisture availability in one year of this study (2021). The crop did not perform differently with changes in plant population with severely limited moisture, but there was a 14% decrease in yield at 15,000 plants $ha^{-1}$ relative to all greater densities tested with ample moisture. There was also a pattern of slightly increasing yield between 30,000 and 120,000 plants $ha^{-1}$, but there were no significant differences. Similar trends were reported by Dai et al. (2015) and Li et al. (2021) in irrigated conditions. In these cases, including the current study, the increase in lint yield from 30,000 or 33,000 plants $ha^{-1}$ (close to the population threshold at which yield is typically optimized) to the maximum reported yield ranged from 4% to 22%. It is important to highlight that there was inconsistency in these studies, with the increase in yield occurring with high population densities in some years and not others. The underlying cause of occasional yield increases with high plant densities is not entirely clear, but the effect may result from interactions with other cultural or environmental factors. For example, Butler et al. (2019) indicated there is an interaction in cotton yield between plant density and planting date in the conditions of their study, with yield at very early planting dates benefiting from greater plant densities. Most notably, however, the majority of studies reported on this topic show no increase in yield above a population of about 35,000 plants $ha^{-1}$ (Adams et al., 2019). All these results indicate that the economics of increased seed costs should be carefully weighed by cotton producers who are considering high seeding rates for potential improvements in lint yield.

There were no effects of stand uniformity on lint yield in this study. This includes a result of no yield loss with uneven stands containing gaps as large as 238 cm at an overall population density of 15,000 plants $ha^{-1}$. These results are a display of the highly adaptable nature of the cotton plant to changes and inconsistencies in planting pattern, including large gaps between plants. There is some, but limited other research reported in the peer-reviewed literature to provide additional information or insight on this topic. In a two-year study, Hasna (1982) reported an increase in boll number per plant with gaps between plants of 180 to 210 cm. They observed reduced yield only after the stand loss reached 30 to 35% (the loss was not expressed in absolute terms). Simulating hail damage, McGinty et al. (2019) studied cotton stands of a range of plant densities with uneven plant spacing within rows (achieved by mixing herbicide-resistant varieties with a conventional variety at different rates, then terminating the conventional variety) and studied the effect of removing different plant nodes. They showed that cotton yield largely recovered from uneven crop stands (no characterization was provided of gap size) and plant damage in irrigated conditions down to 14,003 plants ha$^{-1}$, though yield loss occurred in dryland conditions at 12,172 plants ha$^{-1}$. In a two-year study, Penna Martinez (2021) reported a decrease in yield in one year with an increase in gaps between plants from 61 to 122 cm, but no effect on yield the other year. In two Extension bulletins, Hake et al. (1991) and Supak and Bonan (1999) mentioned research trials in which stand loss reduced yield, but the primary sources on which these were based could not be found. Likewise, some scientific conference abstracts mentioned research on uneven cotton stands (e.g., Jost, 2005), but full and peer-reviewed descriptions of the research could not be found.

Given that so little research has been conducted on stand quality or uneven plant stands in cotton, further research is needed. This should include studying the effects of even greater stand non-uniformity than addressed in the current study (i.e., gaps greater than 2.38 m at an overall density of 15,000 plants ha$^{-1}$) and investigating interactions with other cultural factors. For example, plant compensation for changes in stand uniformity are expected to be variety-specific to some extent, similar to differences among cotton varieties in responding to population density in even stands (Nie et al., 2019). Another cultural factor to evaluate could be planting date, as Butler et al. (2019) indicated that optimal plant population density can vary with planting date and, thus, it makes sense that adaptation for non-uniform stands could likewise vary with this factor. Poor stand quality is often the basis for terminating and replanting a troubled cotton crop, but the results of this study and McGinty et al. (2019) suggest that this is not justified with stand loss in the range tested in these studies. Replanting is a major decision cotton producers face when seedling emergence is poor and young plants die for various reasons, and can have major economic implications (Butler et al., 2020). Replanting involves costs for crop termination and reestablishment, plus the potential for lower yields due to delayed planting.

Although this study showed no or minimal yield penalty to low plant population densities and uneven stands, producers considering lowering their seeding rates must consider the risks associated with poor stand establishment that can accompany seeding rates that are too low. Reducing seeding rates will result in savings on seed costs, but producers need to ensure they seed at sufficient rates to avoid crop failure and economic losses. Imperfect stands are common in actual cotton production systems due to planting equipment errors and other factors that affect seed/plant mortality (Rothrock et al., 2017). For example, low soil temperature (below 15°C) for 5 to 10 days after sowing negatively affects cotton emergence (Kerby et al., 1989) and rainfall between time of planting and seedling emergence can cause crusting that impedes emergence (Varco, 2020). Virik (2021) reported emergence reduction by 40 to 70% in dry soil conditions. Seeding rate considerations are system-specific and depend on the availability of overhead irrigation, soil type, planting depth, seed quality, environmental conditions, and other factors (Virk et al., 2021; Vories et al., 2007). In some Extension reports, like by Collins (2015), seeding rate overages of 20 to 50%, depending on conditions, are suggested to overcome risks of poor emergence and crop stand.

*Yield Attributes*

In general, higher plant density in cotton can result in more boll production along the main plant stem, earlier canopy coverage, earlier maturity, greater sunlight interception, and better competitiveness with weeds. But dense populations can also decrease boll size, lead to more fruit shed due to increased canopy shading, and exacerbate disease incidence especially in humid environments (Johnson et al., 2013; Li et al., 2020; Yang et al., 2014). In lower plant densities, overall boll size increases, fruit retention can be higher, and incidence of some diseases can be lower. But lower density can also increase fruit production on later maturing sympodial branches and additional monopodial branches, and decrease fiber quality (Adams, et al., 2019; Bednarz et al., 2000; Kumar et al., 2020; Wheeler et al., 2010). Similarly, the yield attribute results of this study showed that plant density affected boll number per plant, boll size, canopy height, and canopy coverage in both dryland and irrigated conditions. At lower plant densities, the plants had the greatest canopy height, a greater number of bolls per plant, and bolls of a bigger diameter, but lowest average canopy cover (Table 2.5). Similar results were reported by Liu et al. (2019), Zhi et al. (2016), and Wang et al. (2016) for average boll numbers per plant with changes in plant density. From the highest to the lowest plant density tested (120,000 to 15,000 plants ha$^{-1}$), boll number per plant increased by 291% - 366% and average boll diameter increased by 11% - 12% in the current study. The pattern of change was quadratic for boll number per plant and linear for boll size (Table 2.4). This indicates that changes in boll number per plant is the primary mechanism by which a cotton crop maintains lint yield across wide ranges in population density, through increased boll size also plays a role. Although the pattern of change in boll number per plant with plant density was quadratic in both seasons, there was a large absolute difference in boll numbers between seasons. This difference could be due to contrasting weather conditons, the difference in the timing of data collection (98 DAP vs. 90 DAP) between seasons, or experimental error (e.g. different researchers collected the data each year).

*Fiber Quality*

There was no consistent effect of plant population density and stand uniformity on fiber quality parameters, though irrigation affected most fiber quality parameters measured by both HVI and AFIS in both years. HVI measurements are used as the industry standard (Cotton Inc., 2021), while AFIS parameters provide unique fiber data based on individual fiber analysis.

Industrial quality standards for different fiber parameters are used to determine fiber quality (Cotton Inc., 2021). Micronaire is a measure of fiber fineness and maturity. Fiber with micronaire of 3.7 - 4.2 are considered premium, 3.5 - 3.6 and 4.3 - 4.9 are considered base, and ≤ 3.4 and ≥ 5.0 are considered discount quality. UHML < 25.14 mm, 25.14 - 27.94, 27.95 - 32, and > 32 mm are considered short, medium, long and extra-long, respectively. Length uniformity index < 77%, 77% - 79%, 80% - 82%, 83% - 85% and >85% are classified as very low, low, intermediate, high, and very high, respectively. Fiber strength ≤ 23, 24 - 25, 26 - 28, 29 - 30, and ≥ 31 $gtex^{-1}$ are classified as weak, intermediate, average, strong and very strong, respectively. Fiber elongation at break < 5%, 5% - 5.8%, 5.9% - 6.7%, 6.8% - 7.6% and >7.6% are classified as very low, low, average, high, and very high (Cotton Inc., 2021). Cotton with shorter, less uniform, weak, and lower elongation fiber produces low-quality yarns, which is not preferred (Kelly et al., 2015). However, plant breeders and spinning mills are also interested in detailed fiber quality results like SFC, fineness, maturity ratio, and UQML that are obtained from the AFIS. Cotton lint with the lowest SFC content can produce the highest quality yarns (McCreight et al., 1997). Fineness is the measure of linear density of the fiber and fineness ranging from 135 to 175 mTex is considered fine and coarseness increases with the increasing value (Coton Inc., 2021). Fiber development, or the relative thickening of the secondary cell wall, is measured by maturity ratio. Fiber with a maturity ratio below 0.8 is considered immature (Cotton Inc., 2021). Immature fibers are weaker and tend to break more during harvesting, ginning, and cleaning (Kelly et al., 2015). Standard fineness (Hs) is proportional to the diameter of the fiber and is computed as ratio of AFIS fineness and AFIS maturity ratio (Hequet et al., 2006; Kelly et al., 2015).

