EVALUATING THE IMPACTS OF VARIABLE IRRIGATION MANAGEMENT STRATEGIES ON THE PERFORMANCE OF COTTON AND GRAIN SORGHUM USING MONITORING AND MODELING TECHNIQUES

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Abstract: Diminishing water resources have threatened irrigated agriculture in many semi-arid and arid regions across the globe. In these regions, both surface and groundwater resources have declined due to persistent droughts and severe groundwater abstractions. Resultantly, producers are finding it difficult to irrigate to meet full crop water needs. Hence, there is an immediate need to find irrigation management strategies that ensure efficient utilization and conservation of water resources while optimizing crop yields in these areas. To achieve these goals, monitoring tools and crop models can be used to evaluate various irrigation management scenarios, so that meaningful irrigation recommendations could be offered to producers. The main goal of this research was to investigate crop and irrigation management practices for improving water conservation in the southern Great Plains, using a combination of field monitoring and crop modeling techniques. The specific objectives were: (1) To investigate the impacts of irrigation termination date on cotton yield and irrigation requirement, (2) To calibrate and validate a crop model for cotton and to apply the model to study the impact of irrigation capacity and seasonal weather conditions on cotton performance, and (3) To calibrate and validate a crop model for variably irrigated grain sorghum and apply the model to evaluate the performance of key water management scenarios. Evaluation of the effects of irrigation termination revealed that early irrigation terminations of cotton resulted in significant reductions in irrigation requirement, but this water conservation caused considerable declines in cotton yield. The performance of the crop model showed that it could be used as an effective tool for evaluating the impacts of variable crop and irrigation managements on the production of cotton and grain sorghum in the southern Great Plains. In both modeling studies, the results revealed a significant impact of planting date on crop yield and irrigation requirements, and this information gives the producers an opportunity to carefully consider this variable to optimize irrigation utilization. Additionally, simulations revealed that equally high cotton yields could be obtained with low irrigation capacities in the Southern High Plains region and this presents an opportunity to prolong the life of the Ogallala aquifer.

TABLE OF CONTENTS

ACKNOWLEDGEMENTS ... iii
ABSTRACT ... iv
LIST OF TABLES ... vii
LIST OF FIGURES ... x

Chapter | Page

I. INTRODUCTION ... 1
1.1 Background ... 1
1.2 Objectives ... 6

II. IMPACTS OF IRRIGATION TERMINATION DATE ON COTTON YIELD AND IRRIGATION REQUIREMENT ... 7
2.1 Abstract ... 7
2.2 Introduction ... 8
2.3 Materials and Methods ... 11
2.3.1 Study Area ... 11
2.3.2 Experimental Design ... 13
2.3.3 Crop Measurements ... 14
2.3.5 Statistical Analysis ... 15
2.4 Results and Discussion ... 15
2.4.1 Cotton Yield ... 15
2.4.2 Cotton Fiber Quality ... 17
2.4.3 Heat Units ... 20
2.4.4 Soil Water Content ... 23
2.4.5 Water Conservation ... 26
2.5 Conclusions ... 29

III. VALIDATION AND APPLICATION OF AQUACROP FOR IRRIGATED COTTON IN THE SOUTHERN GREAT PLAINS OF U.S. ... 31
3.1 Abstract ... 31
3.2 Introduction ... 32
3.3 Materials and Methods ... 35
3.3.1 Study Sites ... 35
3.3.2 Soil, Crop, and Climate Data ... 37
3.3.3 AquaCrop Model ... 40
3.3.4 AquaCrop Calibration and Validation ... 41

3.3.5 AquaCrop Application 44
3.4 Results and Discussion 46
3.4.1 AquaCrop Calibration and Validation 46
3.4.1.1 Canopy Cover 47
3.4.1.2 Soil Water Content...48
3.4.1.3 Evapotranspiration 51
3.4.1.4 Seed Cotton Yield 53
3.4.2 AquaCrop Application..57
3.5 Conclusions...61

IV. SIMULATING SOIL WATER CONTENT, EVAPOTRANSPIRATION AND YIELD OF VARIABLY IRRIGATED GRAIN SORGHUM USING AQUACROP..63
4.1 Abstract 63
4.2 Introduction...64
4.3 Materials and Methods...67
4.3.1 Study Sites 67
4.3.2 Agronomy 70
4.3.3 Irrigation Management..72
4.3.4 Evapotranspiration and Soil Water Content 74
4.3.5 AquaCrop Model Description...74
4.3.6 AquaCrop Model Input Data 75
4.3.7 AquaCrop Model Calibration 76
4.3.8 AquaCrop Model Validation...78
4.3.9 AquaCrop Model Application...79
4.3 Results and Discussion 80
4.4.1 Canopy Cover 80
4.4.2 Soil Water Content...81
4.4.3 Evapotranspiration 84
4.4.4 Grain Yield..88
4.4.5 AquaCrop Model Application...92
4.5 Conclusion 94

V. CONCLUSIONS...96

REFERENCES 99

LIST OF TABLES

Table Page

Table 2.1. Meteorological parameters for May–September during each of the three study years and the long-term (1981–2010) period. 12

Table 2.2. Chemical characteristics of topsoil at the study site. 12

Table 2.3. Dates of actual irrigation termination (IT) for each treatment and year 13

Table 2.4. Planting and harvest dates and final plant stand (plant ha^{-1}). 13

Table 2.5. Lint and seed yields for all treatments and years. Means followed by the same letter are not significantly different within years, at a 0.05 significance level according to the least significant difference (LSD). 16

Table 2.6. Cotton HVI properties. Within each year, means followed by the same letter are not significantly different at the 0.05 level. 18

Table 2.7. Cotton advanced fiber information system (AFIS) properties. Within each year, means followed by the same letter are not significantly different at the 0.05 level according to the LSD. 19

Table 2.8. Cumulative heat units (HU) during different periods of the growing season.21

Table 2.9. Coefficients of the quadratic equation: soil matric potential = a + b × yield + c × yield2. 26

Table 2.10. Percent changes in irrigation amount, lint and seed yields, lint value, and fiber quality relative to the IT3 treatment. 27

Table 3.1. 30-year average temperature and rainfall data for May-November at the Conservation and Production Research Laboratory (CPRL) and Southwest Research and Extension Center (SWREC). 36

Table 3.2. Soil parameters at the Conservation and Production Research Laboratory (CPRL) and Southwest Research and Extension Center (SWREC). 37

Table 3.3. Agronomic information for each study year and treatment at the Conservation and Production Research Laboratory (CPRL) and Southwest Research and Extension Center (SWREC) 39

Table 3.4. Default cotton parameters used in the AquaCrop model 42

Table 3.5. Total irrigation amounts applied under each irrigation capacity 45

Table 3.6. Calibrated growth stages used in the AquaCrop model at the Conservation and Production Research Laboratory (CPRL). 46

Table 3.7. Statistical measures for canopy cover simulation. 47

Table 3.8. Statistical measures for SWC simulation. 50

Table 3.9. Statistical measures for daily ET simulation 52

Table 3.10. Measured and simulated seed cotton yield with model prediction errors for default and calibrated models at CPRL. 54

Table 3.11. Measured and simulated seed cotton yield with model prediction errors at SWREC. 55

Table 3.12. Long-term average cotton yields achieved at each IC and the percent yield difference from the 0.6 l s^{-1} ha^{-1} IC. Means followed by the same letter are not significant between ICs at the 0.05 level according to the LSD. 58

Table 4.1. 30-year average (1981-2010) climatological data at USDA-ARS Conservation and Production Laboratory (CPRL) and Oklahoma Panhandle Research and Extension Center (OPREC) (NCDC, 2017). 69

Table 4.2. Soil parameters at the CPRL and OPREC sites. 70

Table 4.3. Agronomic information for the USDA-ARS Conservation and Production Laboratory site 71

Table 4.4. Agronomic information for the Oklahoma Panhandle Research and Extension Center site 72

Table 4.5. Default and calibrated (italicized) crop parameters used in the AquaCrop model 78

Table 4.6. Planting dates and planting densities for each management strategy 80

Table 4.7. Measured and simulated seasonal ET with model prediction errors. 87

Table 4.8. Measured and simulated sorghum grain yield with model prediction errors.89

LIST OF FIGURES

Figure Page

Figure 2.1. The research field and its location in southwest Oklahoma (Google Earth image). 11

Figure 2.2. Yield response to accumulated heat units from (a) Planting to IT and (b) Cutout to IT...23

Figure 2.3. Treatment averages of soil matric potential in (a) 2015, (b) 2016 and (c) 2017 23

Figure 2.4. Yield response to soil matric potential 25

Figure 2.5. Potential water savings through adoption of earlier irrigation terminations in the Lugert-Altus Irrigation District...29

Figure 3.1. The location of the study sites in Oklahoma and Texas. The base map is the 30-year average annual precipitation..36

Figure 3.2. Measured vs. simulated soil water content validation treatments 49

Figure 3.3. Measured vs. simulated ET for validation treatments...............................51

Figure 3.4. Observed and simulated seasonal ET for calibration (a) and validation treatments (b) 53

Figure 3.5. Observed and simulated cotton yield for calibration (a) and validation treatments (b) 55

Figure 3.6. Measured and simulated cotton yield at SWREC. 56

Figure 3.7. Time series of cotton yield at different ICs for the thirty-three years simulated 57

Figure 3.8. Long-term average yields achieved at each IC in wet, normal and dry years. Means followed with same letter (s) in each rainfall category are not significant at the 0.05 level according to the LSD 59

Figure 3.9. Probability of exceedance curves of simulated cotton yields for each IC.61

Figure 4.1. Locations of the study sites at USDA-ARS Conservation and Production Laboratory (CPRL) and Oklahoma Panhandle Research and Extension Center (OPREC). The base map shows water level changes (WLC) from predevelopment to 2011.......68

Figure 4.2. Simulated and measured canopy cover for the 1993/Full (calibration) and 1993/50% treatments 81

Figure 4.3. Time series of simulated and measured soil water content at the USDA-ARS Conservation and Production Laboratory site..83

Figure 4.4. Simulated and measured daily ET at the at USDA-ARS Conservation and Production Laboratory site...86

Figure 4.5. A 1:1 plot of the simulated and measured seasonal evapotranspiration for the USDA-ARS Conservation and Production Research Laboratory site.........................88

Figure 4.6. Simulated and measured grain yield for all the study years at the two sites. 92

Figure 4.7. Grain yield achieved by each strategy..93

Figure 4.8. Seasonal irrigation requirement achieved by each strategy 93

CHAPTER I

INTRODUCTION

1.1 Background

Irrigated agriculture plays a vital role in the production of food, feed and fiber in the U.S. and around the world (Howell, 2001). In addition, irrigation has consistently been the largest single consumer of water in the U.S., accounting for 80-90% of total consumptive water use (Schaible & Aillery, 2012). However, pressure on available water resources has increased because of population growth, changing climate, and excessive water resources depletion, particularly groundwater (DeJonge, Andales, Ascough II, & Hansen, 2011; Kisekka, DeJonge, Ma, Paz, & Douglas-Mankin, 2017). In light of these factors, water has become the major limiting factor for crop production, especially in dry regions (Rogers & Elliott, 1989; Kisekka et al., 2017). Many areas in U.S., such as the southern Great Plains, are facing water shortages and producers are now unable to irrigate to meet the full crop water needs under current irrigation and cropping scenarios (Lamm et al., 2016).

The southern Great Plains is one of the most productive irrigated agricultural regions in the U.S. (Weinheimer, Johnson, Mitchell, Johnson, & Kellison, 2013; Chen et al., 2018). Irrigation water sources in this region are rivers and aquifers, with the latter being the primarily water source (Evett et al., 2014). However, severe groundwater withdrawals from aquifers have resulted in significant declines of well capacities and increased pumping costs in the southern Great Plains (Gowda, Colaizzi, & Howell 2009). In areas that rely on surface water resources, water availability challenges are mainly due to poor quality and limited adequacy (Colaizzi, Gowda, Marek, & Porter, 2009; Mittelstet, Storm, & Stoecker, 2015). Previous studies have reported that the region will have severe water scarcity within the next 20 to 30 years if no significant changes in irrigation management are adopted (Haacker, Kendall, & Hyndman, 2016; Chen et al., 2018). Therefore, as water resources continue to dwindle in this region, improved agricultural water management will become crucial to guarantee continued success of irrigated agriculture (Evett et al., 2014). Sustainable water management under these conditions will require determination of innovative irrigation strategies that enhance agricultural water use efficiency (Greaves & Wang, 2017).

Over the past several decades, significant strides were made towards increasing efficiency of irrigation systems through technological improvements to combat water scarcity in the southern Great Plains region (Howell, 2001; Evett et al., 2014). Most gravity systems in the region were converted to efficient center pivot and subsurface irrigation systems (Colaizzi et al., 2009). Nonetheless, this has been a partial triumph towards water conservation and more irrigation management efforts will certainly be required (Evett et al., 2014). Weinheimer et al. (2013) identified strategic irrigation management to be a key factor in the conservation of water resources in the region. Management strategies involving changing of crop types and cultivar, sowing date, planting density, irrigation amount, and scheduling were pinpointed as potential adaptation measures to cope with water scarcity (Debaeke & Aboudrare, 2004). In the Texas High Plains, Chen et al. (2018) underscored the need to shift from water-intensive corn to less water demanding crops like cotton, grain sorghum and winter wheat to extend the lifespan of the Ogallala aquifer. Although cotton production has expanded into traditional corn production areas, more conversions from corn to drought tolerant crops could result in additional water savings in the region (Colaizzi et al., 2009).

In addition to better crop choices, Bordovsky, Mustian, Cranmer, and Emerson (2011) stated that producers in the southern Great Plains region should adopt management practices that involve low levels of irrigation as opposed to the current irrigation practices. This is in agreement with other studies that have proposed for the adoption of irrigation management strategies that target maximizing production per unit of water as opposed to the traditional thrust of production per unit area (Fereres & Soriano, 2006; Evans & Sadler, 2008). In line with these views, several studies have highlighted the potential of deficit irrigation as a strategy that can reduce irrigation water use to cope with water scarcity (Geerts & Raes, 2009; Bell, Schwartz, McInnes, Howell, & Morgan, 2018). This strategy could be significantly enhanced by incorporating various monitoring technologies to estimate crop water demand, soil moisture availability, irrigation application rates, and precipitation in cropping fields (Weinheimer et al., 2013). However, Fereres and Soriano (2006) emphasized that deficit irrigation strategies still need to be developed for most crops, and that there is lack of knowledge on whether this strategy can be used effectively over long periods in the growing season.

In other studies, irrigation timing was cited as an important factor in advancing agricultural water conservation (DeJonge et al, 2011). Proper selection of the first and last irrigation date based on the soil type, crop type, crop growth stage, and evapotranspiration rate could lead to significant water savings. Although simple in theory, this was reported to be a complex process, which requires both strategic and tactical planning (Unger & Howell, 2000). The timing of earliest and last irrigation affect the level of water conservation. First irrigation applications should be done such that water losses are minimized while last irrigation should ensure no significant water deficits and overall yield losses. The decision on when to start and terminate irrigation may be facilitated through the use of simulation models as well as soil water monitoring, possibly using soil moisture sensors (Kisekka et al, 2015).

Several studies have reported that decision support systems and monitoring tools may enhance water conservation in irrigated agriculture (Sadler, Evans, Stone, & Camp, 2005; Fereres & Soriano, 2006). This followed the findings by Adeyemi, Grove, Peets, and Norton (2017), who revealed that incorporating monitoring tools such as soil, plant and weather sensors into irrigation decision support systems like crop simulation models could be critical to achieve optimal use of limited water resources. However, adoption of monitoring tools has been slow in the U.S. For instance, less than 10% of the irrigated farms use soil moisture sensors or any other advanced on-farm water management decision tools (Schaible & Aillery, 2012). In Oklahoma, Taghvaeian (2014) reported that 8% of the producers utilize the daily evapotranspiration (ET) products despite the availability of extensive and well-maintained Mesonet weather stations. Many factors like cost and level of education could have contributed to the low adoption levels. Sadler et al. (2005) reported that most of the available precision tools were developed with disregard to the level of skillsets, knowledge and abilities of producers making it difficult for effective use. As highlighted by Taghvaeian (2014), there is potential to improve adoption of technology for irrigation management by producers, however, more research on the application of these technologies is required to enhance confidence.

Douglas-Manking (2018) listed simulation studies as one of the future research focus areas that would address the needs of decision makers as they work to ensure sustainability of land and water resources. Simulation models may be beneficial in water and irrigation management to quantify the effects of water on yield by virtue of their capacity to integrate the impacts of soils, weather and irrigation management on crop production at various scales (Evett & Tolk, 2009; Heng, Hsiao, Evett, S., Howell, & Steduto, 2009). While field research are equally important, valuable information can be obtained from modeling studies of different irrigation management practices, and various alternatives can be evaluated quickly and more efficiently than field experiments (Cabelguenne, Jones, & Williams, 1995; DeJonge et al., 2011; Modala et al., 2015, Kisekka et al., 2017). In most cases, field experiments could not allow easy evaluation of management alternatives and their potential outcomes, and generated recommendations are not normally generalizable for larger scales (Araya, Kisekka, & Holman, 2016). Additionally, several studies have noted a drop in field research on cropping systems, thus, simulation models may fill that gap and could be applied to optimize irrigation under limited water supplies while reducing risk and uncertainty in crop production (Fereres & Soriano, 2006; Kisekka et al., 2017). With historical long-term weather data, crop models provide a platform to evaluate the effectiveness and trade-offs among different irrigation scenarios, thereby allowing timely decision-making and provision of quality recommendations for producers (Debaeke & Aboudrare, 2004; Greaves & Wang, 2017). Nevertheless, Evett and Tolk (2009) reported that a gap still exists between what can be done using crop simulation models and what policymakers and water managers need to address water challenges. Incorporating producers' objectives and their potential operational limitations in irrigation modeling studies is more likely to generate relevant and reliable information, which will ultimately enhance adoption (Greaves & Wang, 2017). These views suggests that there is potential for more application of crop models in irrigation research and management.

Crop models should have a balance between accuracy and complexity in order to be useful (Monteith, 1996). Some models often require more specific crop data that may not be easily obtainable to perform simulations (García-Vila & Fereres, 2012). For instance, some studies have pointed out that the Decision Support System for Agrotechnology Transfer (DSSAT) is complex and require numerous input parameters for making thorough evaluations of crop growth and development and water dynamics (Modala et al., 2015). On the other hand, the AquaCrop model developed by the Food and Agricultural Organization (FAO) of the United Nations balances accuracy and usability (Heng at al., 2009). This crop model simulates yield in response to water management, and has relatively low requirement of specific inputs (Raes, Steduto, Hsiao, & Fereres, 2012). According to Heng et al. (2009), this model could be used to design and study the effect of water management options including irrigation management, planting dates and planting densities. Despite its potential, very few studies are available in the literature that have utilized the AquaCrop model for irrigation management research in the U.S. One of the known study was conducted by Araya et al. (2016) who used the model for evaluating deficit irrigation management strategies for grain sorghum in southwest Kansas. In the same area, similar deficit irrigation studies were done for corn (Linker & Kisekka, 2017; Araya, Kisekka, Prasad, & Gowda 2017). Even so, no published AquaCrop simulation studies were found for cotton, which is one of the major important crops, particularly in Texas and Oklahoma.

If water resources continue to decline at the current rate, the regional economy, rural communities, and the agricultural industries that depend on agricultural production in the southern Great Plains region will be affected negatively (Weinheimer et al., 2013). However, just like in many water-limited regions, water conservation is possible provided new water management strategies are adopted (Zwart & Bastiaanssen, 2004). Thus, several strategies will be explored in this research to determine how they affect crop yield and water use, and ultimately select best possible options for conserving water.

1.2 Objectives

The main goal of this research is to investigate crop and irrigation management practices for improving water conservation in the southern Great Plains using a combination of field monitoring and crop growth simulation models. The specific objectives are:

1. To investigate the impacts of irrigation termination date on cotton yield and irrigation requirement,

2. To calibrate and validate a crop model for cotton and to apply the model to study the impact of irrigation capacity and planting date on cotton performance, and

3. To calibrate and validate a crop model for variably irrigated grain sorghum by simulating soil water content, evapotranspiration and yield, and to apply the model to evaluate the performance of key water management scenarios.

CHAPTER II

IMPACTS OF IRRIGATION TERMINATION DATE ON COTTON YIELD AND IRRIGATION REQUIREMENT

2.1 Abstract

Optimization of cotton irrigation termination (IT) can lead to more efficient utilization and conservation of limited water resources in many cotton production areas across the U.S. This study evaluated the effects of three IT timings on yield, fiber quality, and irrigation requirements of irrigated cotton in southwest Oklahoma during three growing seasons. The results showed cotton yield increased with later IT dates, but this response was highly dependent on the amount and timing of late-season precipitation events. Only a few fiber quality parameters were significantly different among treatments, suggesting a more limited impact of IT on fiber quality. When averaged over the three study years, the lint yield was significantly different amongst all treatments, with an average increase of 347 kg ha^{-1} from the earliest to the latest IT. Additionally, the seed yield and the micronaire were similar for the two earlier IT treatments and significantly smaller than the values under the latest IT treatment. The differences in fiber uniformity and strength were also significant amongst IT treatments. Strong positive relationships were found between yield components and average late-season water content in the root zone. Lint and seed yields plateaued at an average late-season soil matric potential of about −30 kPa and had a quadratic decline as soil moisture depleted. When benchmarked against the latest IT treatment,

the earlier IT treatments achieved average reductions of 16–28% in irrigation requirement. However, this water conservation was accompanied with considerable declines in yield components and micronaire and smaller declines in fiber length, uniformity, and strength.

Keywords: lint; seed; fiber quality; heat units; soil matric potential; water conservation; Oklahoma

2.2 Introduction

The United States (U.S.) is amongst the top cotton producers in the world, ranking third in production and first in exports (Evett, Howell, Ibragimov, & Hunsaker, 2012; National Cotton Council of America [NCCA], 2018). Cotton is predominantly grown in the cotton belt region of the U.S., mostly in states below the 37° N latitude (Gowda, Baumhardt, Esparza, Marek, & Howell, 2007). Among these, Oklahoma has been consistently listed as one of the leading cotton producing states, ranking fifth for the year 2017 (United States Department of Agriculture—National Agricultural Statistics Service [USDA-NASS], 2017). Furthermore, cotton is the third most important field crop in Oklahoma and contributes significantly to the economy of this state (Franke, Kelsey, & Royer, 2009; Strawn, 1994). More than 80% of cotton by area and production is cultivated in Southwest Oklahoma (Evers, Elliott, & Stevens, 1998). Due to the semi-arid climate of this region, irrigation plays an important role in sustaining the production and enhancing the market value of cotton (Ziolkowska, 2018).

Irrigation water resources in southwest Oklahoma are scarce due to several reasons. First, many local surface and groundwater resources have poor quality caused by dense salt deposits (Mittelstet, Storm, & Stoecker, 2015). Osborn and Hardy (1999) reported total dissolved solids (TDS) in the range of 1500 to 5000 mg L^{-1} in the Blaine aquifer, one of the major aquifers in the region. The critical TDS of irrigation water for cotton production is 3264 mg L^{-1}, above which yield starts to decline (McFarland, Lemon, & Stichler, 2002). The high salt levels found in irrigation water resources in southwest Oklahoma mostly originate from the abundant thick gypsum beds that have a high concentration of calcium and sulfate. These geological features have affected local rivers that supply most of the surface water resources in the region. For instance, Mittelstet et al. (2015) reported heavy contamination of the North Fork of the Red River as water flows through salt deposits via its tributaries.

In addition to these water quality challenges, southwest Oklahoma has suffered severe droughts in recent years, and this has affected surface water availability (Taghvaeian, Fox, Boman, & Warren, 2015). The latest drought that occurred from 2010 to 2015 led to a significant decline of water level in Lake Altus-Lugert, which supplies the Lugert Altus Irrigation District (LAID), the largest irrigation district in southwest Oklahoma (Krueger, Yimam, & Ochsner, 2017). This water level decline resulted in the failure to release irrigation water from the lake since the water level had dropped below the intake to the main canal (Krueger et al., 2017). Consequently, cotton production experienced all-time low records during this period, with devastating impacts on the local economy. Moreover, water demand in the Lake Altus-Lugert catchment has been projected to increase by approximately 70 percent by 2060. Based on this forecast, southwest Oklahoma has been listed as a water resource “hot spot” in the state (CDMSmith & OWRB, 2012). Other cotton production areas in the region, such as in the Texas Panhandle, face similar water scarcity challenges (Bordovsky, Mustian, Ritchie, & Lewis, 2015).

Considering the highlighted water resources issues in cotton production, it is imperative that producers employ irrigation practices that conserve water. Even though cotton has been reported to have relatively higher drought resistance and lower water requirement compared to other field crops (Gowda et al., 2007), more ways to reduce cotton irrigation demand should be investigated. One approach is through optimizing the time of irrigation termination (IT), an important factor in cotton irrigation management that can boost crop maturity by accelerating boll opening, reducing boll rotting, and facilitating defoliation by inhibiting vegetative overgrowth (Grimes & Dickens, 1974; Karam et al., 2006; Reeves, 2012).

Reba, Teague, and Vories (2014) reported that water conservation could be realized following a precision IT based on growth stages and weather conditions without negatively affecting cotton lint yield. However, several studies have shown divergent views regarding the earliness of cotton IT without causing yield and quality losses. Monge, Teague, Cochran, and Danforth (2007) and (Vories et al., 2011) determined an optimal IT time of approximately 200-degree days (15.6 °C base temperature) after physiological cutout. They argued that irrigation beyond this point added neither yield nor profit. Conversely, Hogan Jr et al. (2005) estimated an optimal IT time at 306-degree days after cutout and Buttar, Aujla, Thind, Singh, and Saini (2007) showed significant cotton yield increases with later IT. In another study where IT treatments ranged from two to six weeks after physiological cutout, Reeves (2012) found contradictory results in different years. Cotton fiber quality improved in the later treatment in one year and the earlier treatment in another year. In the study by Karam et al. (2006), termination at first open boll achieved higher yields compared to later termination treatments.

These variable results demonstrate the need to further investigate the effects of irrigation termination on cotton yield. This is also evident and in support of the study by Lascano, Baumhardt, Goebel, Baker, and Gitz (2017), who argued that even though there is an abundance of data on cotton yield response to the amount and timing of irrigation, very little information is available pertaining to the impact of irrigation termination timing on cotton yield and fiber quality. Vories et al. (2011) made the same observation, particularly for the U.S. Mid-South region, and highlighted that more research on cotton IT could help improve management practices by cotton producers, and more importantly complement water conservation efforts in arid and semi-arid regions. The goal of this research was to evaluate the effects of variable irrigation termination timings on the quantity and quality of cotton yield in southwest Oklahoma.

The more specific objectives were: (i) to determine the impact of three irrigation termination dates on cotton seed and lint yield, fiber quality, and irrigation requirement during three growing seasons; and, (ii) to explore the relationships between cotton yield and two key management parameters: heat units and end-of-season soil water content.

2.3 Materials and Methods

2.3.1 Study Area

This study was conducted at the Oklahoma State University's Southwest Research and Extension Center, near Altus, Oklahoma (Figure 2.1), during three years from 2015 to 2017. The area is within the Lugert-Altus Irrigation District, which delivers water to over 18,000 ha of irrigated land through a 435 km system of open canals (Evers et al., 1998). The irrigation district draws its water from Lake Altus-Lugert, with a capacity of about 120 million m^3 (Evers et al., 1998; Krueger et al., 2017).

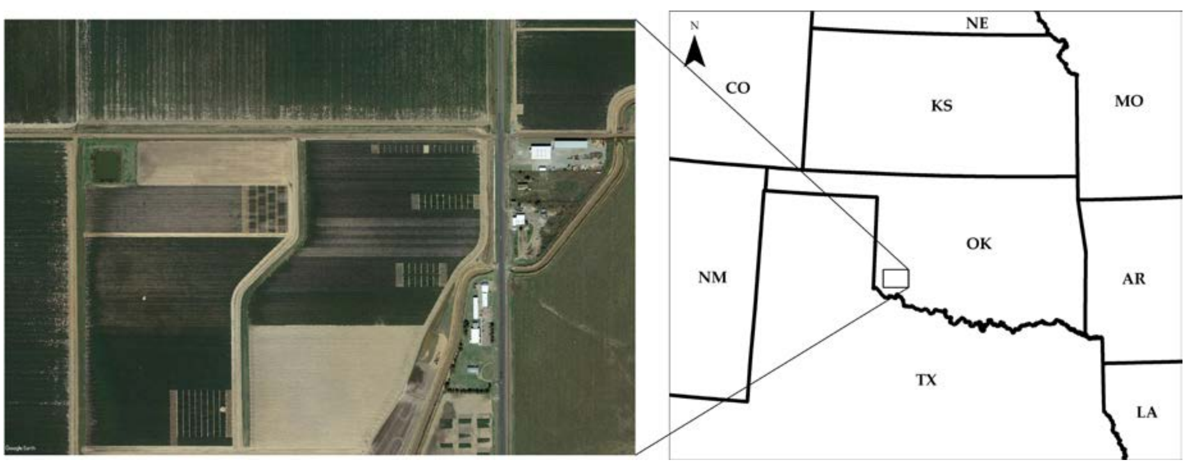


Figure 2.1. The research field and its location in southwest Oklahoma (Google Earth image).

The study area has a sub-humid climate characterized by hot and dry summers (Evers et al., 1998). The average annual rainfall is 638 mm. Table 2.1 presents the meteorological parameters for the three growing seasons (May–September) of the study, as well as the long-term averages.

Weather data were acquired from the Oklahoma Mesonet station that is located within the borders of the same Research Center and about 700 m south of the research plots.

Table 2.1. Meteorological parameters for May–September during each of the three study years and the long-term (1981–2010) period.

Parameter	2015	2016	2017	Long-term
Total Prec.[1] (mm)	451	525	472	409
Mean Rs[2] (MJ m^{-2})	22.3	23.1	23.6	23.9
Min. Tair[3] (°C)	19.3	19.1	18.5	18.5
Max. Tair (°C)	32.5	31.8	31.6	33.1
Min. RH[4] (%)	38.8	42.7	40.8	38.0
Max. RH (%)	90.1	94.4	93.5	86.0
Mean U2[5] (m s^{-1})	3.1	2.9	3.0	4.5

[1] Annual precipitation; [2] Daily accumulation of solar radiation; [3] Daily air temperature; [4] Daily relative humidity; [5] Daily wind speed at 2.0 m above the ground.

The soil of the research plots was Hollister silty clay loam (Fine, Smectitic, Thermic Typic Haplusterts), which is also the predominant soil in the irrigation district (Larson, Mapp, Verhalen, & Banks, 1996). Chemical properties of the soil were determined from samples taken at different depths of the soil profile and analyzed at the Soil, Water, and Forage Analytical Laboratory at Oklahoma State University. Table 2.2 presents the mean electrical conductivity (EC), pH, and sodium adsorption ratio (SAR) for three soil layers.

Table 2.2. Chemical characteristics of topsoil at the study site.

Soil layer (m)	EC (dS m^{-1})	pH	SAR
0.0 - 0.15	4.0	8.0	8.7
0.15 - 0.30	9.3	7.8	8.7
0.30 - 0.45	13.7	7.8	11.3

2.3.2 Experimental Design

The field layout in this study followed a randomized block design, consisting of three treatments of weekly spaced irrigation termination (IT) dates, replicated three times in each of the growing seasons. The study targeted IT dates of August 16, August 23, and August 30, based on the usual irrigation season dates specified by the irrigation district in each year. Table 2.3 presents the actual dates of each IT treatment that were achieved during the study period.

Table 2.3. Dates of actual irrigation termination (IT) for each treatment and year.

Treatment	2015	2016	2017
IT1	17 Aug.	16 Aug.	10 Aug.
IT2	24 Aug.	23 Aug.	10 Aug.*
IT3	31 Aug.	30 Aug.	29 Aug.

* The second IT date could not be achieved in 2017 due to continued precipitation.

Each replicate was comprised of 8-row plots of Deltapine DP 1044 B2RF cotton cultivar, resulting in 24 rows for every treatment. Normal fertilizer, insect, herbicide, plant growth regulator, and harvest aid management were carried out in all plots so that variations could be attributed solely to irrigation termination treatments. Each weekly irrigation event provided 76 mm of water via a furrow irrigation system. This irrigation approach (type and timing) is predominant in the Lugert-Altus Irrigation District. Table 2.4 shows planting and harvest dates and the final plant stand for each growing season.

Table 2.4. Planting and harvest dates and final plant stand (plant ha^{-1}).

Year	Planting date	Harvest date	Plant stand
2015	04 Jun.	12 Nov.	165,560
2016	28 May	21 Nov.	101,313
2017	25 May	01 Nov.	93,900

2.3.3 Crop Measurements

Several crop parameters were estimated throughout the growing season, and after harvest and processing to determine the effects of IT on yield and fiber quality. Crop maturity was tracked during regular site visits using two common indicators of nodes above white flower (NAWF) and nodes above cracked boll (NACB). A NAWF of five is often used as an indicator of reaching physiological cutout, a stage when flower development ceases and boll development commences (Ritchie, Bednarz, Jost, & Brown, 2007). To determine cotton yield and quality parameters, the center 4 rows (15.2 m long) in each plot were harvested using a John Deere 482 modified plot stripper (without field cleaner). Grab samples were taken from each plot and were ginned on a plot gin. Cleaned lint, cottonseed, trash, and burs were collected and weighed to obtain lint turnout. Lint turnout for each plot was used to convert plot bur cotton weights to lint per hectare.

For fiber quality assessment, the ginned lint samples from each plot were sent to the Cotton Phenomics Laboratory at the Fiber and Biopolymer Research Institute at Texas Tech University for the high volume instrument (HVI) and advanced fiber information system (AFIS) analyses. HVI data produces several important fiber measurements that include micronaire, fiber length, uniformity, and fiber strength. Per Lascano et al. (2017), micronaire is defined as the degree of fineness and maturity; and fiber length represents the average length of the longer half of the fibers. Uniformity is equivalent to the ratio between the average fiber length and the upper-half mean length of the fibers, expressed as a percentage. Fiber strength gives a measure of a force in grams required to break a 1000 m bundle of fibers. AFIS measures the neps content, short fiber content, fineness, and maturity ratio. The ratings of these quality parameters determine the value of cotton.

Finally, the economic value for lint was estimated by multiplying lint yield and the adjusted Commodity Credit Corporation (CCC) upland loan premiums and discounts. The adjusted loan rates were obtained using the Upland Cotton Loan Calculator program available on the Cotton Incorporated website and HVI factors determined as explained above. The rates for the 2018/2019 growing season were applied to all three years of study.

2.3.5 Statistical Analysis

The yield and fiber quality data were analyzed for each year and across the entire study period using the analysis of variance (ANOVA) at a significance level of 0.05 in SigmaPlot 14.0 (SigmaPlot, 2018). To allow for pairwise comparisons among the means, the Fisher's Least Significant Difference (LSD) was also calculated and reported (Lascano et al., 2017).

2.4 Results and Discussion

2.4.1 Cotton Yield

The largest lint yield averaged over all three irrigation termination (IT) treatments was achieved in 2016, followed by 2017 and 2015 with estimates of 2006, 1214, and 1016 kg ha^{-1}, respectively. The seed yields had a somewhat similar pattern, with average values of 2949, 1801, and 1882 kg ha^{-1} during the same years, respectively. This was consistent with the order of the total amounts of rainfall received in each of the three seasons, where 2016 recorded the largest amount, followed by 2017 and 2015 (Table 2.1). Bordovsky et al. (2015) found similar cotton lint yields under full irrigation application in Texas Panhandle and reported that rainfall had a significant impact on lint yield.

The effect of rainfall amount and distribution was also evident in the response of cotton to IT treatments. In general, cotton lint and seed yield increased with later IT dates. However, this increase was not statistically significant in all years (Table 2.5). In 2015, the increase in cotton lint and seed yields with IT date was statistically different amongst all treatments. In this year, dry conditions occurred after the first IT treatment in August and persisted into September, which registered just 11 mm of rainfall, 16% of the long-term average for this month. The enhanced yield in IT3 appeared to be a result of the irrigation applied at the end of August, which provided better soil moisture conditions for crop growth during the hot and dry September experienced that year. These results are similar to the findings of Teague [28] in Arkansas, who observed significant differences in yield with each additional irrigation after cutout in a year characterized by a mid-season hot and dry period.

In contrast to 2015, there were no significant differences in cotton yield during the 2016 season. This season recorded average rainfall in August and twice the long-term average in September, which subdued the treatment effects on cotton performance. In 2017, August recorded almost twice the long-term average rainfall, affecting the treatment structure (only two IT treatments were possible). September rainfall in 2017 was near average. In this year, the IT3 resulted in a significant increase in cotton lint and seed yield compared to IT1 (Table 2.5).

Table 2.5. Lint and seed yields for all treatments and years. Means followed by the same letter are not significantly different within years, at a 0.05 significance level according to the least significant difference (LSD).

Treatment	Lint yield (kg ha^{-1})				Seed yield (kg ha^{-1})			
	2015	2016	2017	3-year	2015	2016	2017	3-year
IT1	802 a	1962 a	1131 a	1276 a	1541 a	2923 a	1707 a	2035 a
IT2	965 b	1951 a	1031* a	1369 b	1841 b	2900 a	1591* a	2182 a
IT3	1282 c	2106 a	1481 b	1623 c	2264 c	3025 a	2106 b	2465 b
p-value	< 0.001	0.087	0.001	< 0.001	< 0.001	0.369	0.003	< 0.001
$LSD_{0.05}$	49	NS	122		96	NS	184	

IT: Irrigation termination; NS: Not significant; * Termination date was the same as for IT1.

The findings of the present study were in agreement with Reba et al. (2014), who reported larger yields in wet years for furrow-irrigated cotton. Furthermore, various studies have highlighted the correlation between growing season rainfall distribution and cotton yield (Cetin & Basbag, 2010;

Cull, Hearn, & Smith, 1981; Snowden, Ritchie, Cave, Keeling, & Rajan, 2013). In particular, Cull et al. (1981) reported a significant effect of late-season rainfall on the number of bolls set in cotton. In addition to rainfall, the length of the growing season may have contributed to the high yield attained in 2016. This season had the longest growing season in terms of calendar days and thermal time. The length of the growing season was shorter and comparable in 2015 and 2017, despite their differences in rainfall.

When data were combined over the three-year period, there were statistically significant differences in lint yield ($p < 0.001$) amongst all treatments. For seed yield, there was no statistically significant difference between IT1 and IT2 treatments ($p = 0.056$). However, both IT1 and IT2 were significantly smaller than IT3 ($p < 0.001$). Overall, the results of this study showed an increase in yield with increase in the length of the irrigation season. This was consistent with the results of Vories and Glover (2000) and Teague (2007). On the other hand, Karam et al. (2006) studied three IT timings at first open boll, early boll loading, and mid-boll loading under the semi-arid conditions of Lebanon and found a reduction in lint yield with later IT treatments. They argued that the decrease in yield caused by additional irrigations was due to reduced boll opening, which generally occurs in high water supply conditions.

2.4.2 Cotton Fiber Quality

The results indicated that except for 2015, HVI properties had mostly no significant differences among IT treatments (Table 2.6). The 2015 growing season had the smallest values of micronaire compared to 2016 and 2017, and the differences in this parameter among treatments were statistically significant. A number of previous studies have highlighted the increase of micronaire with late IT, and its susceptibility to environmental conditions including rainfall and temperature (Lascano et al., 2017; Silvertooth & Galadima, 2003). Teague (2007) observed an increase in micronaire with each additional irrigation after cutout, in a year characterized by a hot and dry mid-season in Arkansas. In case of other HVI parameters (length, uniformity, and strength), IT2 and IT3 attained similar values that were significantly larger than those of IT1 in 2015. None of the HVI properties were significantly different across IT treatments in 2016. In 2017, one of the IT1 treatments achieved a significantly lower micronaire compared to IT3, but there was no significant difference in length, uniformity and strength qualities.

Table 2.6. Cotton HVI properties. Within each year, means followed by the same letter are not significantly different at the 0.05 level.

Micronaire (units)				
Treatment	2015	2016	2017	3-year
IT1	2.87 a	4.40 a	3.73 ab	3.65 a
IT2	2.87 a	4.40 a	3.60* a	3.64 a
IT3	3.30 b	4.47 a	3.90 b	3.89 b
p-value	0.018	0.907	0.035	0.021
$LSD_{0.05}$	0.27	NS	0.20	
Length (mm)				
Treatment	2015	2016	2017	3-year
IT1	28 a	29 a	29 a	29 a
IT2	30 b	29 a	28* a	30 a
IT3	29 ab	30 a	29 a	29 a
p-value	0.040	0.585	0.327	0.121
$LSD_{0.05}$	0.02	NS	NS	
Uniformity (%)				
Treatment	2015	2016	2017	3-year
IT1	80.7 a	82.4 a	82.0 a	81.7 a
IT2	82.5 b	82.7 a	81.5* a	82.6 b
IT3	82.4 b	83.4 a	82.5 a	82.8 b
p-value	0.035	0.232	0.279	0.007
$LSD_{0.05}$	1.3	NS	NS	
Strength (g tex^{-1})				
Treatment	2015	2016	2017	3-year

IT1	28.80 a	31.80 a	29.83 a	30.02 a
IT2	30.80 b	31.27 a	29.37* a	30.89 ab
IT3	30.57 b	31.33 a	30.90 a	30.93 b
p-value	0.008	0.670	0.301	0.079
LSD0.05	0.96	NS	NS	

IT: Irrigation termination; NS: Not significant; * Termination date was the same as for IT1.

When samples from the three years were combined, the average micronaires in IT1 and IT2 were not significantly different, but both were smaller than in IT3. Even though the averages seemed very close, cotton uniformity was higher in IT2 and IT3 than in IT1. Although slight increases in fiber length and strength were observed with later IT treatments, there were no significant differences in these two properties across treatments. The results of this study are in agreement with previous studies conducted in Arizona (Grimes & Dickens, 1974) and in the U.S. Mid-South (Vories et al., 2011), where significant differences in fiber quality with irrigation termination timing were rarely observed.

Overall, the results of AFIS quality properties were similar to those of HVI, showing mostly no significant impact caused by the IT treatments (Table 2.7). Fiber fineness and maturity ratio were the only parameters that had significantly different values among IT treatments in 2015 and 2017. When the data from the three seasons were combined, IT date had no significant effect on any of the AFIS parameters.

Table 2.7. Cotton advanced fiber information system (AFIS) properties. Within each year, means followed by the same letter are not significantly different at the 0.05 level according to the LSD.