The effects of plant population density and stand uniformity on fiber quality parameters in this study were characterized by inconsistency. Premium micronaire, long UHML, average to high uniformity index, strong fiber strength, and average-to-high fiber elongation, maturity ratio > 0.8, and fine fiber were observed across all plant densities and uniformities. No effect of plant density was observed on micronaire, UHML, uniformity, elongation, or Rd. These results are largely similar to results observed by Larson et al. (2004) and Wrather et al. (2008) in plant population studies. However, Larson et al. (2004) and Zhi et al. (2016) reported higher micronaire below 15,000 plants $ha^{-1}$ in at least some years. There were inconsistent effects of population density on fiber strength and +b observed in this study and similar inconsistencies were also reported by Larson et al. (2004), Wrather et al. (2008), and Zhi et al. (2016). AFIS-measured parameters like SFC, fineness, and maturity ratio have been reported in few cotton plant population studies. In those studies, inconsistent effects of population density were observed, similar to the current study (Larson et. al., 2004; Feng et al., 2014).

Unlike plant density and uniformity, irrigation affected most of the measured fiber quality parameters. Irrigation is reported to decrease micronaire, but increase the uniformity, UHML, and fiber strength (Feng et al. 2011; Feng et al. 2014; Larson et al., 2004; Pinnamaneni et al., 2021;

Travis et al., 2018), which was also observed in the current study. Previous studies by Feng et. al. (2014) and Pinnamaneni et al. (2021), in which AFIS parameters were measured, reported inconsistent effects of irrigation on SFC, fineness, and maturity index. In the current study, SFC and fineness were not affected by irrigation in either year, while maturity ratio was lower in dryland conditions in one year.

## 2.6. Conclusion

Many studies have been conducted on plant population dynamics in cotton, though there have been critical knowledge gaps in several areas. These include a lack of clarity on the effects of plant density on cotton in relatively low-yielding dryland production settings, insufficient information on the effects of stand uniformity on cotton in any setting, and a need to understand how plant population and stand uniformity affect AFIS fiber quality parameters. Cotton is a highly adaptable plant, maintaining equal lint yield across wide ranges in plant population density and stand uniformity. Interactions between water inputs and plant population sometimes occur, however, with lint yield increasing modestly with increased plant density only in well-watered conditions. That occurred in just one year of this study, with a 14% decrease in yield at 15,000 plant $ha^{-1}$ relative to all greater densities tested in irrigated conditions, but no difference in dryland conditions. There were no negative effects of uneven stands on lint yield, including stands containing gaps as large as 238 cm at an overall population density of 15,000 plants $ha^{-1}$. Poor stand quality is often the basis for terminating and replanting troubled cotton crops, but these results suggest this is not justified with stand loss in the range tested here. Further study on this topic is needed. Yield compensation for low plant density and uneven stands was primarily by increased number of bolls per plant, then secondarily by increased boll size. Fiber quality parameters were minimally and inconsistently affected by population density and stand uniformity, suggesting these are not critical factors cotton producers must consider in optimizing the fiber quality of their product.

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# 3. TESTING AN ALL-INCLUSIVE PIVOT IRRIGATION SYSTEM-MOUNTED SENSOR PLATFORM TO DETECT WATER STRESS IN COTTON

## 3.1. Abstract

Water is typically the most limiting factor for cotton (*Gossypium hirsutism* L.) production in Texas and scarce ground and surface irrigation water resources are critical to producers. Innovative water-saving irrigation management strategies are needed to sustain cotton production in the state. The difference between crop canopy temperature and the air temperature (Tc-Ta) has been long used to compute the crop water stress index or CWSI as a relative indicator of crop water status and control irrigation, but it requires in-field sensors and producer adoption of the technique is low. Hence, the utility of an all-inclusive sensor system attached unintrusively to a pivot irrigation system, which calculates the Water Deficit Index (WDI) through NDVI, Tc, and in-field weather data, was tested. A sensor system was deployed in a two-year study that included four irrigation treatments (0, 30, 60, and 90% ET replacement) and systems were placed on two cotton production fields located about 1.5 km and 5 km distance from a standard weather station. A UAS-mounted multispectral sensor was used to generate fraction canopy cover (Fc) data to relate with NDVI from the pivots. The pivot-mounted NDVI data was linearly related to Fc, but the variability and slope of the relationship was altered relative to purely aerial measurements. The WDI values were greater than expected, especially before full canopy closure, likely due to inadequate accounting for the background soil heat flux. Integration of a mini weather station into the WDI sensor system was effective in representing on-site weather, with relatively little variation observed from a nearby standard weather station. Wind speed and precipitation measurements were particularly improved by using an integrated mini weather station in production fields when compared with a distant weather station. The results indicate that more study is needed to better

establish the relationship between Fc and NDVI and adjustments to the WDI model are needed to better account for soil heat flux.

## 3.2. Introduction

According to climate change models, hotter temperatures and more severe droughts are expected in the American Southwest (Christensen et al., 2013; Overpack and Udall, 2020). Since water availability is a primary factor determining plant productivity, the changing climate will become an increasingly important issue for crop producers. Upland cotton (*Gossypium hirsutum* L.) is popularly grown in Texas, for example, including most regions of the state. An average of 32% of cotton in Texas was irrigated in 2018, but that percentage varied from just 8% in the Rolling Plains to about 55% in the Northern High Plains (USDA, 2021). However, approaches to crop water management are shifting in response to a variety of factors. Irrigated cotton typically produces more lint with better quality fiber, making irrigation a desirable choice for producers if water is available (Feng et al., 2014; Pinnamaneni et al., 2021). Increasing droughts and extreme weather are making dryland cotton production more unpredictable and increasing rates of ET, also increasing the demand for irrigation water (Ajaz et al., 2020). But the sources of irrigation water in the state, which are primarily underground water from aquifers, are also depleting rapidly due to the elevated demand for irrigation. For example, water from the Seymour and Ogalala Aquifers in the Texas Rolling Plains and High Plains regions, respectively, are rapidly depleting due to overuse (Modala et al., 2017). This has reduced the capacity to irrigate, especially in the High Plains (Ajaz et al., 2020; Modala et al., 2017).

Flood irrigation using canals and furrows was conventionally practiced in many cotton systems, requiring large volumes of inefficiently used water. Drip and sprinkler irrigation systems, which are more efficient than conventional systems, are now increasingly used to irrigate cotton (Ali et al., 2020; Bronson et al., 2018; Sorensen et al., 2020). Overhead sprinkler irrigation systems (e.g. pivots and linears) are being adopted because they are quick to assemble, durable, relatively easy to operate, and adjustable (Sorensen et al., 2020). But irrigation can result in negative consequences if executed inefficiently. In addition to depleting aquifers, excess irrigation in cotton can induce seedling diseases (Howell, 2002), increase pest infestation (Lytton-Hitchins et al., 2015), and promote leaching of nutrients (McHugh et al., 2008), which can negatively impact yield and environmental quality. Full yield potential can be achieved with more efficient irrigation management with use of relatively little water (Mc Hugh et al., 2008). Thus, an overarching goal in modern irrigation management is to simultaneously optimize yield and irrigation water-use efficiency, which is possible by effectively scheduling the irrigation.

Current approaches to overhead irrigation scheduling often include monitoring soil or plant water status, then irrigating at predetermined thresholds. Some examples include monitoring soil water potential with tensiometers, measuring soil moisture by electronic sensors, tracking leaf-water potential by various means, calculating ET replacement using meteorological data and crop coefficients, and calculating the crop water stress index (CWSI) using canopy temperature and other meteorological variables (O'Shaughnessy and Evett, 2010; Rajan et al., 2013). Each of these irrigation management and scheduling approaches have various benefits and drawbacks. Some of them are difficult to implement, requiring extensive in-field installation of sensors or extensive manual data collection; some have high cost or are inaccessible to most crop producers. In pivot or linear irrigation systems, one possible solution to these practical problems is to use irrigation system-mounted infrared temperature and NDVI sensors, in conjunction with meteorological data, to implement CWSI-based irrigation scheduling without extensive in-field sensor deployment.

Canopy temperature has been long recognized as an indicator of water availability and stress in plants, and CWSI is one of the primary crop water status models used (Jackson et al., 1981; Maes and Steppe, 2012). In the CWSI model, various meteorological and crop measurements are used to compute theoretical upper and lower bounds for the difference between canopy temperature (Tc) and air temperature (Ta), which are compared to actual Tc-Ta (Colaizzi et al., 2003; Idso et al. 1982; Jackson et al., 1981; Maes and steppe, 2012; Sharma and Ritchie, 2015). Canopy temperature is measured by non-contact infrared thermometers (IRT). However, until full canopy cover is reached, canopy temperature measurements from IRTs placed above the canopy are influenced by soil temperature within the field of view of the sensor. To overcome this challenge and limitation, Moran et al. (1994) modified CWSI into the Water Deficit Index (WDI) by introducing a crop cover fraction (Fc) parameter that addressed the influence of soil background at partial vegetation cover.