Neps (count g^{-1})				
Treatment	2015	2016	2017	3-year
IT1	464.3 a	181.0 a	260.7 a	309.8 a
IT2	415.0 a	219.7 a	303.3* a	302.4 a
IT3	414.0 a	185.0 a	248.7 a	282.6 a
p-value	0.733	0.260	0.219	0.450
$LSD_{0.05}$	NS	NS	NS	

Short fiber content (%)				
Treatment	2015	2016	2017	3-year
IT1	10.47 a	8.50 a	10.57 a	10.29 a
IT2	9.67 a	9.80 a	12.93* a	10.38 a
IT3	10.40 a	8.77 a	11.07 a	10.09 a
p-value	0.864	0.315	0.205	0.908
$LSD_{0.05}$	NS	NS	NS	
Fineness (mtex)				
Treatment	2015	2016	2017	3-year
IT1	143.0 a	165.3 a	164.3 a	156.3 a
IT2	144.3 ab	163.0 a	157.3* b	156.0 a
IT3	152.0 b	164.3 a	165.7 a	160.7 a
p-value	0.076	0.871	0.051	0.121
$LSD_{0.05}$	NS	NS	NS	
Maturity ratio (units)				
Treatment	2015	2016	2017	3-year
IT1	0.827 a	0.867 a	0.840 ab	0.839 a
IT2	0.837 a	0.847 a	0.817* a	0.838 a
IT3	0.833 a	0.860 a	0.847 b	0.847 a
p-value	0.758	0.174	0.091	0.517
$LSD_{0.05}$	NS	NS	NS	

IT: Irrigation termination; NS: Not significant; * Termination date was the same as for IT1.

Cotton yield and fiber quality data were used in estimating the economic value of lint. The variations in lint value were similar to those of lint yield, where the smallest value of 895 USD ha^{-1} was estimated for IT1 in 2015 season and the largest value of 2659 USD ha^{-1} belonged to IT3 in 2016 season. The impact of IT on lint value was most significant in 2015, with IT1 and IT2 resulting in 633 and 432 USD ha^{-1} less revenue compared to IT3. The reductions in revenue were smallest in 2016 at 179 and 192 USD ha^{-1} for the same two treatments, respectively. The 2017 season was in the middle, with 587 and 436 USD ha^{-1} less revenue for the two IT1 treatments when compared to IT3.

2.4.3 Heat Units

In this study, IT treatments were based on calendar dates with weekly intervals following the common practices and the irrigation delivery scheme in the study area. Nonetheless, the accumulated heat units (HU) prior to and after irrigation termination were estimated for each treatment to investigate the impact of thermal conditions on cotton yield. Previous studies have reported a direct influence of prevailing thermal conditions on the growth and development of cotton and recommended the use of degree heat units as a tool to make decisions about irrigation termination (Cetin & Basbag, 2010; Lascano et al., 2017; Peng, Krieg, & Hicks, 1989). In the present study, variations in air temperatures, planting dates, and IT dates resulted in different HUs by each treatment amongst the three years. Table 2.8 presents the HUs accumulated during the three periods of planting to IT, cutout to IT, and IT to harvest in each year. Heat units were calculated based on a daily lower temperature threshold of 15.6 °C (Gowda et al., 2007).

Table 2.8. Cumulative heat units (HU) during different periods of the growing season.

Year	Treatment	Cumulative HU (°C)		
		Planting-IT	Cutout-IT	IT-harvest
2015	IT1	951	37	578
	IT2	1017	103	512
	IT3	1100	186	429
2016	IT1	1000	80	540
	IT2	1060	141	480
	IT3	1132	213	408
2017	IT1	907	13	558
	IT2*	907	13	558
	IT3	1100	193	366

* Termination date was the same as for IT1.

As shown in Table 2.8, the magnitude of heat units accumulated between IT and harvest decreased with increase in IT date since a smaller period was used in HU calculation for later IT treatments. For each treatment, the largest HU after IT was achieved in 2015 due to the hot and dry conditions of August and September in this season compared to others. Previous studies have generally targeted physiological cutout to be the first IT date (Vories et al., 2011; Vories &

Glover, 2000). Monge et al. (2007) included a treatment before physiological cutout (NAWF = 7.2) and latest treatments of 167–361 °C HU past cutout. In another study, Reeves (2012) had the latest treatments of 378 and 538 °C HU past cutout during the first and the second year of study, respectively. In the present study, the earliest treatment (IT1) accumulated 13 to 80 °C HU past cutout among the three years, suggesting that despite using calendar dates, IT1 in this study occurred about the physiological cutout. The latest treatment (IT3) accumulated 186 to 213 °C HU past physiological cutout, similar to Monge et al. (2007).

Other studies have used different periods for HU-based irrigation termination. For example, Lascano et al. (2017) evaluated three HUs of 890, 1000, and 1110 °C from emergence to IT over a 4-year period in the Texas High Plains. In this study, average HUs of 941, 1039, and 1111 °C were estimated from planting to IT for IT1, IT2, and IT3 treatments, respectively. Considering that cotton requires about 28 °C HUs from planting to emergence (Ritchie et al., 2007), the evaluated range of thermal times by Lascano et al. (2017) was similar to the one implemented in the present study. Considering the entire growing season, cotton accumulated 1529, 1540, and 1466 HUs in 2015, 2016, and 2017, respectively, which are larger than the 1444 °C limit required for complete maturity according to Gowda et al. (2007).

The linear regression models revealed weak positive relationships between cotton lint/seed yield and cumulative HUs during planting-IT and cutout-IT periods (Figure 2.2), with coefficients of determinations ranging from 0.34 to 0.45. However, the only regression model that was statistically significant was the one between seed yield and HUs during planting-IT ($p = 0.047$). Peng et al. (1989) found that cotton yield was highly correlated to accumulated HUs when water availability was not a limiting factor. They also highlighted that water supply can alter the yield-HU relationship and observed no significant correlation between lint yield and HU under water stress in the Southern High Plains of Texas.

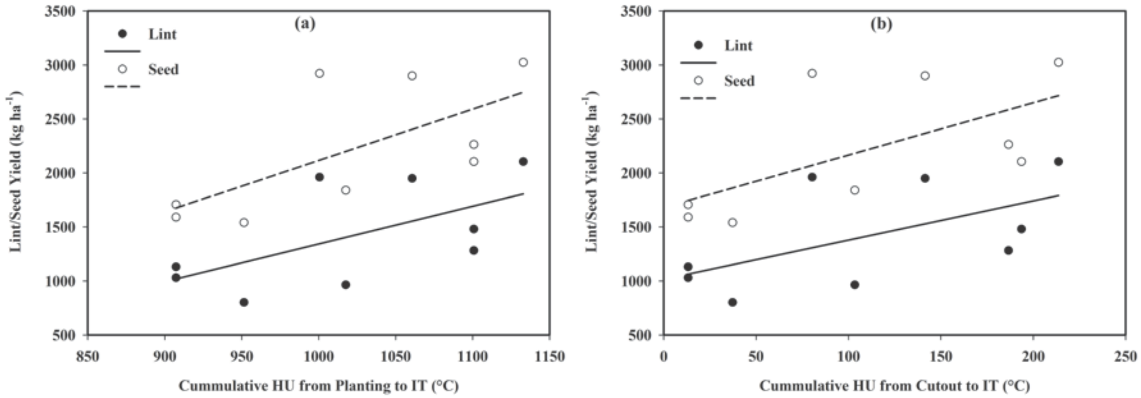
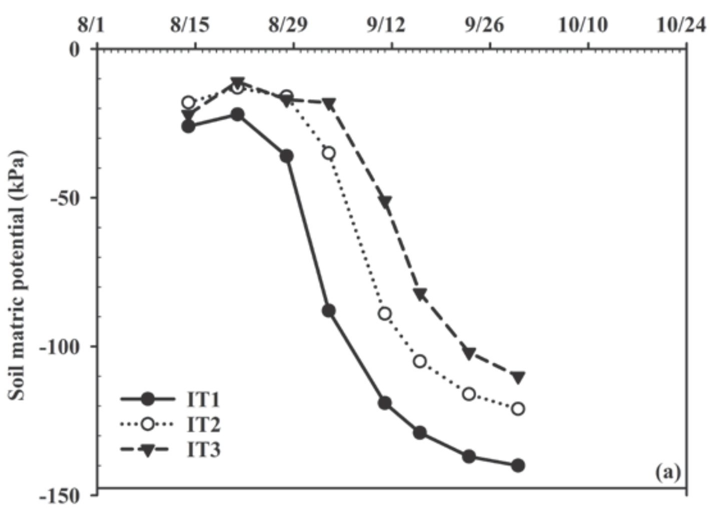


Figure 2.2. Yield response to accumulated heat units from (a) Planting to IT and (b) Cutout to IT.

2.4.4 Soil Water Content

The root zone soil water content declined following IT dates for all treatments and years, but the rate of decline was significantly larger in 2015 and 2017 compared to 2016 (Figure 2.3). The range of observed soil matric potentials (SMP) was greater in 2015 and 2017, with driest IT treatments reaching approximately −140 kPa before harvest. In 2016, however, the driest IT treatment reached a SMP of −64 kPa due to above average rainfall events.



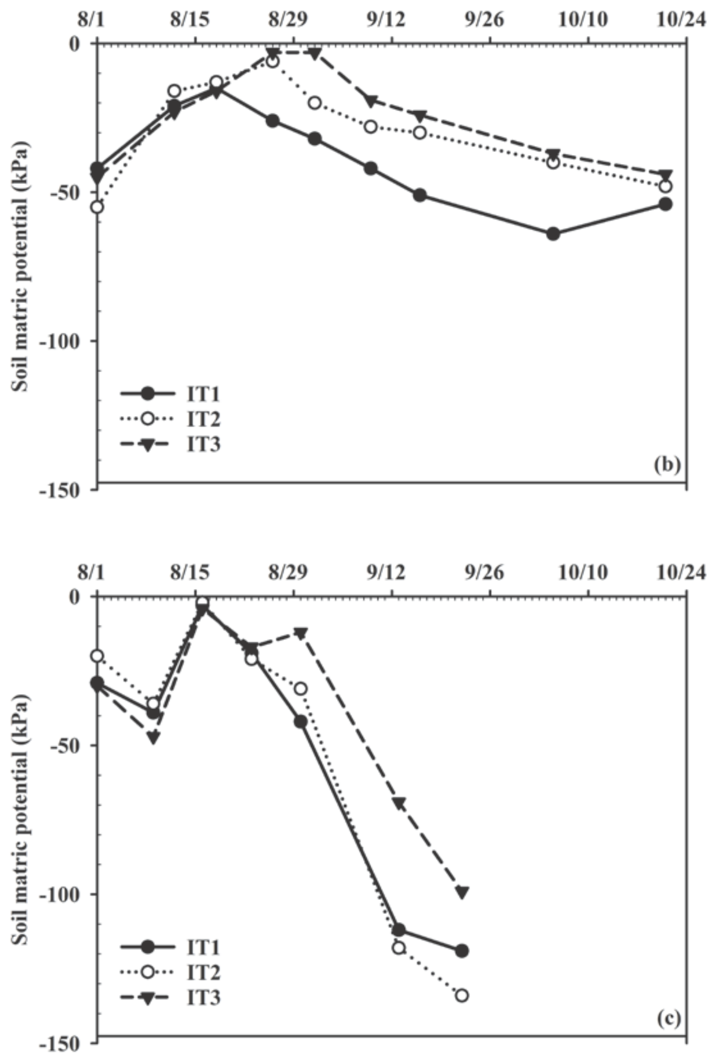


Figure 2.3. Treatment averages of soil matric potential in (a) 2015, (b) 2016 and (c) 2017.

Thomson (2006) analyzed the relationship between root zone SMP and cotton yield in Mississippi Delta and reported that cotton should be irrigated at SMP of −60 kPa. The soil type of their experiment was clay in the Sharkey series, which is similar to the soil type in the present study. Assuming that their irrigation trigger point applies to this study, no irrigation was required after IT1 in 2016 since root zone SMP did not drop below this limit. In other words, the additional irrigations applied in IT2 and IT3 did not help with removing any water stress. This explains the lack of any significant difference in measured parameters among IT treatments in

2016. In contrast, soil water content was depleted well beyond the −60 kPa threshold in both 2015 and 2017, resulting in a larger response to IT treatments.

Plotting lint and seed yields against the average late-season SMP revealed strong relationships that had the form of quadratic equations with coefficients of determination (R^2) of 0.89 and 0.67, respectively (Figure 2.4). The coefficients of developed quadratic equations are provided in Table 2.9. According to these relationships, lint and seed yields plateaued around average SMP of −30 kPa, which is close to the field capacity limit for most soils. Maintaining SMP at higher levels than −30 kPa would not result in improved cotton performance. Similar relationships have been reported between cotton yield and applied irrigation water in Turkey (Cetin & Bilgel, 2002) and Texas (Wanjura, Upchurch, Mahan, & Burke, 2002) where cotton yield increased with applied water to a certain limit and then decreased if more water was applied, especially during late-season.

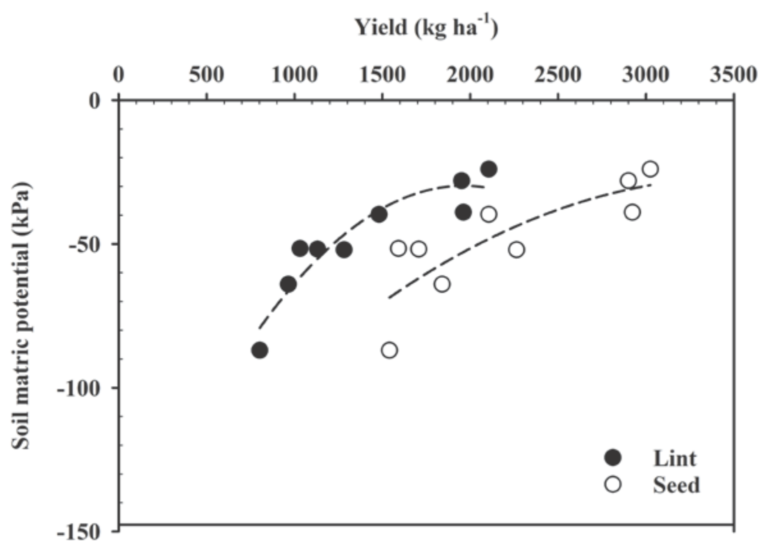


Figure 2.4. Yield response to soil matric potential.

Table 2.9. Coefficients of the quadratic equation: soil matric potential = a + b × yield + c × yield^2.

Yield parameter	a	b	c
Lint	-171.255	0.144	-3.677E-5
Seed	-158.403	0.075	-1.057E-5

To the authors' best knowledge, there is no published research investigating the effects of late-season soil water content on cotton yields. Previous studies have mostly explored yield response to applied water (Cetin & Bilgel, 2002; Stone & Nofziger, 1993; Wanjura et al., 2002). One advantage of developing yield-SMP relationships as opposed to yield-applied water relationships is that the former can be used as a decision-making tool by cotton producers in managing late-season cotton irrigation to achieve target levels of yield. As the results of the present study suggest, the maximum yield can be achieved when average soil moisture is kept around field capacity. However, some level of deficit irrigation may be either unavoidable due to water scarcity, or desirable due to the costs of purchasing and conveying (pumping and pressurizing) irrigation water. Under these conditions, producers can optimize deficit irrigation regimes by monitoring SMP to maximize water and energy savings and minimize yield losses.

2.4.5 Water Conservation

Since earlier irrigation termination can be used as a method to reduce cotton irrigation application and conserve water resources, the effects of variable termination dates on cotton performance and irrigation demand were further investigated. Table 2.10 presents changes in irrigation amount, cotton yield, lint value, and fiber quality for IT1 and IT2 treatments as percentages of the same parameters for the IT3 treatment (the latest termination date). Since the AFIS properties were not significantly different among the three IT treatments, they were not included in this analysis. When averaged across the three study years, reductions in all parameters were observed in response to earlier IT. In other words, irrigation water can be saved by earlier IT, but this will be achieved at the cost of lower lint and seed yields, lower micronaire, and potentially lower uniformity and strength.

Table 2.10. Percent changes in irrigation amount, lint and seed yields, lint value, and fiber quality relative to the IT3 treatment.

Year	IT	Irrig.	Lint	Seed	Lint value	Mic.	Length	Unif.	Strength
2015	IT1	-29	-37	-32	-41	-13	-1	-2	-6
	IT2	-14	-25	-19	-28	-13	+1	0	+1
2016	IT1	-33	-7	-3	-7	-2	-1	-1	+2
	IT2	-17	-7	-4	-7	-2	-2	-1	0
2017	IT1	-25	-24	-19	-24	-4	+1	-1	-4
	IT2*	-25	-30	-24	-32	-8	-1	-1	-5
Mean	IT1	-28	-25	-20	-26	-7	-1	-1	-3
	IT2	-16	-16	-11	-18	-8	-1	-1	1

IT: Irrigation termination; Irrig. : Irrigation; Mic. : Micronaire; Unif. : Uniformity; * Termination date was the same as for IT1.

Changes in studied parameters were highly variable among years and treatments. This large range of variations was mainly due to differences in the amount and timing of rainfall. Both the largest saving in irrigation and the smallest reduction in yield were achieved in 2016, which recorded above average rainfall. This suggests that late-season precipitation plays an important role in the effectiveness of IT practices. It also highlights the need for tools such as soil moisture monitoring to assist producers with making day-to-day decisions on irrigation management. When averaged over the three years of study that included significantly different rainfall amounts and patterns, 28 and 16% savings in irrigation applications were obtained with IT1 and IT2 treatments, respectively. However, these reductions in applied water resulted in similar percentages of declines in lint yield and lint value for the same IT treatments. Seed yield and micronaire were also impacted considerably, but fiber length, uniformity, and strength were minimally affected, with percent changes ranging from −3 to 1%. According to these findings, the yield declines associated with adopting earlier IT dates in the study area are so significant that render these practices economically unviable, unless revenue losses are compensated by economic gains in other areas. Two potential sources of economic gains caused by reducing irrigation applications are (i) increasing harvested area using the salvaged water; and, (ii) reducing pumping and conveyance costs, especially if the water sources (surface or ground) are located far from the application site.

The potential water savings from adoption of IT and IT2 treatments can be extrapolated to the entire Lugert-Altus Irrigation District, using water release data from Lake Altus-Lugert. Total water releases were 65, 73, and 46 million m^3 in 2015, 2016, and 2017, respectively (United States Army Corps of Engineers [USACE], 2018). The water delivery to the district is usually terminated around the end of August (Strawn, 1994), which coincide with the IT3 timing in this study. Thus, the IT3 treatment was used as the benchmark for estimating the potential water savings across the district in each study year and on average. The estimated water savings ranged from 11.6 to 24.0 million m^3 for IT1 and from 9.2 to 12.4 million m^3 for IT2 during the study years. The average potential water savings for IT1 was 17.2 million m^3, about 1.75 times larger than the average saving of 9.8 million m^3 for IT2 (Figure 2.5).

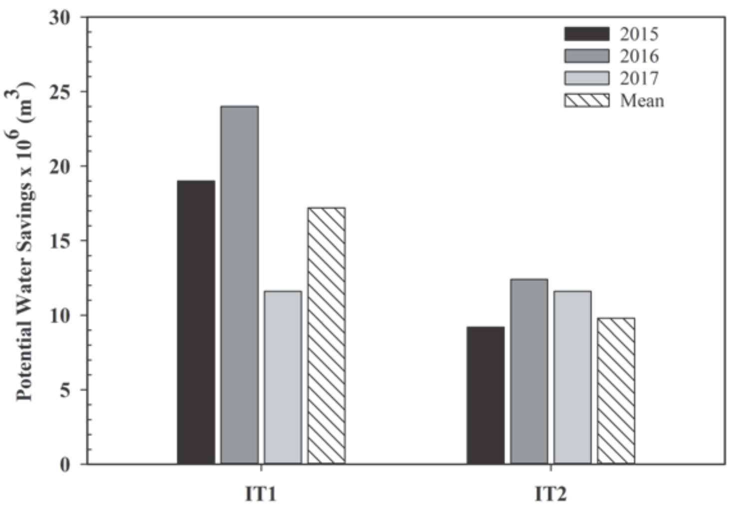


Figure 2.5. Potential water savings through adoption of earlier irrigation terminations in the Lugert-Altus Irrigation District.

2.5 Conclusions

The effects of variable irrigation termination (IT) dates on cotton yield, fiber quality and irrigation requirement were investigated in a field experiment in southwest Oklahoma during three growing seasons. Three weekly-spaced IT treatments were implemented in each year, with IT1 and IT3 treatments representing the earliest and the latest termination dates, respectively. The results showed a general increase in cotton yield with delaying of irrigation termination. However, the magnitude and statistical significance of this increase were largely dependent on the amount and distribution of late-season rainfall. A season characterized by hot and dry conditions during the months of August and September resulted in lint and seed yields that were significantly different amongst the IT treatments, whereas no difference was observed during a season with above normal rainfall. When averaged over the three seasons, lint yields were significantly different among all treatments. Seed yields for IT1 and IT2 were both similar to each other and significantly smaller than the yield of IT3. Late-season rainfall had a similar impact on fiber quality. On average, micronaire, uniformity, and strength were significantly impacted by IT treatments.

The relationships between cotton yield parameters and heat units accumulated from planting to IT and from physiological cutout to IT were positive, but weak and not significant, except in case of the seed yield and heat units from planting to IT. In contrast, strong positive relationships were found between cotton yield and root zone water content. The late-season soil matric potential can be monitored in the cotton root zone using soil moisture sensors and then used as a practical decision-making tool in optimizing IT management. When benchmarked against the latest IT treatment (IT3), the earlier treatments of IT1 and IT2 resulted in 28 and 16% reductions in applied irrigation amounts on average. However, these reductions were accompanied with similar percentages of declines in lint yield and value. Seed yield and micronaire were also impacted negatively, along with smaller declines in fiber length, uniformity, and strength. Additional research is needed to investigate the economic trade-offs between revenue losses from declined lint value and reductions in water and energy expenses when implementing earlier irrigation termination. Assuming all cotton producers within the major irrigation district in southwest Oklahoma adopt earlier IT practices, an average water savings of 17.2 and 9.8 million m^3 can be achieved on a seasonal basis for IT1 and IT2 treatments, respectively. Future research should utilize long-term weather data in conjunction with additional tools such as crop growth models to further evaluate the effects of variable IT scenarios.