Colazzi et al. (2003) demonstrated that WDI determined using a pivot-mounted system (4 m height aboveground), called "The Agricultural Irrigation Imaging System," or AgIIS, could detect water stress in cotton. The system included a thermal sensor to record canopy temperature, a spectroradiometer with reflectance bands to estimate NDVI, and Fc was manually measured by destructive sampling to establish a relationship with NDVI. They used capacitance probes to record change in volumetric soil moisture content in soil and found no good relationship between water depletion and WDI. However, good correlation ($R^2$ = 0.84 to 0.87) was observed between WDI and the soil moisture deficit index SWDI, which is based on ET and a crop water stress coefficient (Ks). Since this report, relatively inexpensive NDVI sensors are now commercially available that can continuously measure NDVI in outdoor conditions, normalized to incident radiation using an upward-facing sensor that records incoming red and NIR wavelengths from the sky (Meter, 2021; Gamon et al., 2015). Additionally, an on-farm weather station was used to collect needed meteorological parameters for the study of Colazzi et al. (2003). On-site weather stations are usually available in such research settings, but the source of this data will typically be farther away from actual producer fields where the systems are intended to be utilized. There have been recent advances development and commercial availability of all-in-one, compact weather stations that can be economically deployed anywhere (Dombrowski et al., 2021).

Crop producers need relatively simple and accessible technologies to improve irrigation water management. Use of a WDI-based sensor platform mounted unintrusively on a pivot irrigation system has been demonstrated to successfully predict soil moisture status. However, additional research is needed to develop the technology for use by producers. This includes testing improved NDVI sensors to estimate Fc, plus testing a practical solution to collect needed meteorological data on-site, even in remote production locations. One such solution could be to integrate a mini weather station into the WDI system, which are now commercially available (e.g., ClimaVue50, Campbell Scientific, Logan, UT). We hypothesized that an all-inclusive pivot-mounted sensor platform with modern IRT, NDVI, and weather station sensors can be used to determine crop water status in cotton. Thus, the objectives of this study were to evaluate the relationship between NDVI determined by pivot-mounted sensors and fraction canopy cover, compare the performance of integrated mini weather stations to a standard weather station at various distances, and, ultimately, evaluate the existing WDI model to detect the moisture stress conditions in cotton using these data sources.

## 3.3. Material and Methods

### 3.3.1. Experimental Design and Site Description

A two-year study was conducted at the Texas A&M AgriLife Chillicothe Research Station near Chillicothe, TX, USA (34°11'39"N, 99°31'07" W) in the 2020 and 2021 summer growing seasons. A two-tower center pivot irrigation system, equipped with FieldNet (Lindsey Corporation, NE) to allow programming of irrigation schedules in zones along the pivot path, was used in this study. Half of the area covered by the pivot was utilized, which was divided into pie slices each occupying 1/12th of the area, laid out in a randomized complete block design with three replications of four irrigation treatments. The treatments were based on the percent evapotranspiration (ET) replacement method, including 90%, 60%, 30% and 0% ET replacements. In 2021, two producer-owned and -managed cotton production fields with pivot irrigation systems in Hardman County, TX, USA (Field 1: 34°12'22"N, 99°30'59" W and Field 2: 34°14'10"N, 99°30'24" W) were selected to gather continuous data from pivot-mounted sensor systems. These were located approximately 1.5 and 5 km, respectively, from the Chillicothe Research Station.

### 3.3.2. Experimental Procedures

All 12 plots were planted with 'Phytogen 350 W3FE' cotton, a mid-maturing cotton variety, on 15 June in 2020 and on 27 May in 2021. Planting was done with a precision vacuum planter at a seeding rate of 127,450 seeds $ha^{-1}$ and row spacing of 1.02 m. The weekly irrigation rate for each ET replacement treatment was determined using reference ET output by an on-site weather station (Campbell Scientific, Logan, UT) and the growth stage-specific ET coefficients for cotton published by Ko et al. (2009). In 2020, all plots, including 0% ET replacement, were irrigated on 16 July to wash in applied fertilizers. Fertilizer was washed in by rain in 2021. Other management practices followed regional recommendations.

A sensor platform was mounted on the pivot, approximately 10 m proximal from the second pivot tower, to collect in-season data from the field. Crop canopy temperature was measured by an SI-121-SS infrared radiometer (Apogee Instruments, Logan, UT) with an 18° half-angle field of view. The NDVI spectral index was measured by an S2-112-SS spectral sensor pair (Apogee Instruments, Logan, UT) with a field of view of 30° (15° half-angle). An Atlaslink GNSS smart antenna system (Hemisphere GNSS, AZ) was included to link pivot and plot locations, allowing assignment of data to respective plots and treatments. In 2021, an all-in-one ClimaVue50 mini-weather station (Campbell Scientific, Logan, UT) was added to the sensor platform to collect air temperature, humidity, wind speed and direction, solar radiation, and precipitation data at the exact location of the sensors. All the instruments were connected to a CR1000X datalogging controller (Campbell Scientific, Logan, UT), powered by a battery and a solar panel, which controlled the sensors and stored the data they collected. The temperature and NDVI sensors were mounted on 45° angle, pointing forward relative to the movement of the pivot, which allowed measurements to be made without interference by shadows cast by the pivot. Data was collected within two hours of solar noon on 7 July, 6 August, 19 August, and 8 September in 2020, which represented 35, 52, 65, 73 and 85 days after planting (DAP). Similarly, data was collected on 22 July, 31 July, 10 August, 24 August, 4 September, and 6 September in 2021, which represented 57, 66, 76, 90, 101 and 103 DAP. A similar sensor system was also placed on the ground in just one of the 90% ET replacement plots, including an infrared temperature (IRT) sensor and an all-in-one weather station. The temperature sensor was mounted and adjusted to focus on the crop canopy. The ground system was used as a ground truth, allowing WDI to be determined without the influence of soil heat flux, which was compared with the pivot-based data that included both canopy and soil heat flux.

An unmanned aircraft system or UAS equipped with a MicaSense RedEdge-MX multispectral sensor (MicaSense, Seattle, WA, USA) was used to collect standard NDVI and percent canopy coverage data for comparison with the NDVI data collected by the sensor platform. The UAS was deployed over the plots on 22 July, 10 August, 24 August, and 6 September 2021 to collect multispectral images, exactly or nearly coinciding with the dates that data was collected by the pivot-mounted sensors. All flights were made within two hours of solar noon at 30 m height to collect plot-wide multispectral images. The imagery was processed using Pix4D Mapper (Pix4D S.A., Prilly) to produce dense point clouds and Orthomosaics to be used for further analysis in ArcMap 10.8.1 (ESRI, Redlands, CA). The zonal statistics tool in Arc Map 10.8.1 was used to estimate the average NDVI for each plot (ESRI, 2011). The binary thresholding function in ArcMap, which uses the Otsu method in combination with Zonal statistics tool, was used to estimate the average percent canopy coverage (PCC) (Otsu, 1979; ESRI, 2011). The relationship between pivot-mounted NDVI and UAS-based factional canopy coverage (Fc) was determined using linear regression.

The plots were mechanically harvested when mature using a two-row cotton stripper equipped with an on-board weigh system on 19 November 2020 and 11 November 2021. The samples were ginned to remove trash and seed to determine lint turnout, which was applied to the total plot sample weight to determine lint yield.

The sensor platforms deployed on production pivots in 2021 included the same components as the platform used at the Chillicothe Research Station, excluding the GNSS system. All management decisions, including irrigation timing and amounts, were made by the producers. Both fields were planted with the early-mid maturing cotton variety ‘Phytogen 400 W3FE’ on 24 May 2021. A total of 198 mm and 218 mm of irrigation water were applied at Production Pivot 1 and Production Pivot 2, respectively. Lint yield data were obtained from the producers. At both production sites, the pivots were half-pivots (i.e., not full-circle), which limited the amount of sensor data that could be used. The data was filtered to include only data when the pivots were rotating dry or were parked on the east side of the fields with the sensors pointed toward the cotton canopy. When the pivots were parked on the west sides of the fields, the sensors were pointed at weeds along fence lines.

### 3.3.3. Determination of the Water Deficit Index

The canopy temperature, air temperature, other climatic data, and the NDVI-canopy coverage relationship were used to compute the WDI as described by Moran et al. (1994) and Colaizzi et al. (2003). Canopy surface temperatures have theoretical upper and lower limits for a given set of aerodynamic and radiation conditions, which depends on available water for transpiration and evaporation and other meteorological conditions. The measurement of *(Tc- Ta)* should fall somewhere in between these upper and lower limits (Colazzi et al., 2003). After estimating the upper and lower limits, the WDI is calculated as follows:

$$WDI = \frac{(Tc - Ta)_{measured} - (Tc - Ta)_{lower\ limit}}{(Tc - Ta)_{upper\ limit} - (Tc - Ta)_{lower\ limit}} \quad (1)$$

Where, $(Tc - Ta)_{lower\ limit}$ and $(Tc - Ta)_{upper\ limit}$ are theoretical estimations for wet and dry conditions, respectively. These theoretical limits take the fraction canopy cover into consideration and become:

$$(Tc - Ta)_{lower\ limit} = Fc\ (Tc - Ta)_{wet\ vegetation} + (1 - Fc)(Tc - Ta)_{wet\ bare\ soil} \quad (2)$$

$$(Tc - Ta)_{upper\ limit} = Fc\ (Tc - Ta)_{dry\ vegetation} + (1 - Fc)(Tc - Ta)_{dry\ bare\ soil} \quad (3)$$

"Wet vegetation" indicates a well-watered canopy and "dry vegetation" indicates a completely water-stressed canopy. The relationship between the pivot-mounted NDVI sensor and the canopy cover percentage established in the 2021 season was used to compute *Fc* for each observation. To calculate WDI for the ground-based station at Chillicothe, Fc was assumed to be 1.0.

Physical energy balance equations were used to estimate the *Tc- Ta* for wet vegetation, wet bare soil, dry vegetation, and dry bare soil, as described in Collazi et al. (2003) and Virlet et al. (2014):

$$(Tc - Ta)_{wet\ vegetation} = \frac{r_{a1}(R_{n1} - G_1)}{\rho_a C_p} * \frac{\gamma\left(1 + \frac{r_{cp}}{r_{a1}}\right)}{\Delta + \gamma\left(1 + \frac{r_{cp}}{r_{a1}}\right)} - \frac{VPD}{\Delta + \gamma\left(1 + \frac{r_{cp}}{r_{a1}}\right)} \quad (4)$$

$$(Tc - Ta)_{dry\ vegetation} = \frac{r_{a2}(R_{n2} - G_2)}{\rho_a C_p} * \frac{\gamma\left(1 + \frac{r_{cx}}{r_{a2}}\right)}{\Delta + \gamma\left(1 + \frac{r_{cx}}{r_{a2}}\right)} - \frac{VPD}{\Delta + \gamma\left(1 + \frac{r_{cx}}{r_{a2}}\right)} \quad (5)$$

$$(Tc - Ta)_{wet\ bare\ soil} = \frac{r_{a3}(R_{n3} - G_3)}{\rho_a C_p} * \frac{\gamma}{\Delta + \gamma} - \frac{VPD}{\Delta + \gamma} \quad (6)$$

$$(Tc - Ta)_{dry\ bare\ soil} = \frac{r_{a4}(R_{n4} - G_4)}{\rho_a C_p} \quad (7)$$

Where, $r_a$ = aerodynamic resistance (s m$^{-1}$); $R_n$ = net radiation at the crop surface (W m$^{-2}$); $G$ = soil heat flux density (W m$^{-2}$); $\rho_a$ = density of dry air (kg m$^{-3}$); $C_p$ = specific heat of dry air (1.013 kJ kg$^{-1}$ °C$^{-1}$); $\gamma$ = psychrometric constant (kPa °C$^{-1}$); $\Delta$ = slope of the saturated vapor pressure-temperature relationship (kPa °$C^{-1}$); $r_{cp}$ and $r_{cx}$ = canopy resistance at well-watered canopy and completely-stressed canopy respectively (s $m^{-1}$); and *VPD* = vapor pressure deficit (kPa). The parameters $r_a$, $R_n$, $\rho_a$, $\gamma$, $\Delta$ and *VPD* were computed from equations in the FAO 56 database (Allen et al., 1998). To compute $r_a$, the average height of the cotton canopy was assumed to be 90 cm. To compute *Rn*, surface albedo for the Grandfield fine sandy loam (fine-loamy, mixed, superactive, thermic Typic Haplustalfs) soil at Chillicothe, TX was assumed to be 0.23, 0.23, 0.16 and 0.23 for wet vegetation, dry vegetation, wet bare soil, and dry bare soil respectively, according to Fontes (1996).

### 3.3.4. Statistical Analysis

All statistical analyses were run using the SAS 9.4 software (SAS Institute, Cary, NC). Linear regression was used to establish the relationship between Fc measured by UAS and NDVI measured from a pivot-mounted NDVI sensor using the PROC REG procedure. The PROC REG procedure was also used to evaluate the relationships and variability of the weather parameter measurements (solar radiation, wind speed, relative humidity, air temperature and precipitation) among different weather stations and among WDI measurements at each site. The data on WDI and lint yield was analyzed by ANOVA using PROC GLIMMIX procedure, keeping block as random effect and irrigation as a fixed effect in the model. Post-hoc means comparisons were made using the Tukey method with a statistical threshold of $P \leq 0.05$.

### 3.4. Results

### 3.4.1. NDVI and Fc

There was a linear relationship between NDVI and Fc measured by UAS at Chillicothe in 2021, with little variation in the relationship between parameters ($R^2 = 0.97$) (Figure 3.1). The relationship between NDVI measured by the pivot-mounted NDVI sensor pair and Fc measured by UAS was also linear, though with somewhat greater variability ($R^2 = 0.77$). There was also a difference in slope (m) between the two relationships: m = 1.35 for UAS NDVI vs. UAS Fc and m = 0.94 from pivot NDVI vs. UAS Fc (Figure. 3.1).

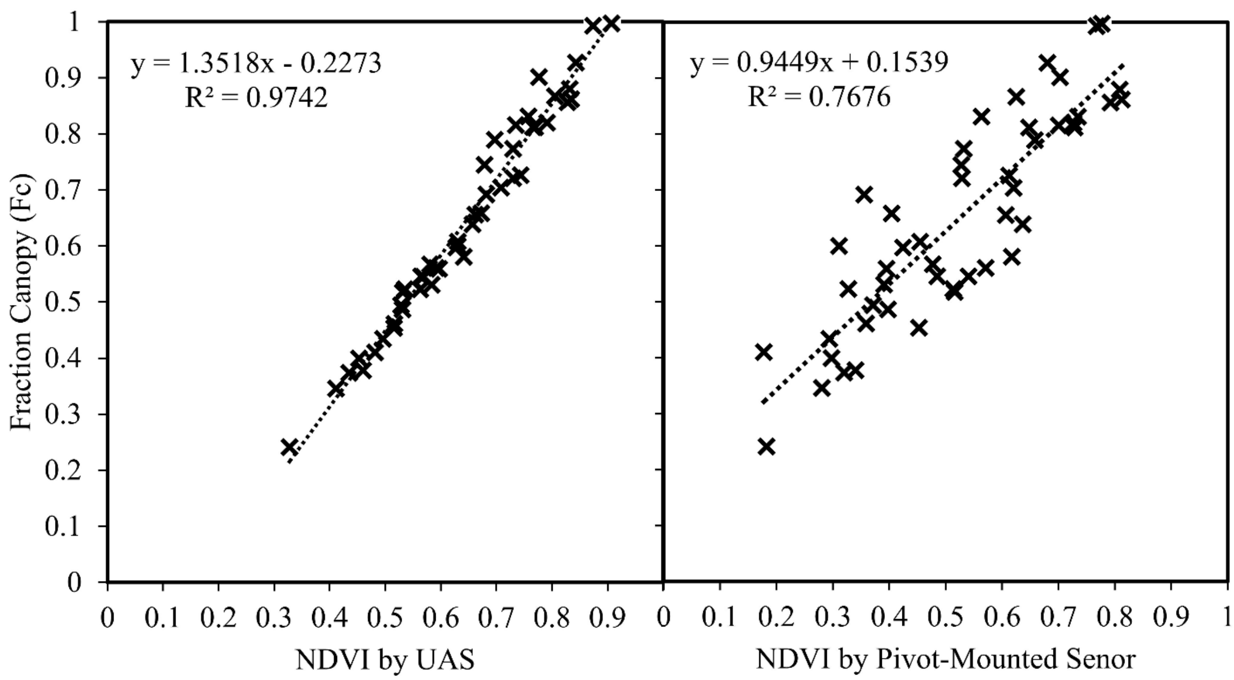


**Figure 3.1.** Relationships between NDVI, as measured by UAS (left) and pivot-mounted sensors (right), and fraction canopy cover (Fc) measured by UAS in 2021 at Chillicothe.

### 3.4.2. Weather Parameters

Comparisons were made between weather data collected by the mini weather stations, which were integrated into pivot sensor platforms at three locations, and the standard weather station at Chillicothe (Table 3.1; Figure 3.2). Comparisons were also made between the weather parameters collected by the pivot-mounted and ground-based mini weather stations at Chillicothe (Table 3.1; Figure 3.3). There was strong agreement among all weather stations in measurements of $r_s$ ($R^2$ = 0.98 – 0.99). There was somewhat more variability among weather stations in measurements of Ta and RH (0.96 – 0.99 and 0.94 – 0.98, respectively), though agreement was still strong. There was no apparent trend in $R^2$ values for Ta and RH consistent with the location or height of the sensors. There was greater variability in wind speed measurements with sensor location and height, with $R^2$ values ranging overall from 0.7 – 0.9. Compared to the wind speed measurements by the standard weather station at Chillicothe, the ground-based station on the pivot had greater agreement than the pivot-mounted sensor ($R^2$ = 0.87 vs. 0.70). For the production pivots, variability in wind speed increased somewhat with distance from the standard weather station ($R^2$ = 0.78 vs. 0.72). Potential variation in precipitation measurements was greater than all other weather parameters, as variability increased with increasing distance between sensors ($R^2$ = 1.00 - 0.46).