CHAPTER III

VALIDATION AND APPLICATION OF AQUACROP FOR IRRIGATED COTTON IN THE SOUTHERN GREAT PLAINS OF U.S.

3.1 Abstract

Dwindling water resources and weather variability present two of the major limiting factors for irrigated cotton production in the southern Great Plains region. Under these conditions, there is a dire need to understand the trends and fluctuations in cotton yields in order to help producers to make better irrigation and crop management decisions. Crop models coupled with long-term weather data provide an opportunity for evaluating yield variabilities by simulating various possible scenarios. In this study, the AquaCrop model was calibrated and validated for cotton at two sites in the southern Great Plains. The AquaCrop model performed within acceptable accuracy for simulating canopy cover, soil water content, evapotranspiration and yield but accuracy was limited under dryland conditions. Overall, the results demonstrated that the AquaCrop model is a potential tool for evaluating irrigation and crop management of cotton in the southern Great Plains. The validated model was applied to study the effect of irrigation capacity and seasonal weather conditions on cotton yield at a site in the Southern High Plains aquifer region. The results revealed no significant increase in cotton yields at irrigation capacities higher than 0.3 l s^{-1} ha^{-1}. Furthermore, cotton yields for years exhibiting average weather conditions were similar for irrigation capacities ranging from 0.1 to 0.6 l s^{-1} ha^{-1}. However,

cotton yields increased significantly with increase in irrigation capacity in years with warm growing season conditions. The results of this study highlights the importance of incorporating available weather platforms when making irrigation and crop management decisions.

Keywords: Simulation; cotton; irrigation; irrigation capacity; evapotranspiration; planting date; Great Plains.

3.2 Introduction

The southern Great Plains is one of the major cotton producing regions in the U.S. (Parton et al. 2007). Furthermore, the states of Texas and Oklahoma, which form part of the southern Great Plains region, rank among the leading cotton producers in the country (Nair, Maas, Wang, & Mauget, 2013; Steiner et al., 2015). Cotton production in these two states contribute significantly to the economy of the region and country at large (Krueger, Yimam, & Ochsner, 2017). According to Steiner, Briske, Brown, and Rottler (2018), Oklahoma and Texas generated a combined revenue of approximately US$1.67 billion from cotton in the year 2012 alone. However, water availability and quality for irrigation have persistently been one of the major limiting factors for cotton production in the southern Great Plains region (Tolk & Howell, 2010; Steiner et al., 2018).

The Ogallala aquifer, which is the major source of irrigation in the western part of the region, has been plagued by significant declines in its level, which has resulted in decreased well capacities and increased energy requirement for pumping (Gowda, Baumhardt, Esparza, Marek, & Howell, 2007; Baumhardt, Staggenborg, Gowda, Colaizzi, & Howell, 2009; Handa, Frazier, Taghvaeian, & Warren, 2019). According to Evett et al. (2014), many of the irrigation wells in the southern Great Plains now have capacities of less than 16 l s^{-1}, with pumping depths of up to 305 m. In the humid eastern areas of the region with more abundant water resources, droughts have frequently occurred affecting surface water resources and limiting cotton production (Krueger, Yimam, &

Ochsner, 2017; Steiner et al. 2018). Additionally, other areas in the region like southwest Oklahoma face irrigation challenges emanating from poor quality of water resources (Mittelstet, Storm, & Stoecker, 2015; Krueger et al., 2017).

Water scarcity in the southern Great Plains has necessitated the need for water managers and producers to search for management strategies that maximize cotton yields while minimizing the irrigation input (Howell, Evett, Tolk, & Schneider, 2004; Baumhardt et al., 2009; Tolk & Howell, 2010). Many strategies have been tested and implemented in the region. For instance, most producers have adopted more efficient irrigation systems throughout the southern Great Plains (Colaizzi, Gowda, Marek, & Porter, 2009). DeLaune, Sij, Park, & Krutz (2012) highlighted the growth of conservation tillage as a water conservation strategy in the region. However, the study indicated that little is known about its combined effects with various irrigation levels on cotton yield. The extensive shifting from corn to cotton and adoption of early maturing varieties in several areas of region have also been motivated by the desire to reduce water use (Howell et al., 2004; Gowda et al., 2007). This is because cotton requires less water while producing an equally acceptable profit compared to corn (Howell et al., 2004; Tolk & Howell, 2010). While there has been significant efforts by researchers, water managers and producers to ensure irrigation sustainability in the region, several studies have stressed the need to seek additional management strategies that maximize cotton yield as water supplies continue to decline (Colaizzi et al., 2009; Tolk & Howell, 2010).

Most of the previous irrigation studies for cotton in the southern Great Plains were based on a few years of field experiments (Howell et al., 2004; Marek & Bordovsky, 2006; Tolk & Howell 2010). According to Nair et al. (2013), the short duration nature associated with using the field experimentation approach limits robust statistical analyses for deriving sound conclusions. This is particularly true in the case of the southern Great Plains region, where growing season conditions, including rainfall and temperature, are highly variable from year to year (Baumhardt et al. 2009).

Hence, three to four years of field experiments might not result in solid conclusions to develop good recommendations for producers. Field experiments tend to be expensive, labor intensive and time consuming too (Liu, Wiberg, Zehnder, & Yang, 2007; Geerts & Raes, 2009). Additionally, Evett and Tolk (2009) highlighted that multiple scenarios cannot be addressed by experimentation, but this could be possible using crop models. As highlighted by Baumhardt et al (2009), crop models present an opportunity to capture climatic variability using long-term weather data. To emphasize the critical role crop models can play, Douglas-Manking (2018) listed simulation studies as one of the future research focus areas that would address the needs of decision makers as they work to ensure sustainability of land and water resources.

Many of the cotton modeling studies conducted in the Ogallala aquifer region of the southern Great Plains assumed fixed planting dates in their long-term simulations, despite significant spatio-temporal variability in temperature within the region (Baumhardt et al., 2009; Nair et al., 2013). Hence, the results may not reflect the dynamic planting decisions made by cotton producers. Deviations from the actual planting dates can have a major impact on model results, since cotton growth and yield are very sensitive to accumulated heat units. In addition, most of previous modeling studies in this region have used crop models such as DSSAT, GYOSSYM and Cotton2K (Baumhardt et al. 2009; Nair et al 2013). There is no known published study to the authors' best knowledge, which has used the AquaCrop model in this region. Steduto, Hsiao, Raes, and Fereres (2012) highlighted that the AquaCrop model has less parameters that require calibration compared to the aforementioned models. This model also benefits from a simple graphical user interface, a key characteristic that allows its application by users outside the research community (e.g. managers and crop consultants). Finally, AquaCrop has been successfully validated and applied for cotton irrigation management in other regions of the world (García-Vila, Fereres, Mateos, Orgaz, & Steduto, 2009; Hussein, Janat, & Yakoub, 2011).

The main goal of this study was to evaluate the performance of AquaCrop in the southern Great Plains and to apply it to identify improved management practices for maximizing yield with limited water resources. More specific objectives were: i) to calibrate and validate the AquaCrop model using measured data collected from two different sites in the southern Great Plains; and, ii) to use the calibrated model to assess the effect of irrigation capacity and seasonal weather conditions on cotton yield at a site that relies on the Ogallala aquifer for irrigation supply.

3.3 Materials and Methods

3.3.1 Study Sites

The measured data used for calibration and validation of AquaCrop model were collected from two sites in the southern Great Plains: the USDA-ARS Conservation and Production Research Laboratory (CPRL) at Bushland, TX (35° 11' 16" N, 102° 05' 49" W, 1170 m above MSL) and the Oklahoma State University's Southwest Research and Extension Center (SWREC) near Altus, OK (34° 35' 33" N, 99° 20' 10" W, 416 m above MSL). The SWREC site is about 240 km to the southeast of CPRL. According to Shafer et al. (2014), the U.S. Great Plains has a distinct north-south gradient in average temperature patterns, with hotter south and colder north mainly because of elevation differences. There is also an east-west precipitation gradient across the region. Thus, the SWREC site is warmer and wetter compared to the CPRL site. The CPRL is characterized by a semi-arid climate and receives average rainfall of 470 mm per annum (Marek et al., 2017). The SWREC exhibits a sub-humid climate characterized by hot and dry summers and receives an average annual rainfall of 638 mm (Masasi, Taghvaeian, Boman, & Datta, 2019). Figure 3.1 demonstrates the locations of the two study sites along with a map of normal precipitation. Table 3.1 presents long-term climatic parameters for the cotton growing season months (May-November) at both sites obtained from PRISM (2019).

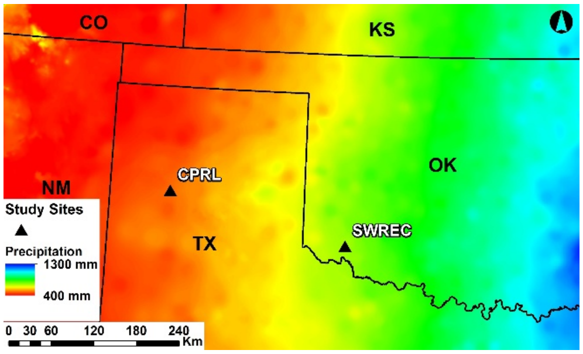


Figure 3.1. The location of the study sites in Oklahoma and Texas. The base map is the 30-year average annual precipitation.

Table 3.1. 30-year average temperature and rainfall data for May-November at the Conservation and Production Research Laboratory (CPRL) and Southwest Research and Extension Center (SWREC).

	CPRL			SWREC		
Month	T_{min} (°C)	T_{max} (°C)	Rain (mm)	T_{min} (°C)	T_{max} (°C)	Rain (mm)
May	9.7	26.6	57	14.7	28.4	95
June	14.9	31.2	79	19.6	32.9	112
July	17.1	33.0	63	21.9	35.5	55
August	16.6	31.9	79	21.2	34.8	66
September	12.2	28.3	51	16.7	30.5	72
October	5.6	22.4	43	10.1	24.4	72
November	-0.7	15.7	19	3.6	17.6	36

T_{min} is minimum air temperature; T_{max} is maximum air temperature

In addition to differences in climatic conditions, the two sites differ in their source of irrigation water. The CPRL lies within the Southern High Plains of the Ogallala aquifer region. Previous studies have highlighted that cotton production in this region is limited by rainfall and growing-season length in terms of available heat units (Peng, Krieg, & Hicks, 1989; Baumhardt, Schwartz, Marek, & Bell, 2018; Mahan & Payton, 2018). On the other hand, the SWREC is within the Lugert-Altus Irrigation District, which draws water from Lake Altus- Lugert and delivers the water through a network of open canals.

3.3.2 Soil, Crop, and Climate Data

The soils at CPRL are deep, well-drained Pullman silty clay loam soil (fine, mixed, Superactive, Thermic Torrertic Paleustoll) and the SWREC has Hollister silty clay loam (fine, Smectitic, Thermic Typic Haplusterts). CPRL soil parameters were determined through laboratory analyses and obtained from published data (Heng et al. 2009; Masasi, Taghvaeian, Gowda, & Marek, 2019), whereas soil properties for SWREC were obtained from a combination of USDA-NRCS Web Soil Survey database and field sampling, which indicated the presence of a hardpan at 0.65 m below the surface. Table 3.2 presents the soil water content limits at saturation (Sat.), field capacity (FC), and wilting point (WP), as well as the saturated hydraulic conductivity (Ksat) for different soil layers at both sites.

Table 3.2. Soil parameters at the Conservation and Production Research Laboratory (CPRL) and Southwest Research and Extension Center (SWREC).

Site	Layer (m)	Water content (m^3 m^{-3})			K_{sat} (mm d^{-1})
		Sat.	FC	WP	
CPRL	0.00-0.18	0.42	0.33	0.18	66.0
	0.18-0.74	0.44	0.33	0.18	18.0
	0.74-1.35	0.43	0.35	0.20	6.6
	1.35-2.30	0.46	0.30	0.16	200.0
SWREC	0.00-0.30	0.41	0.30	0.21	176.6
	0.30-0.65	0.41	0.32	0.24	28.9
	0.65-0.75	0.00	0.00	0.00	0.00
	0.60-1.10	0.39	0.33	0.24	18.6
	1.10-2.00	0.39	0.33	0.23	18.6

Cotton was planted in four adjacent fields at the CPRL site, each covering an area of 4.7 ha (Adhikari et al., 2017). Each field was equipped with a precision weighing lysimeter (9 m^2 surface area and 2.3 m deep) located at the center of the field for monitoring evapotranspiration (ET), as well as two access holes for monitoring soil water content (SWC) using a field calibrated neutron probe. Two fields (east side) contained irrigated treatments and the other two fields (west side) were under dryland cropping in the years cotton was cultivated at CPRL. Fertilizer applications were optimized based on pre-season soil tests conducted every year. Weeds were controlled using herbicides. The irrigated fields were irrigated at full and deficit (50%) levels using a linear-move system, fitted with drop hoses placed 1.52 m apart and 1.5 m above ground (Howell et al., 2004). Full irrigation referred to replenishing the soil profile back to field capacity when SWC approached maximum allowable depletion (Marek et al., 2017). Deficit irrigation treatments were irrigated on the same dates as the full irrigation treatments, and this was achieved by reducing the nozzle size of the linear move system in those fields. Crop data including height, leaf area index (LAI), and seed cotton yield were also measured at each field. Canopy cover was estimated from LAI measurements based on the following empirical equation:

$$CC = 1 - e^{(-\chi * LAI)} \tag{1}$$

where χ is the extinction coefficient and was taken as 0.77 after Farahani, Izzi, and Oweis (2009) and García-Vila et al. (2009).

At SWREC, cotton was planted under three irrigation regimes that differed in irrigation termination date (Masasi et al., 2019). The total amount of seasonal irrigation depended on the termination date, targeted for August 16, August 23, and August 30. Each irrigation event supplied approximately 76 mm of water via siphon tunes and furrows. All crop management practices, including fertilizer application, pests and weed control were optimized to ensure differences in seed cotton yield were a result of irrigation treatments. Only crop yield was measured at this site.

Measured crop data for AquaCrop calibration and validation were collected during six years at CPRL, including 2000, 2001, 2002, 2003, and 2010. Data were available on all irrigation levels (full, deficit, dryland), in 2000, so this year was selected for model calibration and the remaining years for model validation. At SWREC, yield data were collected in three years of 2015-2017 and were used in model validation. Table 3.3 summarizes the agronomic and irrigation information for both sites during each of the study years.

Table 3.3. Agronomic information for each study year and treatment at the Conservation and Production Research Laboratory (CPRL) and Southwest Research and Extension Center (SWREC).

Treatment	**Planting Date**	**Harvest Date**	**Seeding Rate (seeds m^{-2})**	**Variety**	**Irrigation (mm)**
			CPRL		
2000/Full	5/17/2000	11/14/2000	21.0	PAYM2145	485
2000/50%	5/17/2000	11/14/2000	21.0	PAYM2145	249
2000/Dryland 1	5/16/2000	10/18/2000	12.4	PAYM2145	0
2000/Dryland 2	5/16/2000	10/18/2000	17.3	PAYM2145	0
2001/Full	5/17/2001	10/22/2001	19.8	PAYM2145	402
2001/50%	5/17/2001	10/22/2001	19.8	PAYM2145	216
2001/Dryland 1	5/17/2001	10/22/2001	17.3	PAYM2145	0
2001/Dryland 2	5/17/2001	10/22/2001	17.3	PAYM2145	0
2002/50%	5/22/2002	11/12/2002	16.0	PAYM2145	271
2003/Dryland	6/16/2003	11/07/2003	18.5	PAYM2145	0
2010/Full 1	5/26/2010	10/25/2010	20.3	PAYM2145	293
2010/Full 2	5/26/2010	10/25/2010	20.3	PAYM2145	281
			SWREC		
2015 T1	6/04/2015	11/12/2015	16.6	DP1044B2RF	380
2015 T2	6/04/2015	11/12/2015	16.6	DP1044B2RF	456
2015 T3	6/04/2015	11/12/2015	16.6	DP1044B2RF	532
2016 T1	5/28/2016	11/21/2016	10.1	DP1044B2RF	304
2016 T2	5/28/2016	11/21/2016	10.1	DP1044B2RF	380
2016 T3	5/28/2016	11/21/2016	10.1	DP1044B2RF	456
2017 T1	5/25/2017	11/01/2017	9.4	DP1044B2RF	228
2017 T2	5/25/2017	11/01/2017	9.4	DP1044B2RF	228
2017 T3	5/25/2017	11/01/2017	9.4	DP1044B2RF	304

The weather data used for the CPRL simulations were obtained from onsite measurements at a research-grade weather station located adjacent to the research fields. These data included rainfall, solar radiation, maximum and minimum air temperatures, relative humidity, and wind speed. Data quality assurance and quality control methods (QA/QC) were carried out before using the data (Marek et al. 2017b). Three years (2015-2017) of weather data for SWREC simulations were obtained from the Oklahoma Mesonet network for Altus station, which is located within the borders of the same Research Center and about 700 m south of the research plots. The daily ET_o was calculated using the FAO Penman-Monteith equation (Allen, Pereira, Raes, & Smith, 1998).

3.3.3 AquaCrop model

The AquaCrop model simulates crop yield in response to water supply, agronomic management and environmental conditions (Steduto et al. 2012). The underlying principles and main algorithms in AquaCrop are presented in Steduto et al. (2012) and Raes, Steduto, Hsiao, and Fereres (2009), respectively. The crop grows in the model by developing canopy, accumulating biomass (B) and finally yield in daily time steps (Steduto et al. 2012; Vanuytrecht et al. 2014). Contrary to other crop modeling approaches that make use of leaf area index, AquaCrop utilizes canopy cover (CC) as the most important crop parameter (Steduto et al., 2012). CC represents the source for actual transpiration (T_r) that is translated in a proportional amount to biomass (B) based on the concept of normalized water productivity (WP^*) (Steduto et al., 2012). Water stress limits or delays the CC development through stress coefficients in the model. These coefficients describe the impact of water stress on canopy development and ultimately transpiration. T_r is simulated in the model by using the following equation:

$$T_r = K_S(K_{C_{Tr,x}} CC^*) ET_o \qquad (2)$$

where K_S is the stress coefficient, CC^* is the canopy cover adjusted for micro-advective effects, $Kc_{Tr,x}$ is the crop coefficient for maximum crop transpiration, and ET_o is reference evapotranspiration.

Biomass is estimated as a product of WP^* and the ratio of T_r and ET_o, throughout the growing season as presented by equation 3 (Steduto et al., 2012).

$$B = WP^* \times \sum\left(\frac{T_r}{ET_o}\right) \tag{3}$$

Finally, the crop harvestable yield (Y) is estimated as a product of B and the harvest index (HI). HI is defined as the ratio of yield to aboveground dry biomass.

$$Y = B \times HI \tag{4}$$

3.3.4 AquaCrop Calibration and Validation

The AquaCrop model has several default parameters for cotton that are generally conservative and applicable for diverse environments, varieties and management practices (Raes et al. 2012). Steduto et al. (2012) highlighted that the conservative parameters in the model should serve as a starting point, and can be adjusted with good data sets if there is a clear need. Most of the non-conservative parameters that require adjustment to account for specific characteristics of the studied variety and environment are related to crop phenology (Steduto et al., 2012; Li, Yu, & Zhao, 2019). These parameters include time from planting to flowering, canopy senescence and maturity. The length of the growth cycle (planting to maturity) is highly sensitive for cotton in AquaCrop (Li et al. 2019).

In this study, AquaCrop was first run with the default cotton crop-file (in growing degree-days) to determine if it was able to satisfactorily predict cotton yield. This process was carried out for all treatments at CPRL and SWREC. Based on calculated statistical indicators, the results of the initial simulation runs informed whether there was a need for calibration of certain non-conservative parameters for each site. In case of unsatisfactory performance, the default parameters were accepted. Otherwise, cotton growing cycle, times from planting to emergence, maximum canopy cover (CC_x), maximum rooting depth, and canopy senescence, and the duration of flowering were adjusted while tracking the canopy cover development and cotton yield. Table 3.4 presents the default parameters for cotton in AquaCrop.

Table 3.4. Default cotton parameters used in the AquaCrop model.