**Table 3.1.** Relationship measurements of essential meteorological variables measured by different sources and at different locations. The "CRS Weather Station" is a standard weather station, while data was collected using mini weather stations in all other cases.

| Variables | Number of observations | Source X | Source Y | $R^2$ | RMSE |
|---|---|---|---|---|---|
| Solar radiation ($w/m^2$) | 215 | # CRS Pivot | * CRS Pivot Ground | 0.99 | 32.51 |
| | 215 | CRS Pivot | + CRS Weather Station | 0.99 | 34.38 |
| | 1405 | CRS pivot Ground | CRS Weather Station | 0.99 | 35.14 |
| | 1809 | ! Production Pivot 1 | CRS Weather Station | 0.98 | 45.19 |
| | 1809 | ^ Production Pivot 2 | CRS Weather Station | 0.99 | 34.57 |
| Wind speed (m/s) | 215 | CRS Pivot | CRS Pivot Ground | 0.90 | 0.64 |
| | 215 | CRS Pivot | CRS Weather Station | 0.70 | 1.10 |
| | 1405 | CRS Pivot Ground | CRS Weather Station | 0.87 | 0.48 |
| | 1809 | Production Pivot 1 | CRS Weather Station | 0.78 | 0.63 |
| | 1809 | Production Pivot 2 | CRS Weather Station | 0.72 | 0.72 |
| Relative humidity (%) | 215 | CRS Pivot | CRS Pivot Ground | 0.97 | 3.68 |
| | 215 | CRS Pivot | CRS Weather Station | 0.95 | 4.72 |
| | 1405 | CRS pivot Ground | CRS Weather Station | 0.95 | 4.19 |
| | 1809 | Production Pivot 1 | CRS Weather Station | 0.96 | 4.13 |
| | 1809 | Production Pivot 2 | CRS Weather Station | 0.94 | 4.92 |
| Air temperature (°C) | 215 | CRS Pivot | CRS Pivot Ground | 0.98 | 0.82 |
| | 215 | CRS Pivot | CRS Weather Station | 0.96 | 1.08 |
| | 1405 | CRS pivot Ground | CRS Weather Station | 0.99 | 0.53 |
| | 1809 | Production Pivot 1 | CRS Weather Station | 0.98 | 0.71 |
| | 1809 | Production Pivot 2 | CRS Weather Station | 0.97 | 0.88 |
| Precipitation (mm) | 215 | CRS Pivot | CRS Pivot Ground | 1.00 | 0.01 |
| | 215 | CRS Pivot | CRS Weather Station | 0.92 | 0.04 |
| | 1405 | CRS pivot Ground | CRS Weather Station | 0.94 | 0.11 |
| | 1809 | Production Pivot 1 | CRS Weather Station | 0.85 | 0.17 |
| | 1809 | Production Pivot 2 | CRS Weather Station | 0.46 | 0.32 |

[#] ClimaVue 50 mini weather station mounted on the pivot at Chillicothe with sensors at 4 m height from ground.

[*] ClimaVue 50 mini weather station mounted on the ground in a 90% ET replacement plot at Chillicothe with sensors at 2 m height from ground.

[+] Standard weather station at the Chillicothe Research Station located about 500 m from the study field with sensors at 2 m height from ground.

[!] Production Pivot 1 is located about 1.5 km from the standard weather station at Chillicothe.

[^] Production Pivot 2 is located about 5 km from the standard weather station at Chillicothe.

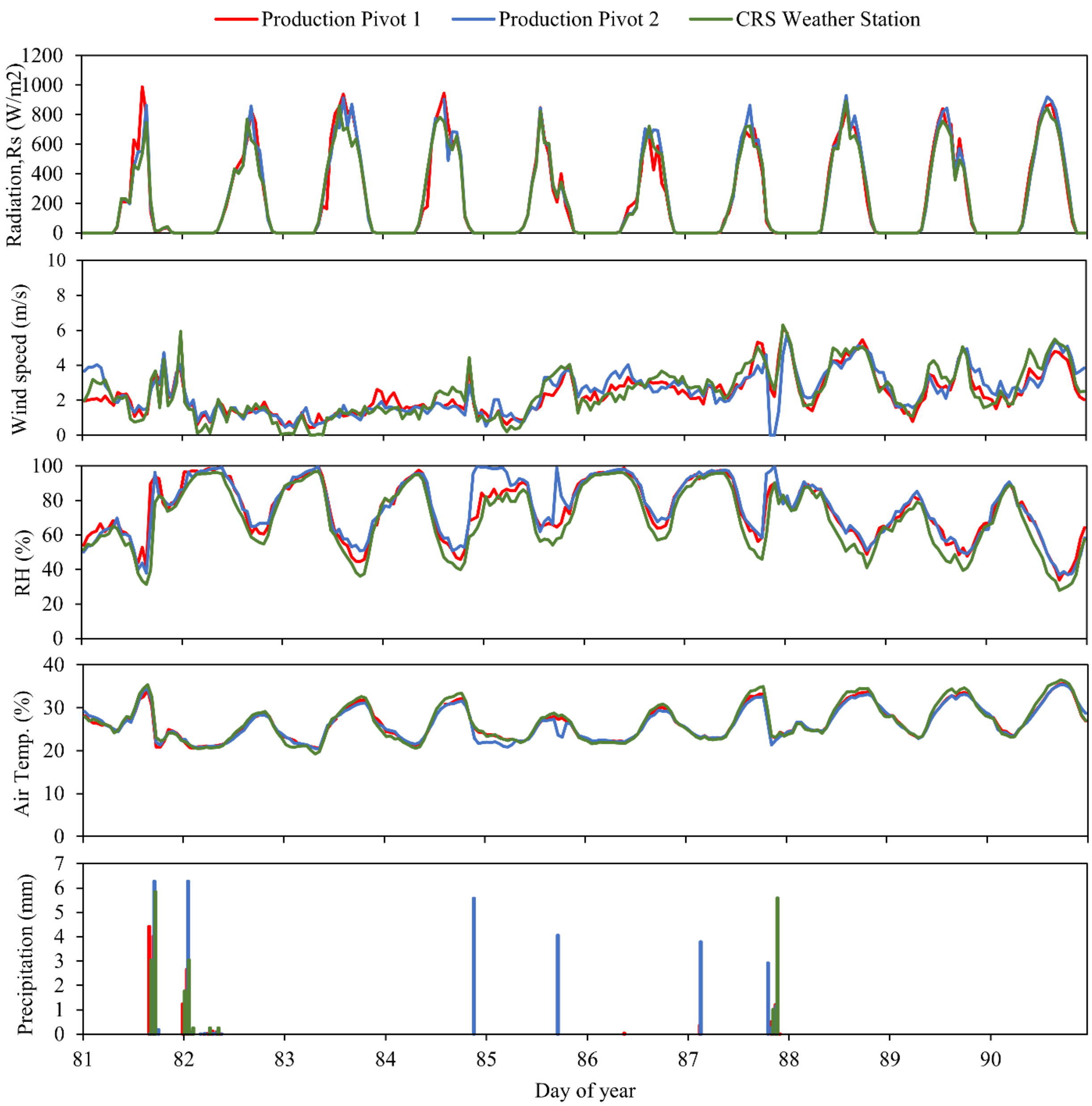


**Figure 3.2.** A comparison of essential weather parameters required to calculate WDI derived from pivot-mounted mini weather stations on two production pivots (sensors at 4 m height) and a standard weather station at the Chillicothe Research Station (sensors at 2 m height). Production Pivot 1 and Production Pivot 2 are located 1.5 km and 5 km distance, respectively, from the Chillicothe Research Station. The timeframe for this observation is from 8/13/2021 to 8/22/2021, during the cotton production season.

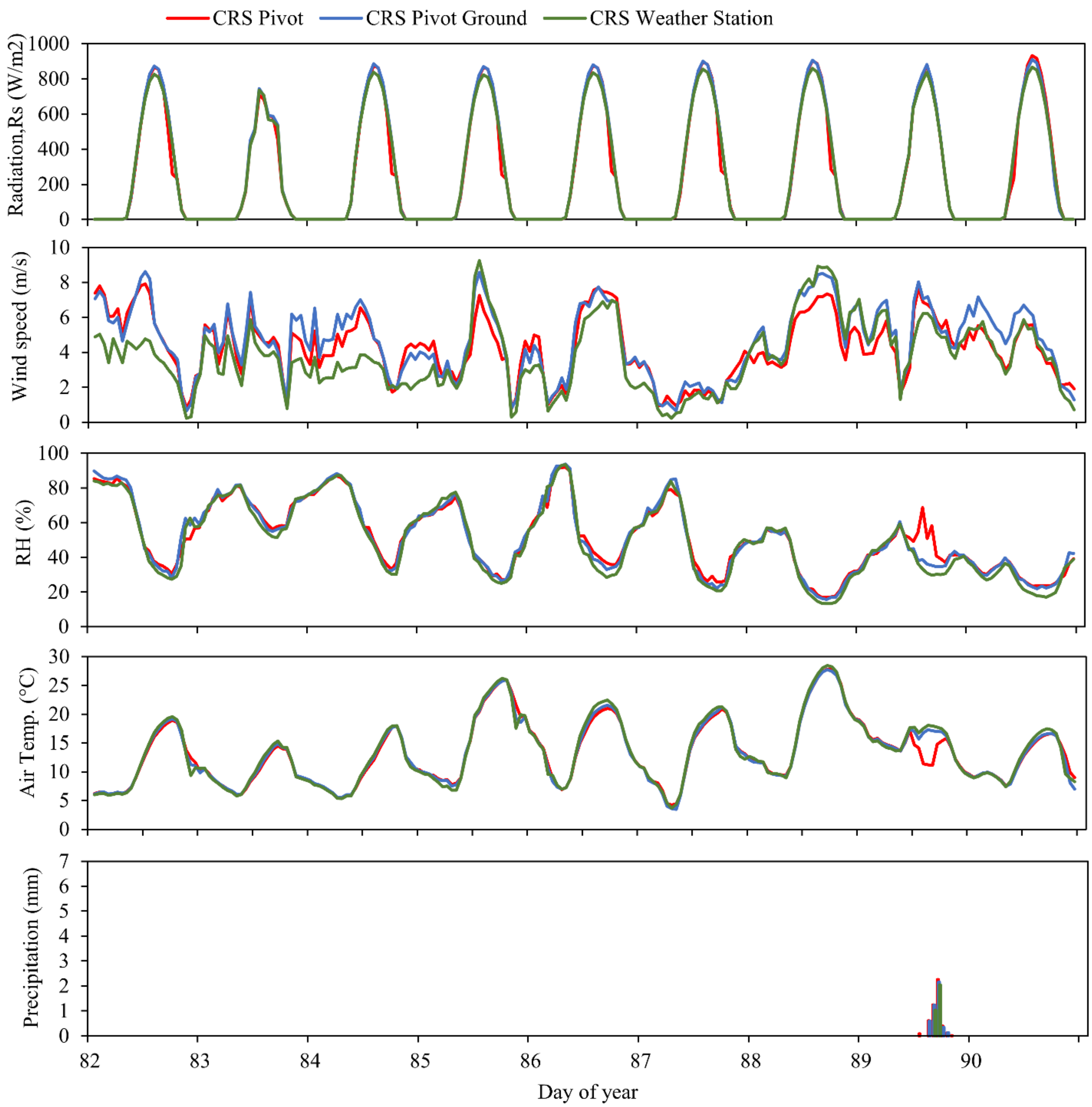


**Figure 3.3.** A comparison of essential weather parameters required to calculate WDI derived from a pivot-mounted mini weather station (sensors at 4 m height), a ground-based mini weather station (sensors at 2 m height), and a standard weather station (sensors at 2 m height), all at the Chillicothe Research Station. The timeframe for this observation is from 3/23/2021 to 3/31/202, prior to the cotton production season.

### 3.4.3. WDI Estimates

There were differences in WDI among ET replacement treatments at Chillicothe in both study years (Table 3.2). The seasonal average value of WDI was the lowest (0.31 - 0.32) at 90% ET replacement, intermediate with 60% ET replacement (0.41 - 0.48), and the greatest with 30% and 0% (dryland) ET replacement (0.61 – 0.69) in both years (Table 3.2). The lack of difference in WDI between the 30% and 0% ET replacements was due to minimal irrigation with 30% ET replacement, because precipitation largely fulfilled water demands at that level. Over the course of the season, the WDI values in each treatment shifted up and down somewhat, reflecting plant responses to irrigation and precipitation events (Figure 3.4). The WDI estimates from the pivot-mounted sensors were lower than from the ground-based sensors until about 90 days after planting. Averaged over the season, WDI derived from the pivot-mounted sensor was about 19% higher (0.31 vs 0.25) than the ground-based WDI, likely due to inadequate accounting for the influence of soil heat flux in Tc measured by pivot-mounted IRT sensor before full canopy cover (Table 3.3).

Similar to the data from Chillicothe, the WDI values from both production pivots shifted up and down over the course of the season, reflecting canopy temperature responses to irrigation and precipitation events (Figure 3.5). The WDI from the production pivots using weather data from pivot-mounted weather sensors were compared with WDI using weather data from the standard weather station at Chillicothe, located 1.5 to 5 km away (Production Pivots 1 and 2, respectively). Variability in WDI increased only minorly with distance from the standard weather station: $R^2$ = 0.96 for production Pivot 1 and $R^2$ = 0.95 for production pivot 2 (Table 3.4).

**Table 3.2.** Statistical significance and summary of lint yield and average seasonal WDI on different irrigation treatments for year 2020 and 2021.

| | Variables | Mean lint yield (kg ha$^{-1}$) | | Seasonal average WDI | |
|---|---|---|---|---|---|
| | | 2020 | 2021 | 2020 | 2021 |
| Irrigation | 0% ET Replacement | 625b$^{+}$ | 576c | 0.60a | 0.69a |
| | 30% ET | 471b | 663c | 0.61a | 0.67a |
| | 60% ET | 739ab | 1126b | 0.42b | 0.49b |
| | 90% ET | 1134a | 1670a | 0.32c | 0.31c |
| Source of Variation | Irrigation | 0.0125 | <0.0001 | <0.0001 | <0.0001 |

$^{+}$Means within the table column followed by the same letter are not significantly different according to ($P \leq 0.05$).

**Table 3.3.** Relationship between WDI calculated using pivot-mounted and ground-based sensor measurements on a 90% ET replacement plot at Chillicothe in 2021.

| Variables | Number of observations | Source X | Source Y | $R^2$ | RMSE |
|---|---|---|---|---|---|
| WDI | 7 | $^{\#}$ CRS Pivot | $^{*}$ CRS Pivot Ground | 0.58 | 0.10 |

$^{\#}$ CRS Pivot mounted IRT sensor is at height of about 4 m and facing towards canopy at 45° angle.

$^{*}$ CRS Pivot Ground IRT sensor is at canopy height directly facing to the canopy.

**Table 3.4.** Relationships between WDI calculated using meteorological data from pivot-mounted mini weather stations on two production fields and a standard weather station located 1.5 to 5 km away at the Chillicothe Research Station.

| Variables | Number of observations | Source X | Source Y | $R^2$ | RMSE |
|---|---|---|---|---|---|
| WDI | 27 | $^{!}$ Production Pivot 1 | $^{+}$ CRS Weather Station | 0.96 | 0.05 |
| | 40 | $^{\wedge}$ Production Pivot 2 | CRS Weather Station | 0.95 | 0.06 |

$^{+}$ Standard weather station at the Chillicothe Research Station, TX.

$^{!}$ Production Pivot 1 is located about 1.5 km from the standard weather station at Chillicothe.

$^{\wedge}$ Production Pivot 2 is located about 5 km from the standard weather station at Chillicothe.