Parameter	**Units**	**Value**
Base temperature	°C	12
Cut-off temperature	°C	35
Canopy cover per seedling at 90% emergence	cm^2	6
Canopy growth coefficient	% GDD^{-1}	0.624
Canopy decline coefficient	% GDD^{-1}	0.247
Sowing to emergence	GDD	12
Sowing to maximum canopy cover	GDD	1156
Maximum canopy cover	%	98
Maximum transpiration coefficient ($Kc_{Tr,x}$)	unitless	1.10
Sowing to flowering	GDD	502
Length of flowering	GDD	709
Sowing to max rooting depth	GDD	956
Sowing to senescence	GDD	1601
Sowing to maturity	°C	1956
Normalized Crop Water Productivity, WP*	$g\ m^{-2}$	35
Canopy expansion function		
P-upper	fraction of TAW	0.20
P-lower	fraction of TAW	0.70
Shape	unitless	0
Stomatal closure function		
P-upper	unitless	0.75
Shape	unitless	3
Early canopy senescence function		

P-upper	unitless	0.7
Shape	unitless	3

Evaluation of AquaCrop performance was based on the accuracy of the model in simulating the following measured parameters at each site: CC, SWC, ET and seed cotton yield at CPRL and seed cotton yield at SWREC. Yang J, Yang Y, Liu, and Hoogenboom (2014) highlighted that a combination of several statistics should be used to evaluate model performance since there is no single statistic that is more robust over others. In this study, the coefficient of determination (R^2), root mean-square error (RMSE), coefficient of agreement (d), Nash-Sutcliffe Efficiency (NSE), and the Prediction Error (P_e) were used for AquaCrop validation:

$$R^2 = \left(\frac{\sum_{i=1}^{n}(M_i - \bar{M})(S_i - \bar{S})}{\sqrt{(\sum_{i=1}^{n}(M_i - \bar{M})^2 \sum_{i=1}^{n}(S_i - \bar{S})^2}} \right)^2 \tag{5}$$

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(M_i - S_i)^2} \tag{6}$$

$$d = 1 - \frac{\sum_{i=1}^{n}(S_i - M_i)^2}{\sum_{i=1}^{n}(|S_i - \bar{M}| + |M_i - \bar{M}|)^2} \tag{7}$$

$$NSE = 1 - \frac{\sum_{i=1}^{n}(M_i - S_i)^2}{\sum_{i=1}^{n}(M_i - \bar{M})^2} \tag{8}$$

$$P_e = \frac{(S_i - M_i)}{M_i} \times 100 \tag{9}$$

where M_i and S_i are the measured and simulated parameters, respectively, n is the number of measurements, and $\bar{M}$ and $\bar{S}$ are the mean values of M_i and S_i, respectively. Values of R^2, d and NSE close to unity indicate good performance of the model. Values of R^2 larger than 0.5 and d larger than 0.65 are generally considered as indicating acceptable model performance (Moriasi et al., 2007; Willmott, 1984). Additionally, RMSE and P_e values near zero demonstrate a good match between the simulated and measured data. The RMSE can be normalized by dividing it by the mean of measured data to give a normalized root mean square (NRMSE). Jamieson, Porter, and Wilson (1991) considered excellent, good, fair, and poor calibration categories for NRMSE ranges of $<10\%$, 10-20%, 20-30%, and $>30\%$, respectively.

3.3.5 AquaCrop Application

After validation and calibration, the AquaCrop model was used to assess the impact of irrigation capacity (IC) and seasonal weather conditions on cotton yield at the CPRL site over a 33-year period from 1981 to 2013. Investigated ICs were 0.6, 0.5, 0.4, 0.3 and 0.1 $l\ s^{-1}\ ha^{-1}$, representing a wide range of well discharges consistent with existing conditions in the Southern High Plains. The irrigation intervals corresponding to each IC were determined by assuming a center pivot system (the most common in the region) irrigated a full circle of 48.6 ha at an application depth of 25 mm and application efficiency of 85%. This resulted in fixed irrigation intervals of 6, 7, 9, 14 and 27 days for ICs of 0.6, 0.5, 0.4, 0.3 and 0.1 $l\ s^{-1}\ ha^{-1}$, respectively. These application scenarios are similar to actual irrigation managements implemented by local producers. Irrigation applications in the model were set to occur within 125 days after planting for all the simulation scenarios. Nair et al (2013) reported a similar length of irrigation season starting from 15 May to 17 September, and indicated that this is an accepted average in the region. A dryland treatment (0.0 $l\ s^{-1}\ ha^{-1}$) was also included in the analysis. Table 3.5 presents the total irrigation amounts applied under each IC.

Table 3.5. Total irrigation amounts applied under each irrigation capacity.

Irrigation capacity ($l\ s^{-1}\ ha^{-1}$)	Total irrigation applied (mm)
0.0	0
0.1	100
0.3	200
0.4	325
0.5	425
0.6	500

Planting dates were varied from year to year during the simulation period (33 years). Marek and Bordovsky (2006) highlighted that selection of planting dates for cotton in the Southern High Plains region is critical, and should be done when soil temperatures are adequate to allow for good emergence and rapid growth early in the growing season. In this study, the planting dates were determined following the approach developed by Esparza, Gowda, Baumhardt, Marek, and Howell (2007) for CPRL. In this approach, two independent estimates of minimum soil temperature are obtained based on minimum and maximum air temperatures. The planting date in each year was considered as the first day when both minimum soil temperatures reach 15.6 °C. This threshold was reported as the minimum soil temperature needed for supporting cotton seedling emergence (Esparza et al. 2007).

Following the observations by Esparza et al. (2007) and Gowda et al. (2007) of common practices in the Southern High Plains region, the crop was terminated in the model when the average air temperature was equal to or lower than -2.2 °C or on 15 October, whichever happened first in each year. The weather data including maximum temperature, minimum temperature, mean dew point temperature and precipitation were obtained from the Parameter-elevation Relationships on Independent Slopes Model (PRISM) database. Wind speed and solar radiation data for the same period were compiled from onsite measurements at a research-grade weather station at CPRL. Analysis of the impact of growing season rainfall was investigated by sorting the 33 years of seasonal rainfall data in descending order, and calculating the probability of exceedance (PE) following classifications by Smith (1992) and Jarihani, Sidle, Bartley, Roth, and Wilkinson (2017) for wet (PE < 20%), normal (PE = 20-80%), and dry (PE >80%) years. A fixed planting density of 21 seeds m^{-2} was adopted for the scenario analysis in this study.

3.4 Results and Discussion

3.4.1 AquaCrop calibration and validation

The length of the cotton growth cycle in the default AquaCrop crop file was consistent with field observations at SWREC, but was too long for CPRL and extended to the following year for all treatments. This is mainly because the warmer conditions of SWREC are more similar to the conditions under which the default model was developed, while CPRL is temperature-limited. As such, the length of the growing cycle was adjusted from 1956 °C degree-days in the default model to 1696 °C degree-days (12 °C base temperature) in case of CPRL. The other growth stages were also calibrated based on the measured datasets from the full, limited (50%) and dryland treatments in CPRL during the 2000 growing season (Table 3.6).

Table 3.6. Calibrated growth stages used in the AquaCrop model at the Conservation and Production Research Laboratory (CPRL).

Parameter	**Units**	**Value**
Canopy growth coefficient	% GDD^{-1}	0.835
Canopy decline coefficient	% GDD^{-1}	0.757
Sowing to emergence	GDD	129
Sowing to maximum canopy cover	GDD	951
Sowing to flowering	GDD	719
Length of flowering	GDD	723
Sowing to max rooting depth	GDD	1232
Sowing to senescence	GDD	1578
Sowing to maturity	°C	1694

3.4.1.1 Canopy cover (CC)

The model performance statistics calculated for calibration and validation of CC simulations are presented in Table 3.7. During calibration, the 2000/50% achieved better agreement between measured and simulated CC followed by the 2000/Full and lastly the dryland treatments, in that order. The d values (0.59-0.84) indicated acceptable model accuracy in three of the four calibration simulations. Based on R^2 and the d values, the 2000/Dryland 2 was the only treatment with unacceptable accuracy. RMSE values ranged from 16 to 25% during calibration. Low accuracy in the dryland treatments during calibration seemed to be a result of the rapid senescence in the late season due to water stress. During the validation process, the model achieved high accuracy in simulating CC particularly for irrigation treatments. Three of the four irrigated treatments attained RMSEs below 10%. In addition, the irrigated treatments attained R^2 and d values above 90% and RMSEs ranging from 5 to 25%, an indication of good agreement between measured and simulated CC. Similar to the calibration results, dryland treatments achieved reduced accuracy for CC simulations. Dryland treatments had R^2, d and RMSE values ranging from 0.44 to 0.85, 0.69 to 0.88 and 9 to 12%, respectively.

Table 3.7. Statistical measures for canopy cover simulation.

Parameter	**Treatment**	**R^2**	**RMSE (%)**	**d**
Calibration	2000/Full	0.84	24	0.73
	2000/50%	0.84	16	0.84
	2000/Dryland 1	0.50	23	0.68
	2000/Dryland 2	0.44	25	0.59
Validation	2001/Full	0.99	6	0.99
	2001/50%	0.92	7	0.97
	2001/Dryland 1	0.44	12	0.69
	2001/Dryland 2	0.61	11	0.70
	2002/50%	0.98	25	0.75
	2003/Dryland	0.85	9	0.88

	2010/Full 1	1.00	5	1.00
	2010/Full 2	1.00	5	1.00

Overall, the validation of the model for simulating CC for all irrigated treatments resulted in R^2, d and RMSE values of 0.93, 0.97 and 11%, respectively. These validation performance statistics are comparable to the findings of Tan et al. (2018) who achieved overall R^2, d and RMSE values of 0.89, 0.97 and 11%, respectively in their AquaCrop study for cotton. In addition, the overall performance statistics from this study are slightly better than the results by Qiao, Farahani, Khalilian, and Barnes (2016) who attained overall R^2, d and RMSE values of 0.83, 0.85 and 18%, respectively.

3.4.1.2 Soil water content (SWC)

The measured and simulated SWC appeared to match better in Full irrigation treatments than in limited and dryland treatments. In the dryland treatments, AquaCrop underestimated SWC from mid- to late-season. This seemed to be a result of increased depletion of SWC in the soil profile due to overestimated simulated CC. Tan et al. (2018) suggested that deviations of simulated SWC might be a result of over-simplification of root development in the model, which considers time and maximum rooting depth. The maximum rooting depth at CPRL was adjusted from 2.0 to 1.8 m following the observations of Baumhardt et al. (2009) at the site. Errors in the value of SWC depletion level threshold (p) may have been responsible for over- and under estimation of SWC too. Figure 3.2 shows the time series of soil water content for the treatments used for model validation.

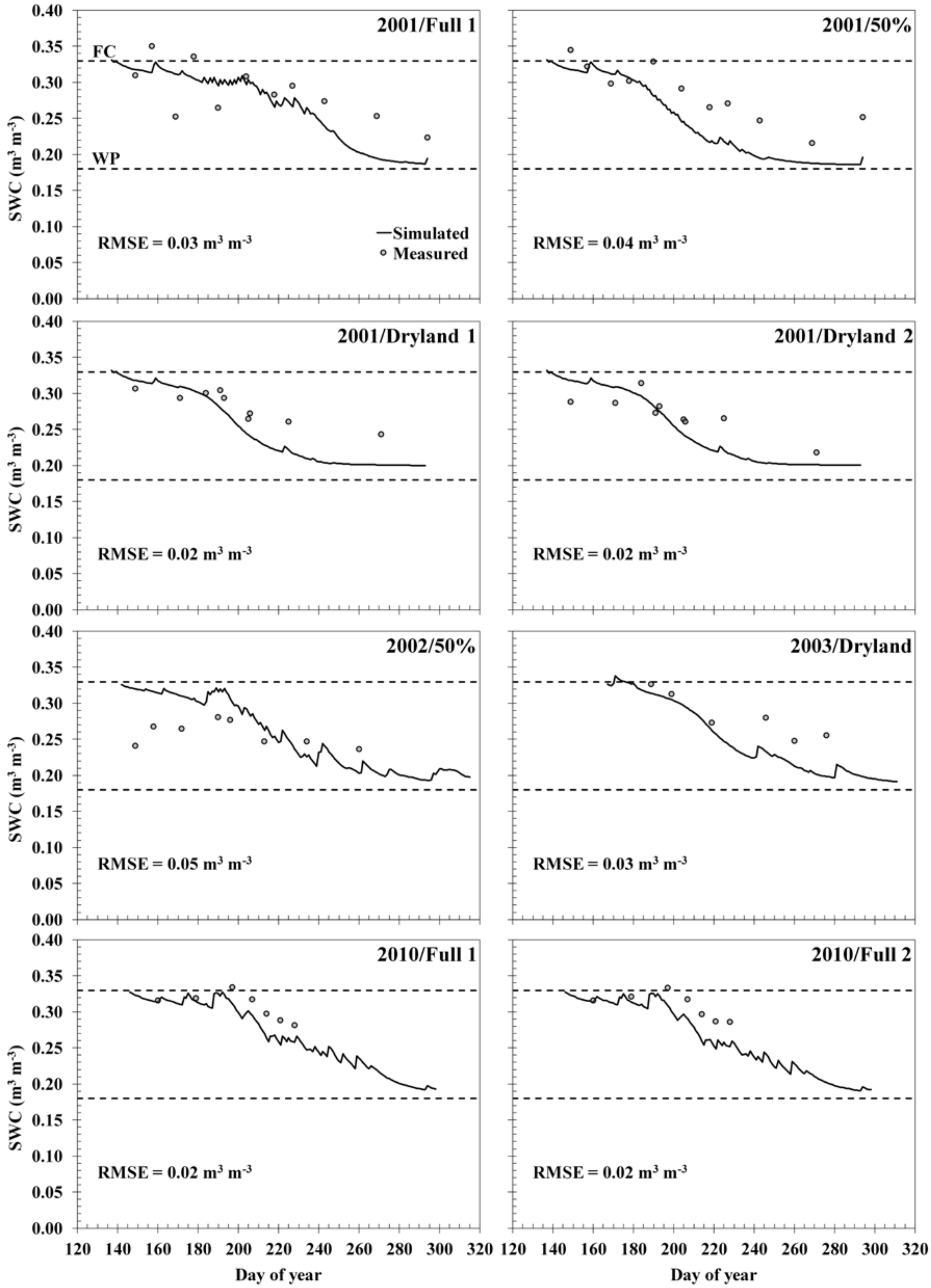


Figure 3.2. Measured vs. simulated soil water content validation treatments.

Performance statistics during model calibration and validation indicated acceptable model accuracy for simulating SWC. The RMSE ranged from 0.02 to 0.06 m^3m^{-3} among all treatments. The overall RMSE for calibration and validation was 0.05 and 0.03 m^3m^{-3}, respectively. The NRMSE for SWC ranged from 11-20% and 6-19% for calibration and validation, respectively. These metrics indicate good and acceptable accuracy according to classifications by Jamieson et al. (1991). In addition, relatively high d values (0.65-0.95) were determined for both calibration and validation. Most R^2 estimates showed strong goodness of fit except for 2001/Full and 2002/50%, which achieved 0.47 and 0.45, respectively. The statistical measures for SWC simulation for all treatments are presented in Table 3.8.

Table 3.8. Statistical measures for SWC simulation.

Parameter	**Treatment**	**R^2**	**RMSE (m^3m^{-3})**	**d**
Calibration	2000/Full	0.59	0.03	0.65
	2000/50%	0.72	0.06	0.85
	2000/Dryland 1	0.86	0.06	0.88
	2000/Dryland 2	0.75	0.05	0.87
Validation	2001/Full	0.47	0.03	0.78
	2001/50%	0.81	0.04	0.84
	2001/Dryland 1	0.86	0.02	0.87
	2001/Dryland 2	0.60	0.02	0.81
	2002/50%	0.45	0.05	0.95
	2003/Dryland	0.89	0.03	0.86
	2010/Full 1	0.84	0.02	0.85
	2010/Full 2	0.87	0.02	0.87

The SWC results for this study are similar to the findings of previous studies (Farahani et al., 2009; Hussein et al., 2011; Qiao et al., 2016)). For instance, Qiao et al. (2016) determined overall R^2, d and RMSE values were 0.76, 0.88 and 0.03 m^3m^{-3}, respectively, during model validation for cotton using AquaCrop.

3.4.1.3 Evapotranspiration (ET)

The daily ET peaks simulated by the AquaCrop model generally corresponded with the measured values, particularly for the full irrigation treatments. However, the model tended to overestimate daily ET in the midseason for the 50% and dryland treatments (Figure 3.3). This appeared to be a result of overestimation of CC during the same period for these treatments.

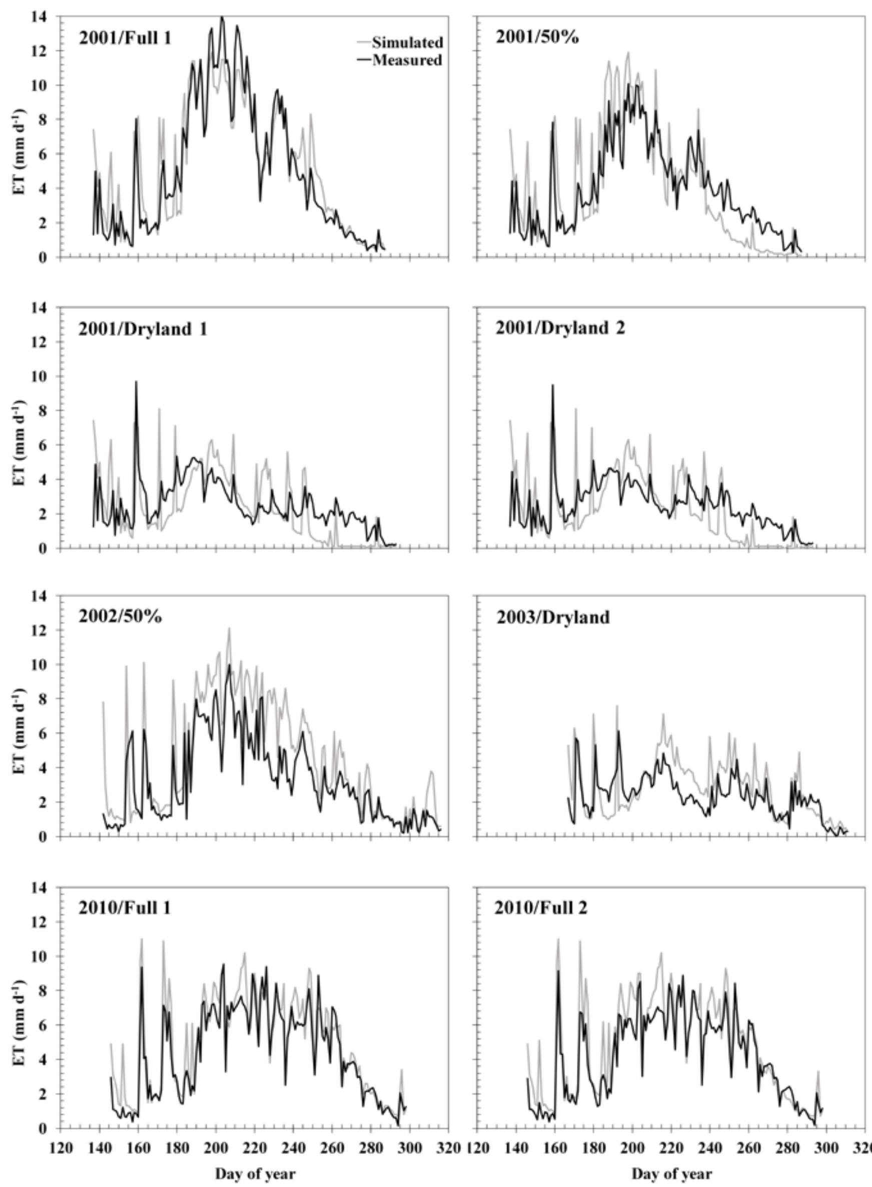


Figure 3.3. Measured vs. simulated ET for validation treatments.

The computed performance statistics for ET simulations are presented in Table 3.9. All indicators showed better model performance during calibration. For validation, all irrigated treatments attained acceptable accuracy. However, the model accuracy was low for simulating ET in dryland treatments as shown by the R^2 below 0.5 in both 2001 and 2003. The average RMSE for full and limited irrigation treatments during validation was 1.3 and 1.9 mm, respectively. The dryland treatments achieved an average RMSE of 1.6 mm for validation.

Table 3.9. Statistical measures for daily ET simulation.

Parameter	**Treatment**	**R^2**	**RMSE (mm d^{-1})**	**d**
Calibration	2000/Full	0.81	1.8	0.94
	2000/50%	0.68	1.9	0.88
	2000/Dryland 1	0.70	1.6	0.95
	2000/Dryland 2	0.64	1.8	0.82
Validation	2001/Full	0.86	1.5	0.96
	2001/50%	0.73	1.8	0.91
	2001/Dryland 1	0.36	1.7	0.74
	2001/Dryland 2	0.37	1.6	0.74
	2002/50%	0.79	1.9	0.88
	2003/Dryland	0.34	1.5	0.72
	2010/Full 1	0.87	1.1	0.95
	2010/Full 2	0.86	1.3	0.99

When considering seasonal ET, high R^2 (1.00, 0.85) values were achieved for calibration and validation steps (Figure 3.4). Furthermore, d values of 0.99 and 0.91, and NSE of 0.88 and 0.56 were determined for calibration and validation, respectively. Calibration and validation RMSEs for seasonal ET were 55 and 93 mm, which corresponded to NRMSE values of 10 and 17%, respectively, and this falls within the good performance category. These statistics are comparable with the findings of García-Vila et al. (2009) who determined d of 0.87 and 0.96 and RMSE of 95 mm and 62 mm for seasonal ET of cotton during the calibration and validation simulations, respectively.

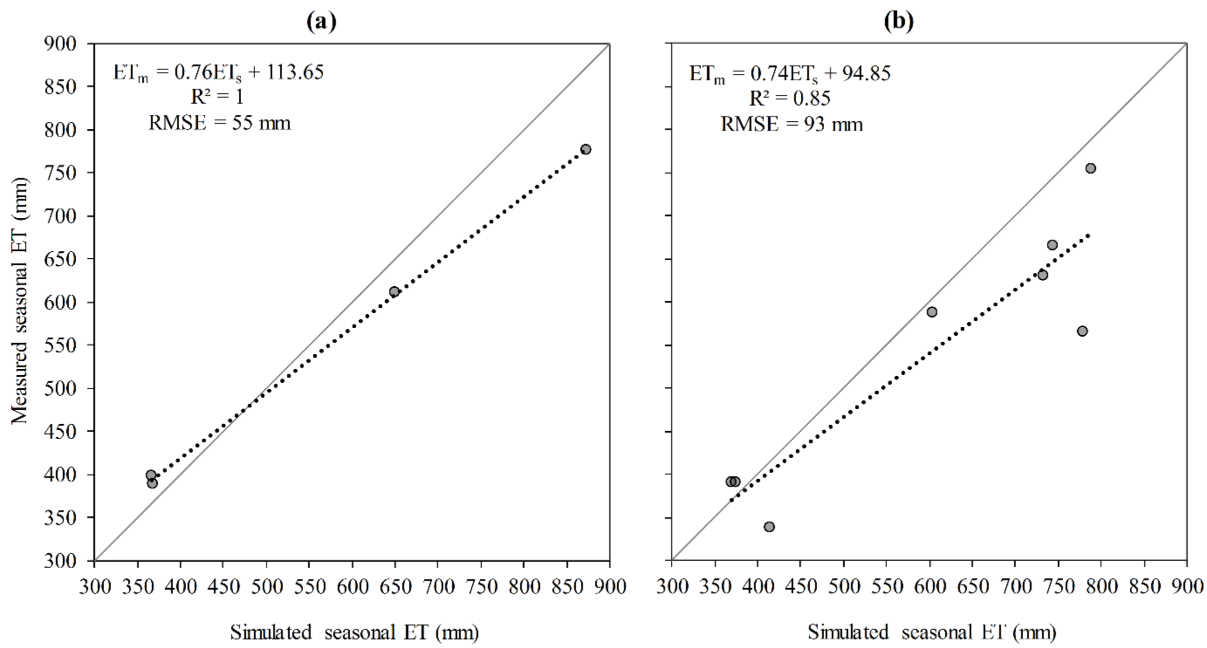


Figure 3.4. Observed and simulated seasonal ET for calibration (a) and validation treatments (b).

3.4.1.4 Seed Cotton Yield

When the default growth stages were used, the model significantly underestimated cotton yield, resulting in large P_e values ranging from -25 to -74% (Table 3.10). As explained earlier, the growth stages and the thermal time from planting to maturity specified in the default model were not suitable for CPRL, where cotton production is limited by temperature (Morrow & Krieg, 1990; Tolk & Howell, 2010). As a result, cotton yield was largely underestimated for all treatments, and the overall RMSE was 1915 kg ha^{-1}, and NRMSE of 76% when normalized. Thus, these results suggest poor performance by the default model for CPRL and the need to adjust the growth stages.

Table 3.10. Measured and simulated seed cotton yield with model prediction errors for default and calibrated models at CPRL.

Parameter	Treatment	Measured (kg ha^{-1})	Default		Calibrated	
			Simulated (kg ha^{-1})	P_e (%)	Simulated (kg ha^{-1})	P_e (%)
Calibration	2000/Full	4581	2023	-56	4372	-5
	2000/50%	2535	1114	-56	2565	1
	2000/Dryland 1	1036	469	-55	700	-32
	2000/Dryland 2	1022	455	-55	738	-28
Validation	2001/Full	3568	1198	-66	4019	13
	2001/50%	2239	630	-72	1888	-16
	2001/Dryland 1	1081	493	-54	920	-15
	2001/Dryland 2	877	499	-43	930	6
	2002/50%	2507	1828	-27	1957	-22
	2003/Dryland	1132	846	-25	726	-36
	2010/Full 1	4882	1313	-73	4937	1
	2010/Full 2	4868	1285	-74	4842	-1

Calibrating growth stages improved the performance of the model, particularly for the irrigated treatments. During model calibration, the P_e ranged from -5 to 1% and -32 to -28% for irrigated and dryland treatments, respectively. For validation, the P_e values ranged from -1 to 13%, -22 to -15% and -36 to 6% for full irrigation, limited irrigation and dryland treatments, respectively. The RMSEs for calibration and validation were 244 and 321 kg ha^{-1}, corresponding NRMSE of 12 and 13%, respectively. Measured and simulated cotton yield showed good agreement with R^2 of 0.99 and 0.97 for calibration and validation, respectively (Figure 3.5). Similarly, the d and NSE values were high (> 0.90) during calibration and validation. Qiao et al. (2016) achieved similar goodness-of-fit statistics with RMSE, R^2 and d values of (327, 265 kg ha^{-1}), (0.91, 0.84) and (0.95, 0.92), respectively. Additionally, Hussein et al. (2011) also found high correlations between measured and simulated cotton yield using AquaCrop in Syria. The results from the current study are better than the findings of Tan et al. (2018), who attained RMSEs of (438, 1204 kg ha^{-1}), R^2 of (0.69, 0.10) and d-statistics of (0.82, 0.57) during calibration and validation, respectively.

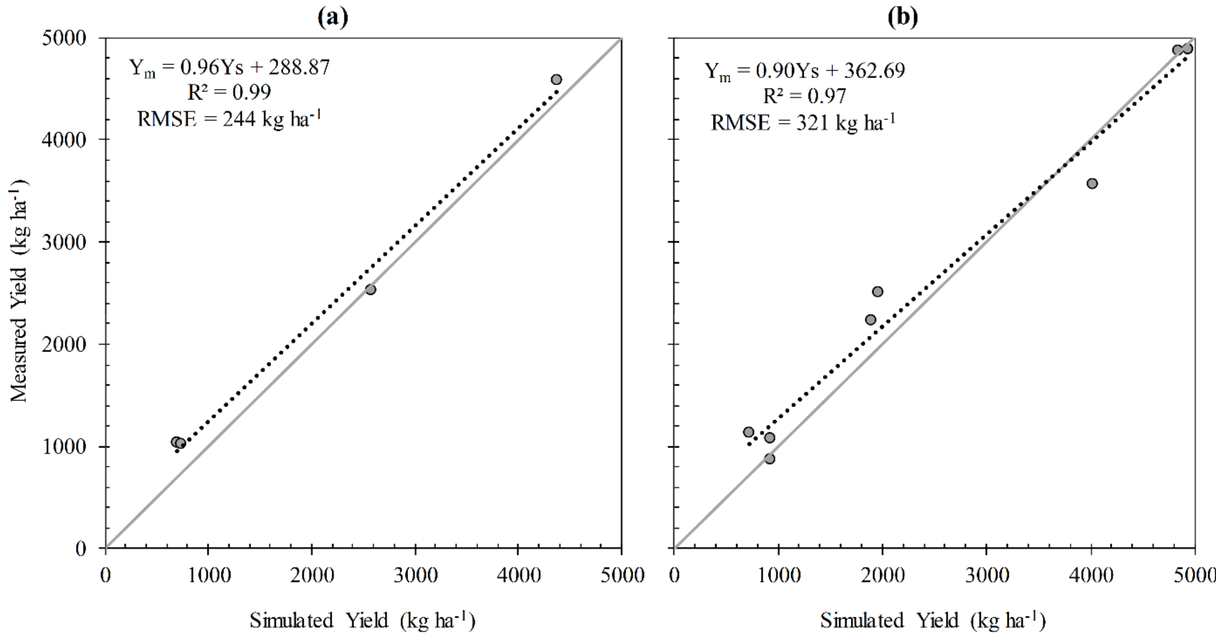


Figure 3.5. Measured and simulated cotton yield for calibration (a) and validation treatments (b) at CPRL.

At the SWREC site, all simulations using the default model parameters resulted in prediction errors within ±20% as presented in Table 3.11. P_e values ranged from -20 to 15%, an indication of good model performance according to Steduto et al. (2012).

Table 3.11. Measured and simulated seed cotton yield with model prediction errors at SWREC.

Year	Treatment	Measured (kg ha^{-1})	Simulated (kg ha^{-1})	P_e (%)
2015	T1	2343	2605	11
2015	T2	2806	2730	-3
2015	T3	3546	2853	-20
2016	T1	4885	4500	-8
2016	T2	4852	4500	-7

2016	T3	5131	4500	-12
2017	T1	2838	3023	7
2017	T2	2623	3023	15
2017	T3	3587	3187	-11

The statistical measures calculated for the SWREC site showed that the model was able to simulate seed cotton yield adequately with high R^2 (0.90), d (1.00) and NSE (0.83). Furthermore, the RMSE of 419 kg ha^{-1} was determined, with a normalized value of 12%, an indication of good model performance according to Jamieson et al. (1991). The good performance of the default model suggests that the heat units available during the growing season were more adequate at SWREC than CPRL and closer to the climatic conditions where the default model was parameterized (Cordoba, Spain). Figure 3.6 shows the one to one plot for measured and simulated cotton yield at SWREC

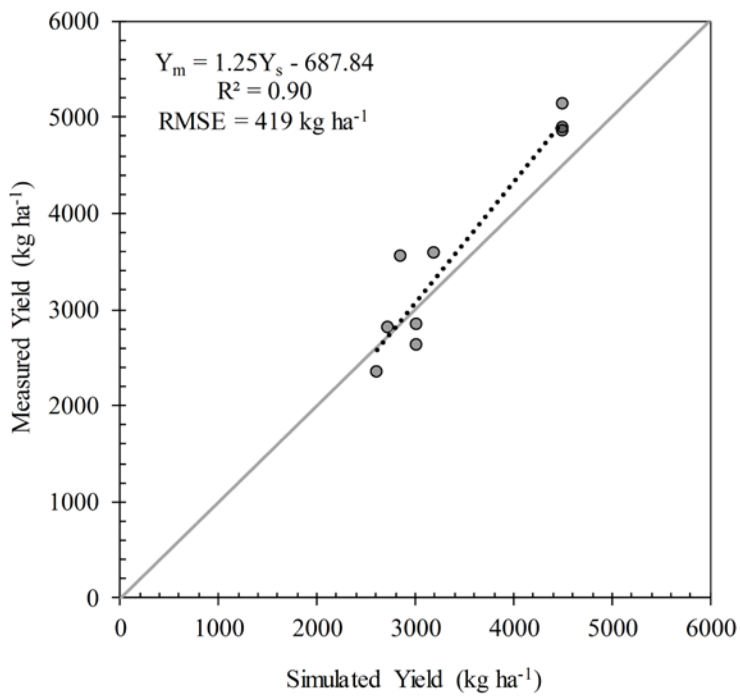


Figure 3.6. Measured and simulated cotton yield at SWREC.

3.4.2 AquaCrop application

The results from the long-term simulations showed significant year-to-year variability of cotton yields for all ICs (Figure 3.7). Cotton yields ranged from 405 to 5514 kg ha^{-1} under irrigated, and from 132 to 5025 kg ha^{-1} under dryland conditions. These values correspond to approximately 153 to 2095 kg ha^{-1} and 50 and 1910 kg ha^{-1} of lint yield for irrigated and dryland treatments, respectively when converted using an average lint percent of 38% reported by Willcutt et al. (2010). Baumhardt et al. (2009) found similar ranges of lint yields in the Southern High Plains region under dryland and variable IC levels when using a fixed planting date of 15 May. Esparza et al. (2007) and Gowda et al. (2007) attributed cotton yield variabilities in the Southern High Plains region to year-to-year variability in growing season conditions.

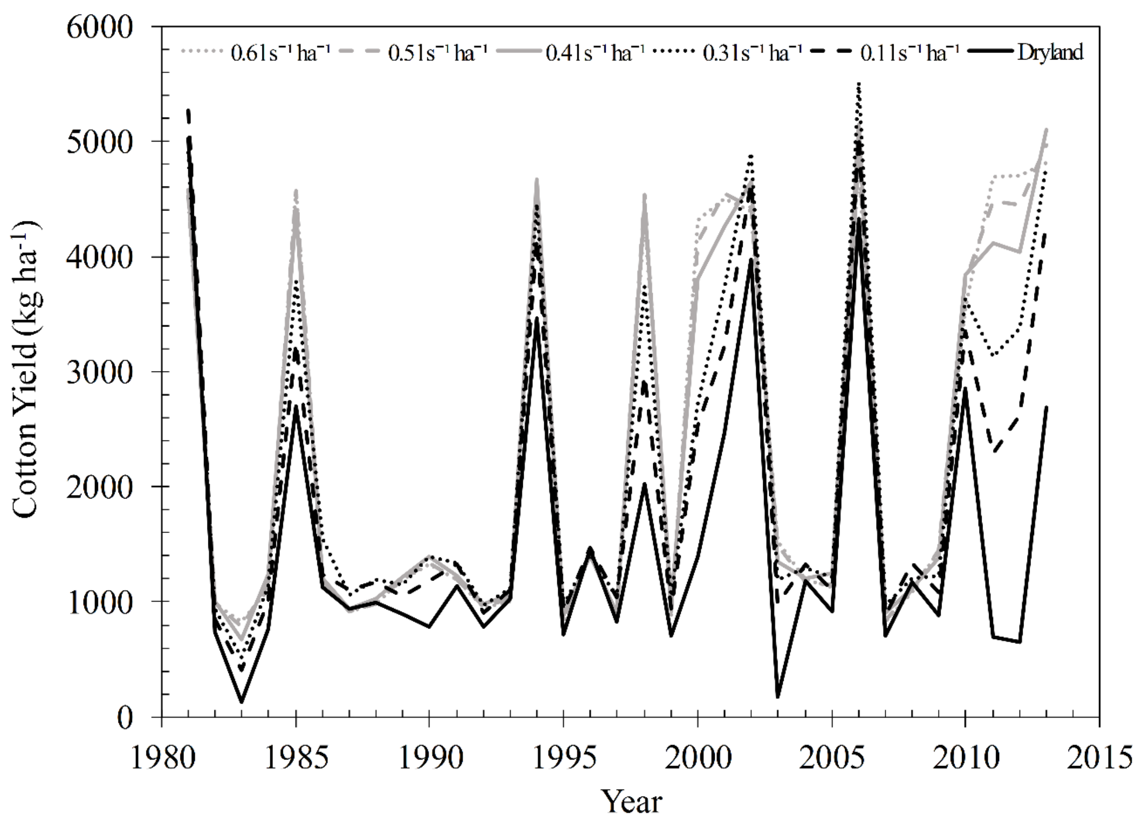


Figure 3.7. Time series of cotton yield at different ICs for the thirty-three years simulated.

The long-term averages of cotton yield ranged from 1525 to 2333 kg ha^{-1}, with the dryland and 0.5 l s^{-1} ha^{-1} IC treatments achieving the lowest and highest yields, respectively. Baumhardt et al. (2009) reported similar findings with average yields of 1905, 2239 and 2363 kg ha^{-1} for dryland, 0.4 and 0.5 l s^{-1} ha^{-1}. Table 3.12 presents the long-term averages for cotton yields, that were achieved, and the relative yield reduction for each IC from the 0.6 l s^{-1} ha^{-1}.

Table 3.12. Long-term average cotton yields achieved at each IC and the percent yield difference from the 0.6 l s^{-1} ha^{-1} IC. Means followed by the same letter are not significant at the 0.05 level according to the LSD.

Irrigation capacity (l s^{-1} ha^{-1})	Yield (kg ha^{-1})	Yield Difference (%)
0.0	1525 a	-34.3
0.1	2004 b	-13.7
0.3	2201 bc	-5.2
0.4	2316 c	-0.2
0.5	2333 c	0.5
0.6	2321 c	0.0

All the irrigated ICs attained significantly larger cotton yields compared to the dryland treatment. No significant differences were observed for cotton yields amongst the 0.3, 0.4, 0.5 and 0.6 l s^{-1} ha^{-1} ICs. These findings suggest that no significant increase of cotton yields may be achieved at ICs higher than 0.3 l s^{-1} ha^{-1} in the Southern High Plains of the Ogallala aquifer region. The long-term average yield for the 0.1 l s^{-1} ha^{-1} was similar to that obtained by the 0.3 l s^{-1} ha^{-1} IC but was significantly lower than for 0.4 to 0.6 l s^{-1} ha^{-1} ICs. Similar to this study, Baumhardt et al. (2009) found no yield increases when irrigation capacity increased from 0.4 to 0.5 l s^{-1} ha^{-1}.

3.4.3 Effect of growing season rainfall on cotton yield

When the thirty-three years of growing season rainfall amounts were classified, the resultant average seasonal rainfall for wet, normal and dry years were 449, 321 and 132 mm, respectively. Simulation results showed no significant differences in the cotton yields amongst all ICs during the wet ($p = 1$) and normal ($p = 0.871$) years (Figure 3.8). In the dry season category, the average cotton yield under dryland cropping was similar to that of the 0.1 l s^{-1} ha^{-1} IC but was significantly lower compared to the 0.3 to 0.6 l s^{-1} ha^{-1} ICs. ICs from 0.3 to 0.6 l s^{-1} ha^{-1} attained statistically similar cotton yields in the dry season category. These results are in agreement with the findings of AbdelGadir et al. (2012) who determined a positive relationship between cotton yield and seasonal irrigation depth in dry years.

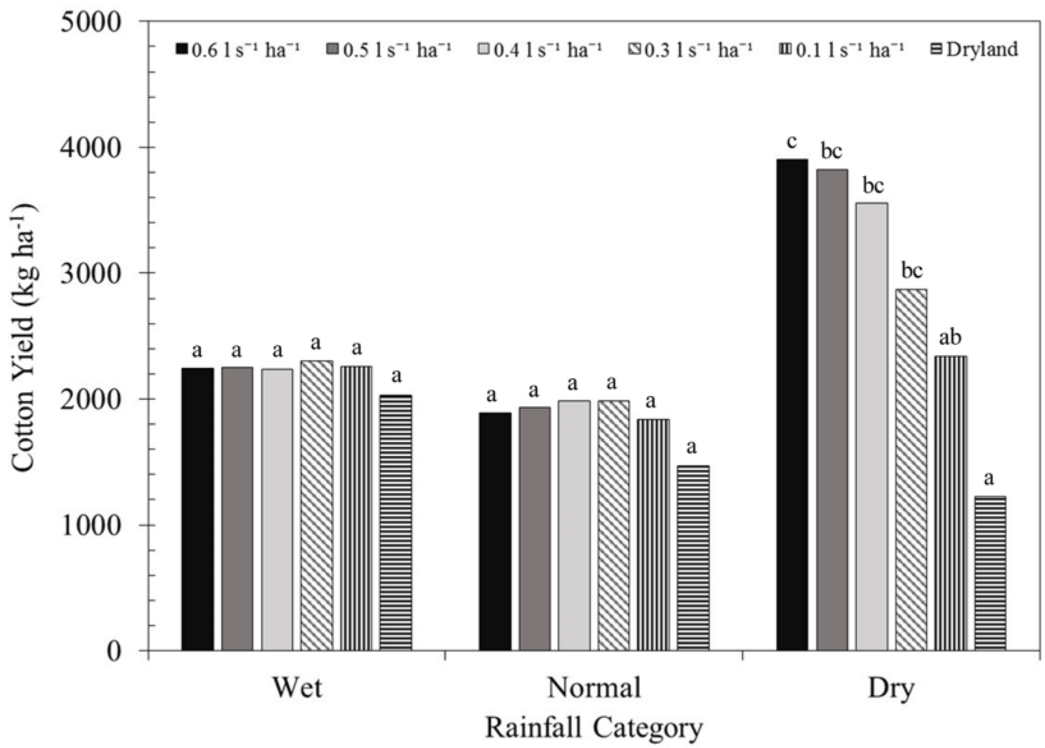


Figure 3.8. Long-term average yields achieved at each IC in wet, normal and dry years. Means followed with same letter (s) in each rainfall category are not significant at the 0.05 level according to the LSD.

The simulated high yields in the dry years under irrigated conditions appeared to be a result of availability of more heat units in those years. For instance, five out of the six years (1998, 2000, 2001, 2011 & 2012) in the dry year category were relatively warm, and as a result, they attained relatively more heat units (> 1100 °C) for optimizing cotton yield under irrigation. However, due to less water available for crop water use in the dry years, the warm conditions appeared not to be conducive for dryland cropping as this treatment attained a significantly lower yield. Peng et al. (1989) determined similar findings in the same study area; and highlighted that cotton yield correlates well to accumulated heat units when water availability was not limiting but no significant relationship exists under water stress.

Since the results of this study showed the influence of seasonal weather conditions on the performance of each IC, the probability of exceedance (PE) curves of simulated yields were used to highlight the frequency of attaining various yield levels at each irrigation capacity. According to Gowda et al. (2007), this information helps producers to set realistic yield goals and to plan appropriate management practices. The PE curves generally showed lower yields under dryland cropping compared to all irrigated ICs at all PE values (Figure 3.9). Furthermore, the results showed minimal differences in cotton yields across irrigated ICs for PE values ≤ 15% and ≥ 38%. On the other hand, the PE curves showed clear yield differences amongst ICs in the range of 15% ≤ PE ≤ 38%. These results suggest that the Southern High Plains experiences optimum environmental conditions for cotton production at most 38% of the time. Significant increases of cotton yields with higher ICs were observed within this range. For instance, the potential cotton yield with a probability of occurrence of one out four years (P = 25%), increased by 1278 kg ha^{-1} from the 0.1 to 0.6 l s^{-1} ha^{-1} IC. On average (PE = 50%), potential cotton yields under irrigated cropping ranged from 1196 to 1298 kg ha^{-1}, with the 0.3 l s^{-1} ha^{-1} achieving the largest average yield.