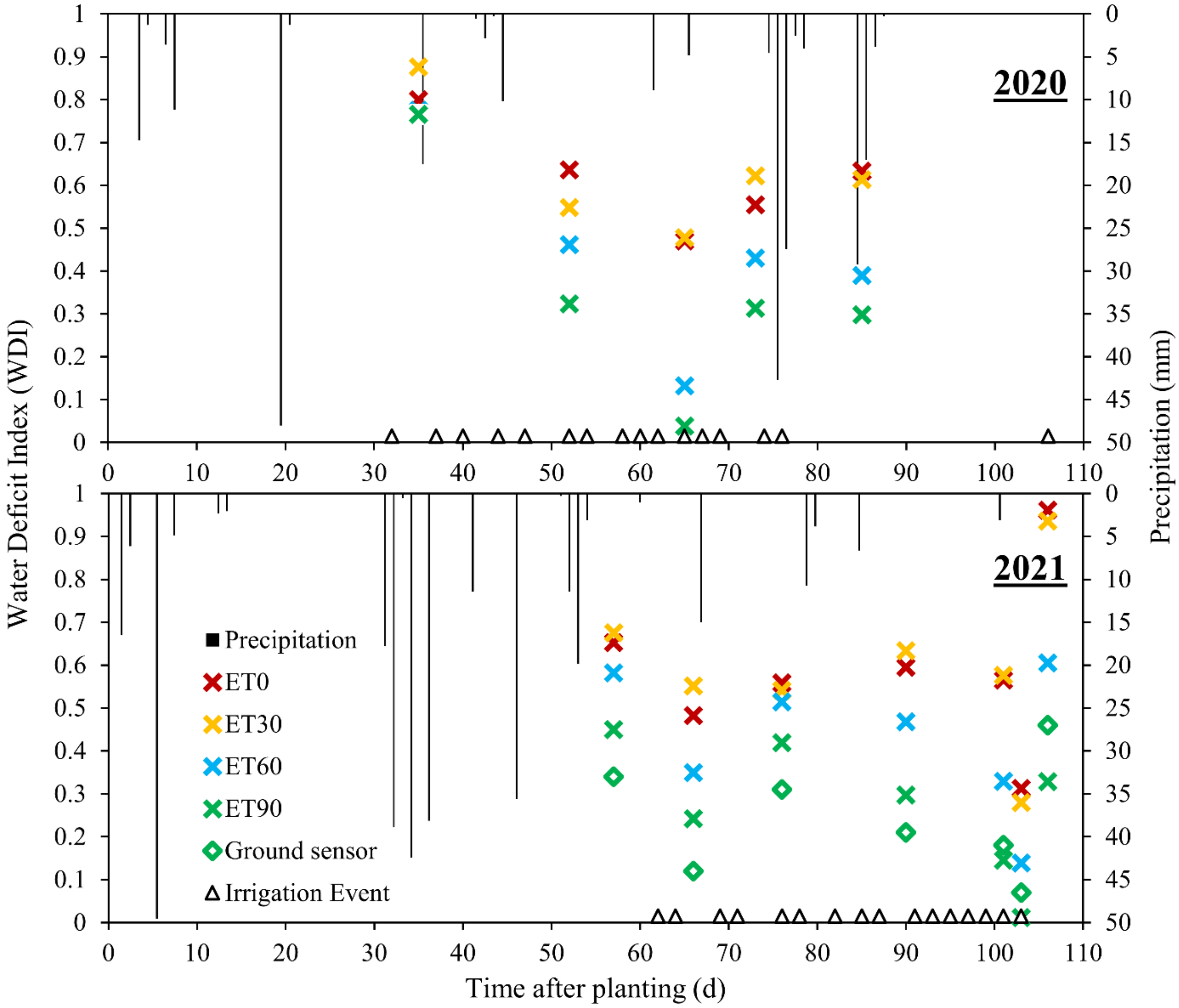


**Figure 3.4.** Water deficit index or WDI computed for different irrigation treatments at the Chillicothe Research Station in 2020 and 2021. ET90 refers to 90% ET replacement, ET60 refers to 60%, and so on.

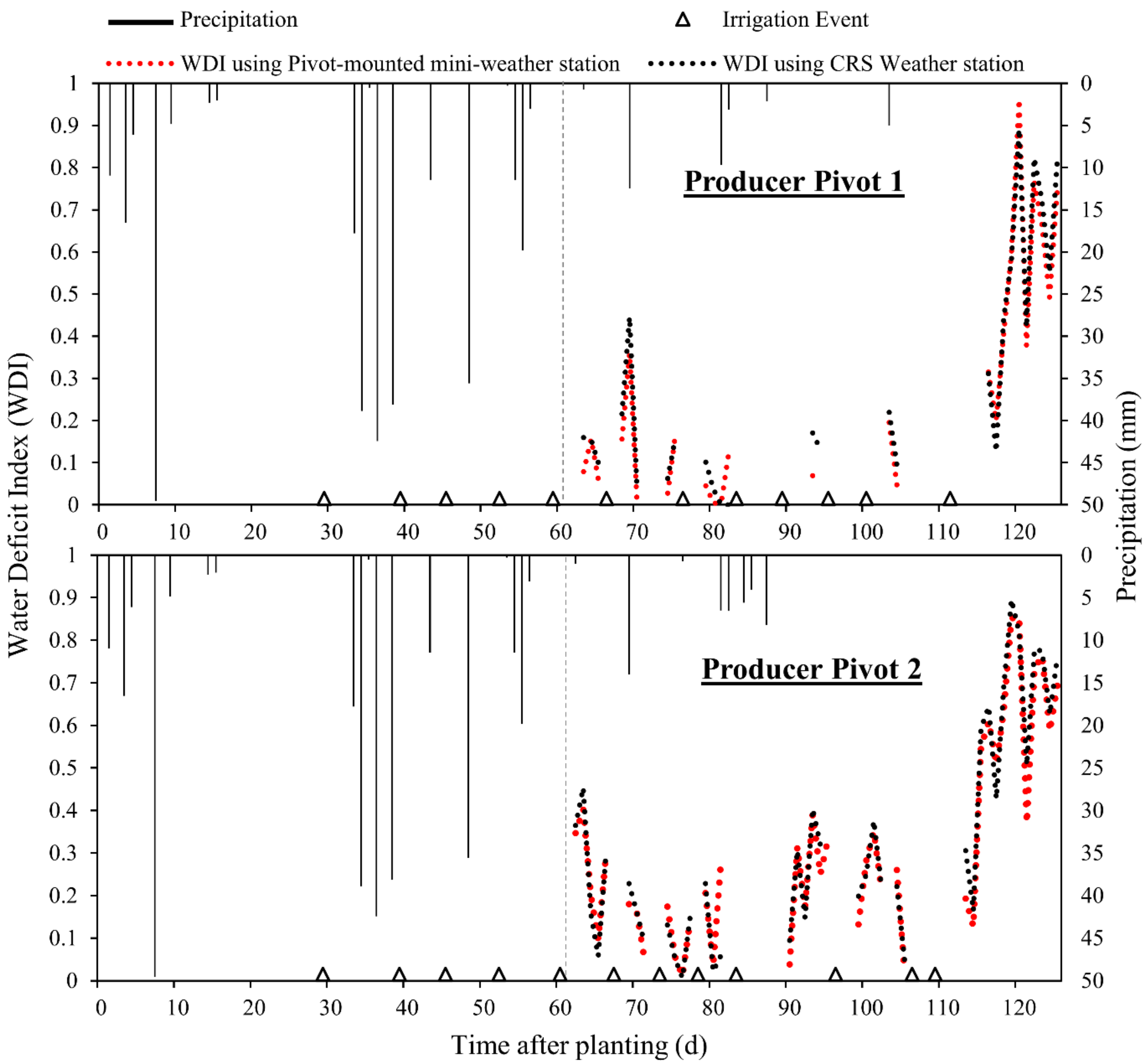


**Figure 3.5.** Water deficit index or WDI computed for cotton on two production pivot irrigation systems in 2021. Sensor platforms were installed on the pivots at just more than 60 days after planting. The precipitation data shown in both graphs before the vertical dashed lines is derived from the standard weather station at Chillicothe.

### 3.4.4. Lint Yield

At Chillicothe, cotton lint yield was affected by irrigation in both 2020 and 2021 (Table 3.2). The 90% ET replacement treatment had the greatest yield, 60% was intermediate, and 30% and dryland yielded the least. There was little (2021) or no (2020) difference in water input between dryland and 30% ET replacement treatments due to precipitation limiting irrigation in the 30% treatment (Table 3.2; Figure 3.6).

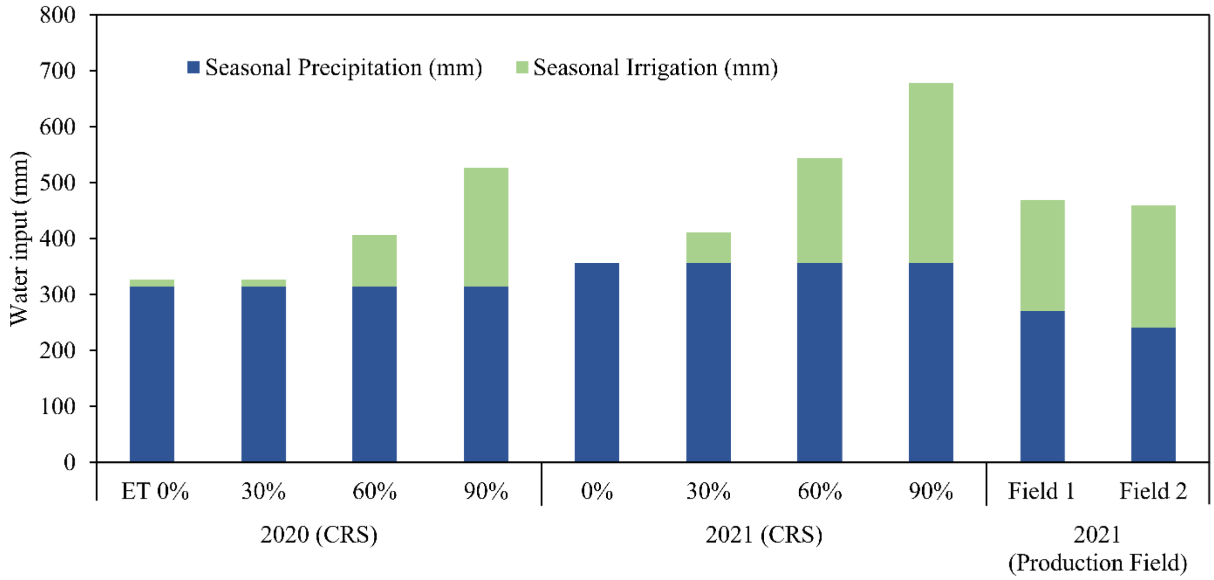


**Figure 3.6.** Total seasonal water input for cotton in 2020 and 2021 at the Chillicothe Research Station (CRS) and on two production fields. Irrigation was applied to replenish the percentage of water loss due to evapotranspiration at different levels at CRS. In production fields, producer-chosen irrigation practices were followed.

### 3.5. Discussion

Crop producers in the U.S. Southern Great Plains region and in many other regions of the world need to improve irrigation water-use efficiency and, ultimately, conserve water resources (Ajaz et al., 2020; Modala et al. 2017; Overpack and Udall, 2020). Producers plan irrigation based on the irrigation water availability, affordability of irrigation water, and expected yield (Amosson et al., 2002; Knapp et al., 2018). In the current study, NDVI and cotton canopy temperature, along with weather parameters collected from pivot irrigation-mounted sensors, were useful in calculating the WDI as an indicator of crop water stress. The relationship between NDVI and Fc from UAS-mounted sensors and pivot-mounted sensors, variability in WDI values using pivot-mounted and direct canopy-facing IRT sensors, and variability in WDI values due to variation in weather parameter measurements at different heights and locations (i.e. pivot-mounted vs. on-site or off-site) are discussed below.