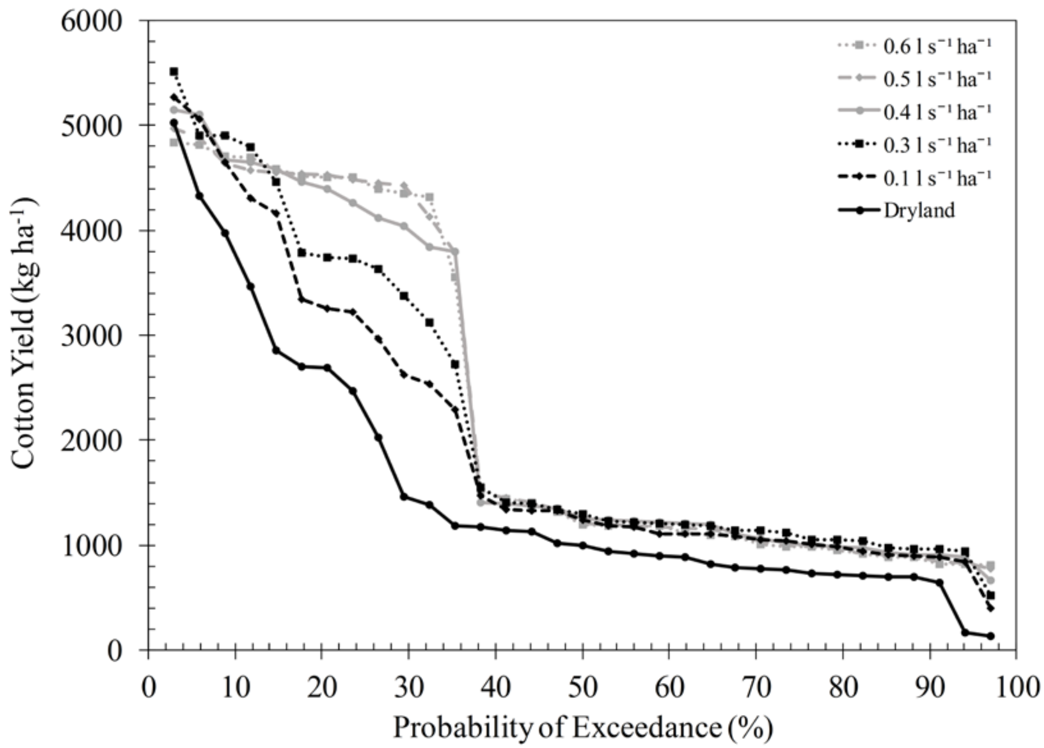


Figure 3.9. Probability of exceedance curves of simulated cotton yields for each IC.

3.5 Conclusions

The performance of the AquaCrop model was assessed for simulating cotton production at two sites in the southern Great Plains: the Conservation and Production Research Laboratory (CPRL) at Bushland, TX and the Southwest Research and Extension Center (SWREC) near Altus, OK. Due to limited heat units available at the CPRL site, the default crop file for cotton developed in in Cordoba, Spain produced poor predictions for yield. Thus, the model was calibrated by adjusting the cotton growth cycle and growth stages based on measured data collected at the site. All conservative parameters developed for cotton were used in this study. The results of calibration and validation at the CPRL site, showed satisfactorily performance of the model for simulating CC, SWC, ET and yield, with better predictions under irrigated treatments compared to dryland treatments. At the SWREC site, the accuracy of the default model was satisfactory for predicting yield and no adjustments to the model were done. This appeared to be a result of similar climatic conditions between the SWREC site and Cordoba, Spain. Considering the few adjustments made to the non-conservative parameters of the default model at CPRL and none at SWREC, the validation results at both sites showed that the AquaCrop model is a potential tool for evaluating irrigation and crop management of cotton in the southern Great Plains. The calibrated model was applied to evaluate the effect of irrigation capacity and seasonal weather conditions on cotton yield at CPRL that relies on the Ogallala aquifer for irrigation supply. The results revealed no significant increase in cotton yields at irrigation capacities higher than 0.3 l s^{-1} ha^{-1}. The simulation results also showed a significant increase in cotton yields under irrigated but a decrease under dryland conditions, during warm years. The results from this study highlight the need for producers in the southern Great Plains particularly the Southern High Plains region of the Ogallala aquifer to incorporate available weather platforms for making irrigation and crop management decisions.

CHAPTER IV

SIMULATING SOIL WATER CONTENT, EVAPOTRANSPIRATION AND YIELD OF VARIABLIY IRRIGATED GRAIN SORGHUM USING AQUACROP

4.1 Abstract

Use of models to simulate crop production has become important in optimizing irrigation management in arid and semi-arid regions. However, applicability and performance of these models differ across regions, due to differences in environmental and management factors. The AquaCrop model was used to simulate soil water content (SWC), evapotranspiration (ET), and yield for grain sorghum under different irrigation regimes and dryland conditions at two sites in Central and Southern High Plains. Prediction error (P_e), estimated as the difference between simulated and measured divided by measured, for SWC ranged from -17 to 4% in fully irrigated, -3 to -10% in limited irrigated and -16 to 25% in dryland treatments. The P_e of less than ±4%, -5%, and 24% were attained for seasonal ET under fully irrigated, limited irrigated, and dryland conditions, respectively. P_e values for grain yield were within those previously reported and ranged from -10 to 12%, -12 to 7%, and 9 to 17% for fully irrigated, limited irrigated and dryland conditions, respectively. Overall performance of the AquaCrop model showed that it could be used as an effective tool for evaluating the impacts of variable crop and irrigation managements on the production of grain sorghum in the study area. Finally, the application of the calibrated model in the study area revealed that planting date has a significant impact on sorghum yield and

irrigation requirements, but the impact of planting density was negligible.

Keywords: Simulation; irrigation; deficit irrigation; evapotranspiration; High Plains; planting date.

4.2 Introduction

Irrigation is crucial for the sustainable agricultural production in the Central and Southern High Plains of the Ogallala Aquifer region, where high evaporative conditions are coupled with erratic growing season rainfall (Yazar, Howell, Dusek, & Copeland, 1999). Guerrero, Wright, Hudson, Johnson, and Ammoson (2010) highlighted that irrigated agriculture is the major economic driver in this region. More than 70% of the agricultural production in economic value was reported to originate from irrigated crop production in the Texas High Plains (Terrell, Johnson, & Segarra, 2002). According to Colaizzi, Gowda, Marek and Porter (2009) and Howell (2001), irrigation in this region resulted in doubled crop yields as compared to dryland production. Guerrero et al. (2010) reported a boost in revenues for producers due to this increased crop productivity.

The Ogallala aquifer, which covers parts of Texas and Oklahoma Panhandles, New Mexico, southwestern Kansas and southeastern Colorado is the main source of irrigation water in the Central and Southern High Plains (Howell, Copeland, Schneider, & Dusek., 1989; Yazar et al., 1999). However, decades of pumping with limited recharge has resulted in severe depletion of the aquifer and its water levels have continuously declined in many parts of the region (Musick & Dusek, 1971; Howell, Schneider, & Evett, 1997; Yazar et al., 1999). Stone and Schlegel (2006) reported widespread declines of greater than 15 m in the eastern parts of Colorado and southwestern Kansas, which occurred from the times of predevelopment to the year 2003. Furthermore, McGuire (2017) reported water level declines of up to 71 m in some areas in the Central and Southern High Plains, from predevelopment to the year 2009. Because of these water level declines, well capacities in this region have significantly decreased, and producers in the area are facing serious water challenges to meet crop water demands (Stone, Lamm, Schlegel, & Klocke 2008).

One approach that can be utilized to ensure efficient management of the rapidly depleting water supply in arid and semi-arid regions such as the Central and Southern High Plains is to investigate strategies that optimize and enhance crop water use efficiency and profitability (Evett et al., 2012; Araya, Kisekka, & Holman, 2016). This can be achieved by studying water production functions (Barrett & Skogerboe, 1980). However, development of water production functions requires intensive data from field experiments. Saseendran, Ahuja, Nielsen, Trout, and Ma (2008) argued that field experiments generally face difficulties in representing all variabilities caused by time, location, climate, soil, and management practices. In addition, numerous studies including Liu, Wiberg, Zehnder, and Yang (2007), and Geerts and Raes (2009), have argued that field and/or controlled experiments meant to investigate the effect of different irrigation regimes on crop yield are very expensive, labor intensive and time consuming.

Alternatively, crop models present a unique opportunity to provide decision support by simulating different crop and irrigation management scenarios for determining best management practices. With proper calibration, crop models have the potential to offer a cost effective and timely means to evaluate potential agronomic and water management strategies for water-limited areas, allowing better recommendations for producers. Utilizing their ability to perform integrated assessments of the factors affecting yield, crop models could be useful in deriving optimum irrigation applications for various crops. However, some of these models often require more specific crop data that may not be easily obtainable for performing simulations (García-Vila & Fereres, 2012).

Unlike many complex crop models that require detailed and extensive input parameters, the AquaCrop model (Steduto, Hsiao, Raes, & Fereres, 2009) developed by the Food and

Agricultural Organization (FAO) of the United Nations was reported to balance between accuracy, simplicity, robustness, and ease of use (Hsiao, Heng, Steduto, Rojas-Lara, Raes, & Fereres, 2009). This water-driven model simulates crop biomass and harvestable yield in response to available water, and has a relatively low requirement of specific inputs (Heng, Hsiao, Evett, Howell, & Steduto, 2009; Steduto et al., 2009; Raes Steduto, Hsiao, & Fereres, 2012). The AquaCrop model has been successfully used for simulating the growth of many crops such as maize (Heng et al., 2009; Hsiao et al., 2009; Ahmadi, Mosallaeepour, Kamgar-Haghighi, & Sepaskhah 2015), cotton (Farahani, Izzi, & Oweis, 2009), sorghum (Araya et al., 2016), potato and sunflower (García-Vila & Fereres, 2012). Todorovic et al. (2009) highlighted the suitability of the AquaCrop model for applications in arid and semi-arid regions where water stress varies in intensity, duration, and time of occurrence. Farahani et al. (2009) parameterized the model for a cotton crop, and predicted evapotranspiration (ET) and yield with reasonable accuracy. Heng et al. (2009) successfully validated the AquaCrop model for maize crop in Bushland, Texas, and concluded its performance to be satisfactory and recommended its application for on-farm water management. Araya et al. (2016) applied the model for evaluating deficit irrigation management strategies at different planting dates for sorghum in southwest Kansas. Their study revealed that planting date had significant bearing on water productivity of grain sorghum, with late planting resulting in high water productivities. Furthermore, the results suggested that deficit irrigation management improved grain sorghum water productivity under optimum conditions. However, some of these studies have highlighted the insufficiency of the model under moderate to severe conditions (Hsiao et al., 2009; Ahmadi et al., 2015).

Grain crops are very important in the Central and Southern High Plains because of their use in livestock production. The major crops cultivated in the region include corn, winter wheat, sorghum and cotton. Of these four crops, grain sorghum is relatively more drought tolerant, and Araya et al. (2016) reported its suitability in water-limited environments. Historically, grain sorghum covered a significant portion of the irrigated area of the Central and Southern High Plains (Musick & Dusek, 1971). In recent decades, corn has become the dominant irrigated feed grain in the region, mainly due to advances in the genetics. However, as Bordovsky and Lyle (1996) pointed out, grain sorghum cultivation may increase and may become preferred over corn as the water supply continues to dwindle. Musick and Dusek (1971) identified the frequent agricultural droughts as the other major driver for grain sorghum cultivation, compared to other grain crops in this region. Therefore, grain sorghum could become more important in meeting food, feed, and fuel demands (Baumhardt, Tolk, Howell, & Rosenthal, 2007). Thus, more research is needed to bring about recommendations that optimize its yield response to water with the aid of crop models.

The objectives of this study were i) to calibrate and validate the AquaCrop model for estimating soil water content, evapotranspiration, and yield of grain sorghum using measured data from two sites in the Central and Southern High Plains that were similar in climatic conditions, but different in planted varieties, management practices, and irrigation systems; and, ii) to use the calibrated model to assess the effect of variable planting dates and densities on grain yield and irrigation requirement in the study area.

4.3 Materials and Methods

4.3.1 Study Sites

The data used in this study were collected from field research plots at two locations in the Central and Southern High Plains; the USDA-ARS Conservation and Production Research Laboratory (CPRL) at Bushland, TX (35° 11' 16"N lat.; 102° 05' 49"W long., 1,170 m elev. above MSL) and the Oklahoma Panhandle Research and Extension Center (OPREC) near Goodwell, OK (36° 35' 21"N lat.; 101° 37' 3"W long.; 992 m elev. above MSL). The two study sites are located within the most agriculturally productive lands in the region. However, some of the largest declines in the Ogallala aquifer have been recorded in the same region. Figure 4.1 shows the location of study sites and highlight the water level changes of the Ogallala aquifer from predevelopment (about 1950) to 2011.

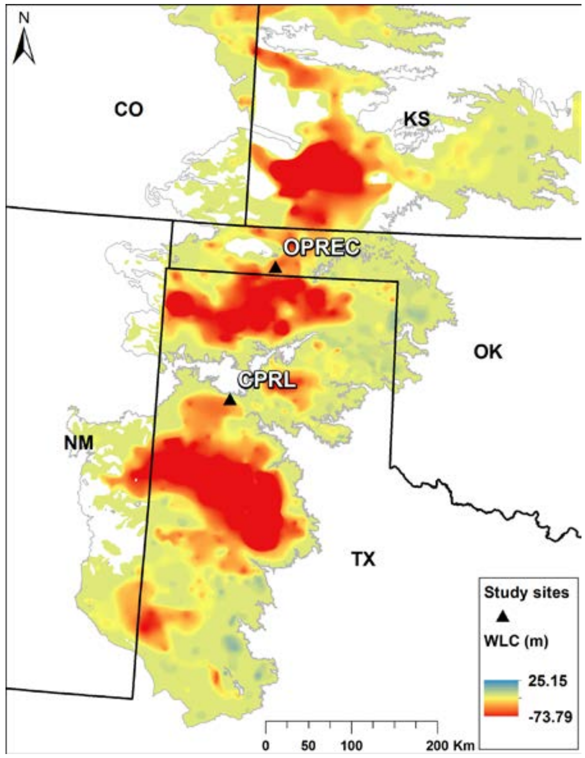


Figure 4.1. Locations of the study sites at USDA-ARS Conservation and Production Laboratory (CPRL) and Oklahoma Panhandle Research and Extension Center (OPREC). The base map shows water level changes (WLC) from predevelopment to 2011.

The two sites have similar climatic conditions characterized as semi-arid as shown by the data in Table 4.1. The average annual precipitation at CPRL is approximately 470 mm (Tolk & Howell, 2003; Marek et al., 2017), and the area generally experiences high wind velocities (Heng et al., 2009). Similarly, the OPREC site is characterized by low precipitation with an annual average of about 440 mm, high temperatures, and frequent strong winds (Rogers & Elliott, 1989). However, the evaporative demand at the OPREC site is relatively higher than at CPRL as seen in Table 4.1.

Table 4.1. 30-year average (1981-2010) climatological data at USDA-ARS Conservation and Production Laboratory (CPRL) and Oklahoma Panhandle Research and Extension Center (OPREC) (NCDC, 2017).

Site	Parameter	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
	T_{max} (°C)	9.8	10.4	12.4	17.0	21.7	26.6	31.1	32.5	31.4	28.0	22.2	15.6
	T_{min} (°C)	-4.5	-4.8	-3.4	0.5	4.9	10.7	15.7	18.0	17.4	13.3	6.8	0.0
	$RH_{avg.}$ (%)	62	60	57	53	57	56	57	62	62	61	59	62
CPRL	U_2 (m/s)	3.2	3.5	3.7	3.7	3.6	3.5	3.2	2.9	3.0	3.1	3.3	3.3
	R_s (MJ/m^2)	11.0	14.0	18.6	22.7	24.8	25.7	25.5	22.5	19.5	15.3	11.8	10.5
	P (mm)	12.6	11.6	29.9	24.4	49.0	71.9	57.7	64.6	42.9	42.8	14.7	14.5
	ET_o (mm/d)	1.7	2.1	2.9	4.1	5.0	6.0	6.5	5.9	5.2	4.1	3.0	2.1
	T_{max} (°C)	10.0	11.1	17.2	21.1	26.1	32.2	34.4	32.8	28.9	22.8	16.1	9.4
	T_{min} (°C)	-6.1	-5.6	0.0	4.4	9.4	16.1	18.3	17.2	13.3	6.1	-0.6	-6.1
	$RH_{avg.}$ (%)	61	60	54	54	55	55	53	60	58	58	57	63
OPREC	U_2 (m/s)	7.6	8.0	8.5	9.4	8.9	8.9	8.0	7.6	7.6	7.6	7.6	7.6
	R_s (MJ/m^2)	10.6	13.7	18.4	22.3	25.5	27.1	26.2	23.0	19.7	15.3	11.6	9.4
	P (mm)	8.9	10.4	26.9	41.4	48.0	58.2	52.3	69.1	36.6	38.1	13.5	16.3
	ET_o (mm/d)	2.4	2.8	4.5	5.8	7.2	9.2	9.6	7.9	6.7	4.9	3.4	2.2

According to Marek et al. (2016a), soils at the CPRL site are Pullman clay loam (fine, mixed, thermic, superlative Torrertic Paleustoll) and soils at the OPREC are Gruver clay loam, formerly Richfield (fine, mixed, superactive, mesic Aridic Paleustoll) (Humphreys et al., 2003). Table 4.2 presents the soil water content limits at saturation (Sat.), field capacity (FC), and wilting point (WP) as well as the saturated hydraulic conductivity (K_{sat}) for different soil layers determined though laboratory analyses and obtained from published data for CPRL (Heng et al., 2009; Marek et al., 2017) and OPREC (Gatlin, 2015).

Table 4.2. Soil parameters at the CPRL and OPREC sites.

Layer (m)	Water content ($m^3\ m^{-3}$) at			K_{sat} (mm d^{-1})
	Sat.	FC	WP	
	CPRL (Pullman clay loam)			
0.00-0.18	0.42	0.33	0.18	66.0
0.18-0.74	0.44	0.33	0.18	18.0
0.74-1.35	0.43	0.35	0.20	6.6
1.35-2.30	0.46	0.30	0.16	200.0
	OPREC (Gruver clay loam)			
0.00-0.30	0.40	0.38	0.17	125.0
0.30-0.60	0.41	0.39	0.20	125.0
0.60-0.90	0.41	0.39	0.23	125.0
0.90-1.20	0.43	0.41	0.20	100.0

4.3.2 Agronomy

Grain sorghum *(Sorghum bicolor (L.)* Moench*)* was planted at both sites. At the CPRL, three lysimeter fields (designated as NE, SE, & NW) each occupying an area of 4.73 ha and equipped with large (3 x 3 x 2.5 m) weighing lysimeters were used in the study. These fields are described in detail by Marek et al. (2017). The NE and SE fields had similar agronomic parameters in any given year, which included the variety, planting dates, planting density and the harvesting date. Table 4.3 reports agronomic information for each water supply level for all the growing seasons that were investigated at the CPRL. The sorghum hybrids grown differed in the duration to maturity. The DK-56 grown in the 1993 season was a medium-full whereas the DK-39Y grown in the 2005 and 2007 seasons was a short season hybrid (Howell et al., 2006).

Table 4.3. Agronomic information for the USDA-ARS Conservation and Production Laboratory site.

Growing season/ Irrigation treatment	**1993/ Full**	**1993/ 50%**	**1998/ Dryland**	**2005/ Full 1**	**2005/ Full 2**	**2007/ Dryland**
Field	NE	SE	NW	NE	SE	NW
Variety	DK-56	DK-56	PIO-8699	DK-39Y	DK-39Y	DK-39Y
Planting Date	27 May	27 May	24 Jun	22 Jun	22 Jun	6 Jun
Planting Density (plants ha^{-1})	200,000	200,000	119,000	160,000	160,000	96,370
Harvest Date	4 Oct	4 Oct	4 Oct	7 Nov	7 Nov	3 Oct
Seasonal Rainfall, (mm)	263	263	422	165	165	192
Irrigation (mm)	380	174	0	219	218	0
Seasonal ET_o (mm)	780	780	855	843	843	713

Optimal fertilization and weed control were performed at the CPRL site in all the study years. Preseason soil tests established the nutrient status of fields and guided optimum fertilizer applications. Herbicides were applied to prevent weed infestations. Data for crop development were taken regularly by taking samples from 1.5 m^2 areas in the fields. These data included crop height, leaf area index (LAI) and grain yield. The grain yield was measured by harvesting three adjacent 1.5-m^2 plant sampling areas in the lysimeters and its moisture content was determined using the procedure outlined in Howell, Tolk, Evett, Copeland, and Dusek (2007).

At the OPREC, sorghum was grown in rotation with corn and winter wheat under no-till management practices. Sorghum was grown in a wheat stubble in all the study years. Each treatment occupied an area of 0.35 ha. Table 4.4 highlights some of the agronomic data for the 3-year study period (2014-2016). These data include plant varieties, planting and harvesting dates, planting density, seasonal rainfall and seasonal irrigation applications. Optimum fertilization and weed control were ensured in all the study years so that yield responses could be attributed largely to water supply (irrigation and rainfall), and hence, these were considered as non-limiting factors in the AquaCrop model simulations. Fertility requirements and fertilizer applications were based on soil tests. At this site, yield data were obtained by harvesting two center rows in each plot.

Table 4.4. Agronomic information for the Oklahoma Panhandle Research and Extension Center site.