In this study, NDVI was measured from the square formation to boll opening stages to estimate Fc. As expected, there was a strong linear relationship between NDVI and Fc of cotton when both measurements were derived by UAS ($R^2$= 0.97, m= 1.35). The pivot-mounted NDVI sensor used in the current system also represented Fc with a linear relationship, but with greater variability and an altered slope ($R^2$ = 0.77, m = 0.94). Relationships between NDVI and Fc reported in the scientific literature for cotton are likewise linear, and differ in variability and slope. For example, for the NDVI-Fc relationship, Jia et al. (2016) reported $R^2$ = 0.91 - 0.93 and m = 0.82 - 0.92 and Fitzgerald et al. (2005) reported $R^2$ = 0.95 and m = 0.95. The NDVI values can be affected by plant water stress (Ballester et al., 2019; Stamatiadis et al., 2010), growth stage (Ashapure et al. 2019), plant nitrogen status (Arnall et al., 2016; Porter, 2010), as well as soil background reflectance before canopy closure (Prudnikova et al., 2019; Todd and Hoffer, 1998). In the present study, the altered slope and increased variability when using the pivot-mounted NDVI sensor could be due to the angled position (45°) and narrow field of view (30°) of the sensor (i.e. unlike the vertical 180° view of the UAS-mounted sensor). These conditions may have decreased the sensitivity of the pivot-mounted NDVI sensor to changes in Fc because less soil was visible to the sensor relative to the UAS. This indicates that more study is needed to better establish the relationship between Fc and pivot-mounted NDVI sensor on a 45° angle.

It was clear in the WDI data that the WDI model did not fully account for the influence of soil temperature flux in the Tc measurements, especially before fully canopy closure. The WDI determined using data from the pivot-mounted sensors generally remained higher than WDI determined using ground-based data with the IRT sensor directly facing the canopy (Figure 3.4). Likewise, WDI measurements were taken very early in 2020—about 35 days after planting, when canopy coverage would have been quite low—and the WDI values for all irrigation levels were substantially greater than would be expected (Figure 3.4). One contributing factor to this issue may have been the variability in the NDVI-Fc relationship. This could have led to inadequate accounting for the soil heat flux and inaccuracy in estimating the lower and upper limits in the WDI model (Allen et al., 1998). Variability in weather parameter measurements also affect WDI measurements and could have been a factor.

The weather parameters ($r_s$, Ta, RH, and precipitation) recorded from the ground-based mini weather station (at 2 m height) and pivot-mounted mini weather station (at 4 m height), both on the same field at Chillicothe, generally showed strong agreement: $R^2$ between sources for $r_{s,}$ Ta, RH and precipitation were 0.99, 0.98, 0.97, and 0.99, respectively. But variability in wind speed measurements between the two stations was somewhat greater ($R^2 = 0.90$). It is well-known that wind speed changes with height (Banuelos-Ruedas et al., 2010; Allen et al., 1998) and weather station anemometers are typically mounted at 2 m to standardize wind speed measurements. Wind speed is inversely related to the aerodynamic resistance, which affects the transfer of heat and water vapor from the crop surface (Allen et al., 1998; Chu et al., 2010). To simulate the effect of changes in wind speed on WDI, the wind speed factor was increased by 10% and 50% in a spreadsheet that was used to make WDI calculations for the present study. This exercise showed that these changes increased the WDI estimates by about 7.7% and 31%, respectively, due to reductions in aerodynamic resistance. The actual variation in wind speed in the current study at 2 m and 4 m height was about 9% and average wind speed was actually greater at 2 m height than at 4 m ($4.7 \pm 2.0$ m $s^{-1}$ vs $4.3 \pm 1.8$ m $s^{-1}$). Similar to differences with height, the wind speed and other weather parameters will also vary depending on the location of the weather station relative to the field site.

Weather stations are located sporadically throughout the agricultural landscape, with some locations better equipped than others. For example, the Oklahoma Mesonet has weather stations at a higher density than most states or regions of the world (McPherson, 2007). For most producers, the closest weather station will be far from their field sites. The potential variation between actual and measured weather parameters will reduce the accuracy of WDI estimates and irrigation prescriptions when relying on off-site weather data. To address this issue, modern, compact, and relatively inexpensive weather stations, as used in this research, could be used to provide on-site weather data. This type of weather station may have somewhat diminished accuracy compared to a standard weather station, but can represent the local weather. For example, Dombrowski et al. (2021) tested the performance of the ATMOS41 all-in-one weather station and reported underestimation of $r_s$ by 3% and ±7.5% variability in precipitation compared to the standard weather station at the same location. They suggested the higher variability in precipitation was a result of wind-induced errors. Comparing the mini weather stations at different locations in the present study within a 5 km distance (Production Pivots 1 and 2 vs. the standard weather station at Chillicothe), the agreement in measurements of $r_s$ ($R^2$ = 0.97 - 0.98), Ta ($R^2$ = 0.97 - 0.98), and RH ($R^2$ = 0.94 - 0.96) was excellent. Variability in wind speed was greater among locations ($R^2$= 0.72 – 0.78). But the potential variability was the greatest for measurements of precipitation ($R^2$= 0.46 - 0.85), as might be expected. Aalbers et al. (2018) mentioned that the spatial heterogeneity in wind and precipitation, even within small areas, could arise due to inherent chaotic nature of atmospheric/oceanic/land surface processes and their interactions. Weaver and Nigam (2008) reported there is high seasonal and diurnal variability of the wind jet structure and moisture fluxes in Great Plains Region, which is something regional crop producers are well acquainted with.

### 3.6. Conclusion

The use of a pivot irrigation system-mounted sensor platform with modern NDVI and IRT sensors, with an all-in-one mini weather station integrated into the system, was useful to identify the water stress status of cotton using the WDI model. The data collected from an angled, pivot-mounted NDVI sensor was linearly related to Fc, but the variability and slope of the relationship was altered relative to purely aerial measurements. This indicates that more study is needed to better establish the relationship between Fc and NDVI determined by pivot-mounted sensors. The WDI values were greater than expected, especially before full canopy closure, likely due to inadequate accounting for the background soil heat flux. This indicates that adjustments to the upper and lower limits of the WDI model with better Fc estimates are needed for this application. Integration of a mini weather station into the WDI sensor system was effective at economically representing on-site weather, with relatively little variability observed from a nearby standard weather station. Production fields are usually located far from standard weather stations, and wind speed and precipitation measurements were particularly improved by using an integrated mini weather station when compared with a distant weather station.

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## 4. CONCLUSIONS

Cotton is one of the primary crops grown in the Rolling Plains region of Texas, where the majority of cotton grown is in dryland conditions. The increasing cost of quality cotton seeds, rapidly depleting aquifers used for irrigation, and increasing droughts and extreme weather are making cotton production more expensive and unpredictable in this region. In this thesis, one study was carried out to explore cotton population density dynamics in irrigated and dryland conditions and another study was conducted to explore use of remote sensing tools in irrigation management.

The first study focused on the impacts of the plant density and stand uniformity on yield, yield attributes, and fiber quality parameters in both irrigated and rainfed conditions. The lint yield remained unaffected by population density in dryland in both years, whereas in irrigated condition lint yield decreased at 15,000 plant $ha^{-1}$ relative to all greater densities tested in one year. Decreasing plant population lead to increasing bolls per plant and boll diameter compensating for low plant numbers. Change in plant population affected some fiber quality attributes like fiber strength, SFC and b+, but the effects were minimal and inconsistent. Stand uniformity did not affect yield, yield attributes, or fiber quality parameters. This suggests that that cotton can adjust to changing plant density and stand uniformity without largely impacting lint yield and fiber quality. Thus, producers can reduce economic loss by avoiding excessively dense planting and by using the data reported herein to guide replanting decisions when stand loss occurs. However, producers also should avoid extremely low plant densities because of the uncertainly regarding stand loss due different mechanical, weather, and disease-related damages.

The second study aimed to evaluate the use of a pivot irrigation system-mounted sensor platform consisting of NDVI sensor angled at 45°, mini-weather station, and infrared temperature sensor to identify water stress conditions in cotton for efficient irrigation management. The NDVI from the pivot-mounted NDVI senor was linearly related with Fc, but the variability and slope of the relationship was altered relative to purely aerial measurements. The WDI values before the full canopy closure were affected likely due to inadequate accounting for the background soil heat flux. The weather parameters recorded from pivot-mounted mini-weather station in the same field experienced less variability when compared at 2 m and 4 m height, whereas the variability in weather parameters, especially wind speed and precipitation increased when infield data was compared with the distant standard weather station. The WDI value shifted up and down over the course of the season, reflecting canopy temperature responses to irrigations and precipitation events. However, further study to better establish the relationship of Fc and NDVI determined by pivot-mounted sensors to better adjust the upper and lower limits of WDI model is necessary before the producers use this system for irrigation management.