Growing season/ Irrigation Treatment	2014/ Full	2014/ 75%	2014/ 50%	2015/ Full	2015/ 75%	2015/ 50%	2016/ Full	2016/ 75%	2016/ 50%
Variety	PIO-84G62	PIO-84G62	PIO-84G62	PIO-84G62	PIO-84G62	PIO-84G62	SP-73B12	SP-73B12	SP-73B12
Planting Date	6 Jun	6 Jun	6 Jun	1 Jun	1 Jun	1 Jun	8 Jun	8 Jun	8 Jun
Planting Density (plants ha^{-1})	154,440	154,440	154,440	154,440	154,440	154,440	154,440	154,440	154,440
Harvest Date	15 Oct	15 Oct	15 Oct	15 Oct	15 Oct	15 Oct	29 Oct	29 Oct	29 Oct
Seasonal Rainfall (mm)	270	270	270	296	296	296	229	229	229
Irrigation (mm)	384	288	193	320	237	160	293	222	151
Seasonal ET_o (mm)	891	891	891	800	800	800	886	886	886

4.3.3 Irrigation Management

At CPRL, each lysimeter field was designated one irrigation treatment. The NE and SE fields were irrigated by a 10-span, 457 m linear move irrigation system (Howell et al., 1997; Marek et al., 2017). The system was fitted with drop hoses placed 1.52 m apart and 1.5 m above ground (Howell et al., 2007). To avoid pressure variation along the lateral, each spray head was equipped with a 100-kPa pressure regulator. Irrigation applications were scheduled to ensure the level of soil water content in the root zone was maintained between field capacity and a Management Allowed Depletion (MAD) of 50% (Howell et al., 1997). Each lysimeter included a tipping-bucket rain gauge to measure irrigation and precipitation events (Marek et al., 2016a), and the irrigation depths were derived from associated changes in the lysimeter storage. Thus, an irrigation efficiency of 100% was assumed. In the 1993 season, the sorghum in the NE field was fully irrigated, whereas the SE field received 50% of the fully irrigated treatment. In 1998 and 2007, sorghum was grown under dryland conditions in the NW field. Both the NE and SE sorghum grown in 2005 received full irrigation. Full irrigation in this study referred to replenishing the soil water content to field capacity when it approached MAD (Marek et al., 2017). Deficit irrigation treatments occurred on the same dates as the full irrigation and were achieved by reducing the nozzle size of the linear move system in those fields. Experienced scientists and technicians managed all agronomic and irrigation operations to ensure lysimeter representativeness of surrounding fields (Marek et al., 2017)

At OPREC, the experimental design was a randomized complete block design with three irrigation treatments (Full, 75% and 50% of the Full), replicated four times. During the 3-year study period at OPREC, sorghum was irrigated using a subsurface drip irrigation system, with drip tapes buried 0.30 m below the soil surface, and drip lines spaced at 1.53 m apart. Irrigation scheduling was based on fully replacing daily crop ET for the Full irrigation treatment. In each zone, a flow meter was used to measure irrigation applications. Two deficit irrigation treatments received 75% and 50% of the amount of water applied to the Full irrigation treatment. The Aquaplanner program (www.Aquaplanner.net) was used to schedule irrigation in 2014 and 2015, whereas the Oklahoma Mesonet irrigation-scheduling tool was utilized for the 2016 season (Murley, 2016). The Aquaplanner program computes daily soil water status by closing a water balance that includes initial soil moisture, effective precipitation, applied irrigation and crop ET. The Oklahoma Mesonet irrigation-scheduling tool calculates short crop reference ET using the

ASCE standardized Penman-Monteith equation based on various measured weather variables. Crop ET is then estimated from the calculated reference ET and the appropriate crop coefficients, determined from both local calibrations and general recommendations of FAO56 (Allen, Pereira, Raes, & Smith, 1998). The tool uses the calculated crop ET to estimate the timing and depth of irrigation.

4.3.4 Evapotranspiration and Soil Water Content

Monitoring of evapotranspiration (ET) and soil water content (SWC) was conducted only at the CPRL site. ET was measured at every 15-min interval and then summed to obtain daily values using large precision weighing lysimeters (9 m^2 surface area and 2.3 m deep) located at the center of each field. Marek (1988) outlined the design specifications of the precision-weighing lysimeters, and their calibrated accuracy was reported to be 0.04 mm (Evett et al., 2016). Daily ET values were calculated as the difference between lysimeter mass losses (from evaporation and transpiration) and lysimeter mass gains (precipitation, irrigation, and dew) divided by lysimeter area (Evett et al., 2016). The performance of AquaCrop in modeling crop ET was assessed through comparing simulated and measured values on daily and seasonal scales.

The SWC was measured periodically at 0.2-m depth increments beginning with the 0.1-m depth using a neutron probe and access tubes installed within the lysimeters (Howell et al., 2007). The probe was field-calibrated for the Pullman soil (Howell et al., 2007). The measurements were taken at different soil depths to 2.3 m. However, only neutron probe readings taken within the root zone depth (1.8 m) were considered for comparisons since the simulated values represented this depth. The measured SWC from each access tube was calculated as the average of the neutron probe readings within the top 1.8 m. The root zone values were averaged among the access tubes within each lysimeter and used as the measured SWC on each day of measurement.

4.3.5 AquaCrop Model Description

The detailed background and principles behind the AquaCrop model are presented in Steduto et al. (2012) and Raes et al. (2012). Unlike other crop models that simulate leaf area index (LAI), AquaCrop utilizes canopy cover (CC) from crop emergence until senescence. CC forms the basis for estimating crop transpiration (T_r) in the model. The AquaCrop model separates T_r and soil evaporation while simulating the daily water balance. T_r is proportional to canopy cover in the absence of crop stress. However, the presence of water stress triggers leaf senescence, and ultimately reduces T_r. Biomass (B) production is simulated as a function of T_r in the model and is estimated as a product of the normalized water productivity (WP^*) and the ratio of T_r and reference ET (ET_o), throughout the growing season as presented by equation 1 (Steduto et al., 2009).

$$B = WP^* \times \sum\left(\frac{T_r}{ET_o}\right) \quad (1)$$

Water productivity (WP) is normalized for evaporative demand on a daily basis throughout the growing season and is obtained by dividing T_r by ET_o (Vanuytrecht et al., 2014). Finally, the crop harvestable yield (Y) would then be estimated as a product of B and the harvest index (HI) as shown in equation 2 (Hsiao et al., 2009).

$$Y = B \times HI \quad (2)$$

HI, defined as the ratio of grain yield to aboveground dry biomass, is affected by environmental conditions.

4.3.6 AquaCrop Model Input Data

The AquaCrop model data requirements include climatic and management data for the crop, soil, field and irrigation (Raes et al., 2012). The climatic input data for the CPRL site consisted of a 21-year dataset (1990-2010) recorded at a research-grade weather station located adjacent to the lysimeter fields (Howell et al., 1997). The weather station, managed by the Texas High Plains ET Network, collected hourly weather data and was maintained following the ASCE-EWRI specifications. This station was situated over a well-watered, mowed reference grass plot (Marek et al., 2017). Twenty-one years (1997-2017) of weather data for the OPREC site were obtained from an Oklahoma Mesonet station (McPherson et al., 2007) located at OPREC near the test plots. These weather data (rainfall, maximum and minimum temperature, wind, radiation, and humidity) were used to create climatic input files for the AquaCrop model and the ET_o was estimated using the FAO Penman-Monteith equation (Allen et al., 1998). Soil parameters (Table 4.2), field conditions and irrigation applications presented in Tables 3 and 4 were used in the calibration and validation of the model for each study site. Since fertilization was optimal at all sites, soil fertility was set as non-limiting in the model for all simulations. A maximum rooting depth of 1.8 m was used for the CPRL site. Several studies at CPRL including Baumhardt et al. (2007) have observed rooting depth for grain sorghum of 1.8 m in Pullman soils. For the OPREC site, a 1.0 m maximum rooting depth was estimated using soil water extraction patterns observed by soil moisture sensors. A subsurface drip irrigation system was used at OPREC, and this appeared to be the cause of the smaller depth compared to that determined at CPRL. All simulations were started one day after a significant rainfall before planting, and thus, the initial SWC was assumed to be at field capacity.

4.3.7 AquaCrop Model Calibration

The AquaCrop model was calibrated using the 1993/Full irrigation treatment at the CPRL-NE field. Since previous studies have emphasized correct calibration of canopy development to be central for good prediction of transpiration and biomass (Farahani et al., 2009; Vanuytrecht et al., 2014), calibration initially focused on ensuring sound prediction of the canopy development curve for the 1993/Full treatment. The initial canopy cover (CC_o) was estimated using the seeding rate option in the model. The model default value for canopy cover per seedling at 90%

emergence (cc_o) was used. The maximum canopy cover (CC_x) was estimated from the leaf area index (LAI) measured at the calibration treatment following the equation used by Araya *et al.* (2016):

$$CC_x = 1 - \exp(-k * LAI) \quad (3)$$

where k is an extinction coefficient and was taken as 0.416 after Araya *et al.* (2016).

Estimates of dates from sowing to emergence, CC_x and maturity were inputted in the model to give initial approximations of canopy expansion and senescence rates. The canopy growth coefficient (CGC) and canopy decline coefficient (CDC) were adjusted through trial-and-error iterations as described by Raes et al. (2012) so that canopy development could closely match the measured values. The CDC and CGC were estimated as 0.016 and 0.986 % GDD^{-1}, respectively (Table 4.5). Although the threshold values for canopy expansion (p_{upper} and p_{lower}) were default, the curve shape indicating response to water stress for canopy expansion was calibrated from a convex to a linear function to give a better representation of the high sensitivity of leaf expansion of grain sorghum to water stress as reported by Wani, Albrizio, and Vajja (2012). Other water stress parameters that affect stomatal conductance (K_{Ssto}) and accelerated canopy senescence (K_{Ssen}) and their shapes were left default. Similarly, default values of the maximum crop transpiration coefficient ($Kc_{Tr,x}$), normalized crop water productivity (WP^*) and a reference harvest index (HI_o) were used. $Kc_{Tr,x}$ and WP^* generally exhibit conservative characteristics (Raes et al., 2012), hence the choice. For HI_o, the same default value was determined from field measurements by Howell et al. (2007). The AquaCrop model was run in growing degree-days (GDD), calculated in degrees Celsius from the temperature data. The most important default and calibrated crop parameters used for the simulations are given in Table 4.5.

Table 4.5. Default and calibrated (italicized) crop parameters used in the AquaCrop model.

Parameter	Units	Value
Base temperature	°C	8
Cut-off temperature	°C	30
Canopy cover per seedling at 90% emergence	cm^2	3
Canopy growth coefficient	*% GDD^{-1}*	*0.016*
Canopy decline coefficient	*% GDD^{-1}*	*0.986*
Sowing to emergence	*GDD*	*121*
Sowing to maximum canopy cover	*GDD*	*921*
Maximum canopy cover	*%*	*90*
Maximum transpiration coefficient ($Kc_{Tr,x}$)	unitless	1.07
Sowing to flowering	*GDD*	*1040*
Length of flowering	*GDD*	*305*
Sowing to max rooting depth	*GDD*	*1315*
Sowing to senescence	*GDD*	*1420*
Sowing to maturity	*°C*	*1773*
Normalized Crop Water Productivity, WP*	$g\ m^{-2}$	33.7
Canopy expansion function		
P-upper	fraction of TAW	0.15
P-lower	fraction of TAW	0.70
Shape	*unitless*	*0*
Stomatal closure function		
P-upper	unitless	0.75
Shape	unitless	3
Early canopy senescence function		
P-upper	unitless	0.7
Shape	unitless	3

4.3.8 AquaCrop Model Validation

Validation of the AquaCrop model was performed using five and nine treatments from CPRL and OPREC, respectively. The five CPRL treatments were 1993/50%, 1998/Dryland, 2005/Full 1, 2005/Full 2 and 2007/Dryland. The OPREC treatments included all full, 75% and 50% from the 2014, 2015 and 2016 growing seasons. The model was validated based on its ability to simulate CC, ET, SWC and grain yield. The measured CC data were only sufficient in the 1993/Full and 1993/50% treatments at CPRL. Additionally, only measured yield data were available for the OPREC site. Model accuracy and performance was evaluated by means of graphical representations and statistical performance parameters: Prediction Error (P_e), Root Mean Square

Error (RMSE) and Nash-Sutcliffe Efficiency (NSE). These parameters were useful in drawing comparisons between the measured and simulated values for SWC, ET and yield, and they were calculated as:

$$P_e = \frac{(S_i - M_i)}{M_i} \times 100 \quad (4)$$

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(M_i - S_i)^2} \quad (5)$$

$$NSE = 1 - \frac{\sum_{i=1}^{n}(M_i - S_i)^2}{\sum_{i=1}^{n}(M_i - \bar{M})^2} \quad (6)$$

where M_i and S_i are the measured and simulated values, respectively, n is the number of measurements, and $\bar{M}$ is the mean value of M_i.

The P_e and RMSE provide an indication of the deviation of the simulated values from the measured values with estimates approaching zero indicating better performance of the model and good agreement of the measured to the simulated values (Ahmadi et al., 2015; Araya et al., 2016). For grain yield prediction, Xie, Kiniry, Nedbalek, and Rosenthal (2001) highlighted that RMSE less than 0.8 Mg ha^{-1} is considered acceptable. NSE compares the variances of the relative magnitude of the residuals and the measured data (Moriasi et al., 2007). Values of NSE range between -∞ to 1.0 (inclusive). Values ranging from 0.0 to 1.0 represent acceptable model performance, whereas those ≤ 0.0 indicate unacceptable performance (Marek et al., 2017).

4.3.9 AquaCrop Model Application

The calibrated model was applied to assess the effect of variable planting dates and planting densities on grain yield and irrigation requirement in the study area. The range of planting dates and planting densities were determined following consultations with producers and local water managers. Twenty-one years (1997-2017) of weather data, obtained from the Oklahoma Mesonet at the OPREC site were used. Ideally, at least 30 years of climate data is recommended, however, the Oklahoma Mesonet was only commissioned in 1994, with the earlier years having significant missing data. Simulations were done for a fully irrigated crop; with irrigation triggered at a MAD of 55%, following the FAO56 guidelines for grain sorghum. Field management practices such as tillage and fertilizer application that are common in the Oklahoma Panhandle for grain sorghum were used for the simulations. Table 4.6 presents the nine management scenarios that were simulated.

Table 4.6. Planting dates and planting densities for each management strategy.

Strategy	Planting Date	Planting Density (seeds ha^{-1})
S1	25-May	135,908
S2	10-Jun	135,908
S3	25-Jun	135,908
S4	25-May	160,618
S5	10-Jun	160,618
S6	25-Jun	160,618
S7	25-May	185,329
S8	10-Jun	185,329
S9	25-Jun	185,329

An early maturing grain sorghum hybrid was used in strategies with the latest planting date (S3, S6 and S9) to be consistent with local practices. The differences in final grain yield and total seasonal irrigation requirement among the nine scenarios were analyzed using the analysis of variance.

4.3 Results and Discussion

4.4.1 Canopy Cover

The simulated CC for both 1993/Full and 1993/50% treatments was smaller than measured CC earlier in the growing season, but their trends closely matched during mid- and late-seasons (Figure 4.2). The RMSEs for the 1993/Full and 1993/50% for CC were 12 and 11%, respectively.

Additionally, the NSE were 0.85 and 0.89, respectively. These metric values show acceptable performance of the model to simulate canopy cover under irrigated conditions.

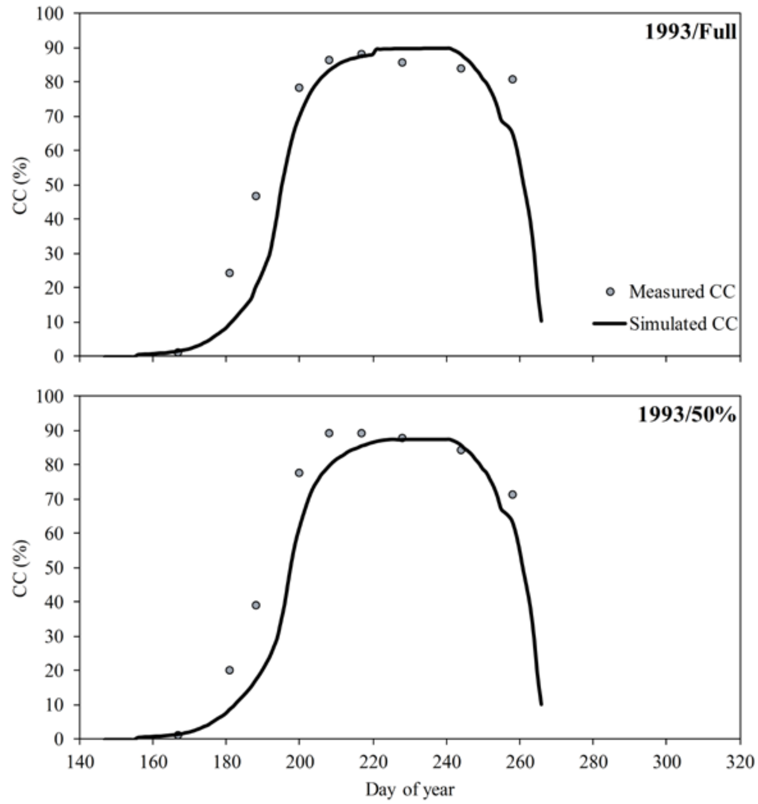


Figure 4.2. Simulated and measured canopy cover for the 1993/Full (calibration) and 1993/50% treatments.

4.4.2 Soil Water Content

The simulated SWC generally followed the trend of the measured values throughout the growing season as shown in Figure 4.3. The model prediction of SWC in irrigated treatments was better than in dryland treatments, particularly during the mid-season. However, the model underestimated SWC late in the season for the two fully irrigated treatments in 2005. Even though there were some soil water response after irrigation and precipitation, the model restricted SWC below field capacity in these treatments. In a simulation study of wheat on various loamy soils in Western Canada, Mkhabela and Bullock (2012) pointed out that the AquaCrop model did not allow SWC to remain above the field capacity for consecutive days, and suspected this occurrence to cause underestimation, particularly when the soil had high water content.

The model made excellent SWC predictions in the 1993 deficit irrigation treatment with slight overestimations towards the end of the growing season. Overestimation of SWC at the end of the growing season could have been a result of relatively faster canopy senescence by the model compared to field conditions. Farahani et al. (2009) reported similar findings for deficit irrigation treatments. For the 1998 and 2007 dryland treatments, the model overestimated SWC throughout the growing season, except for two-single measurements late in the season. Similar findings were reported in several studies when the model was used for simulating SWC for various crops and soil types. Iqbal et al. (2014) investigated winter wheat grown in a loamy soil and highlighted that the model significantly overestimated SWC up to the mid-season under dryland conditions. Furthermore, Hsaio et al. (2009) observed overestimations of SWC in water stressed treatments, and highlighted that this could be a result of the simplification of the model, which assumes that drainage is zero when SWC is at or below FC.

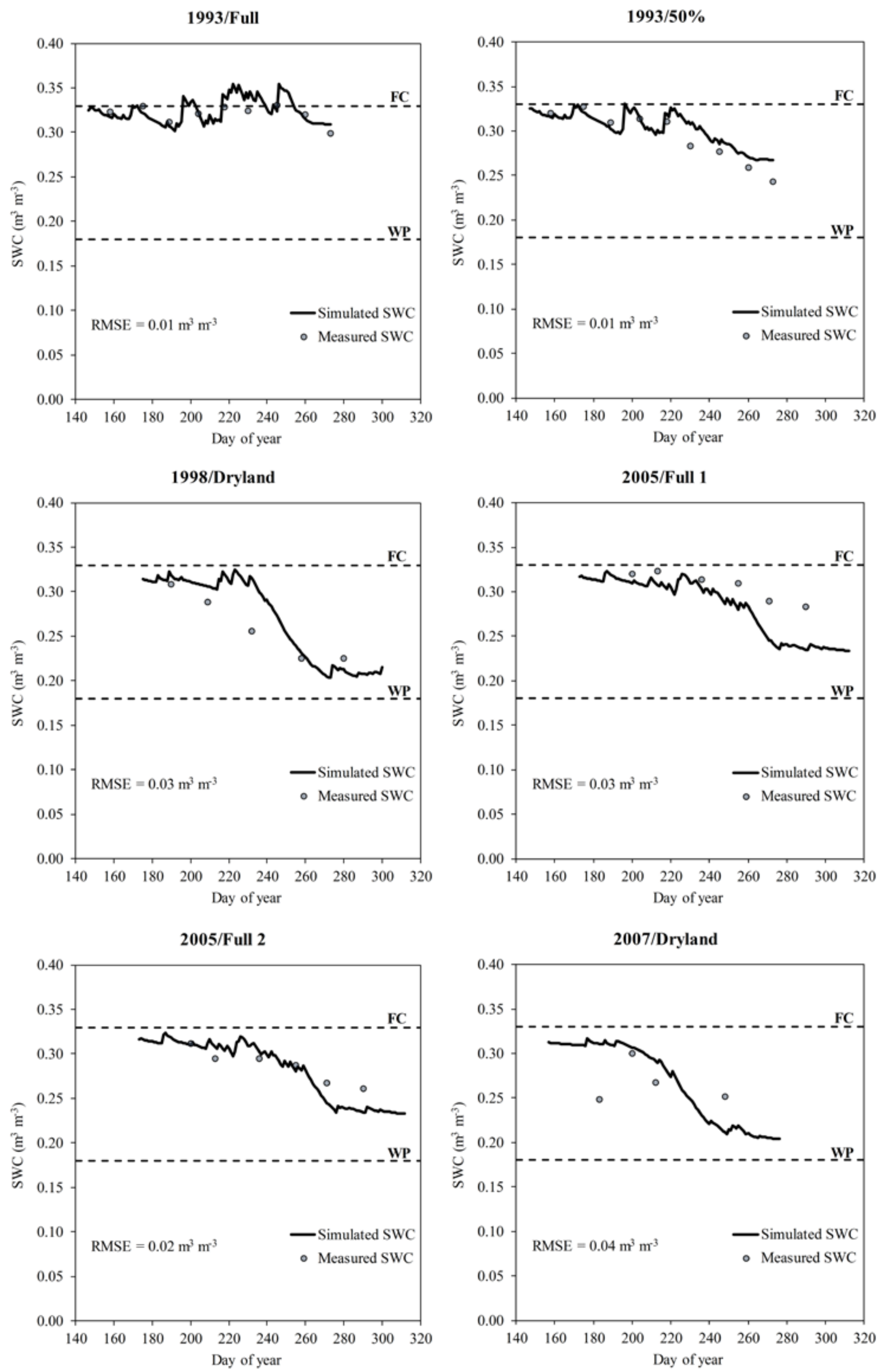


Figure 4.3. Time series of simulated and measured soil water content at the USDA-ARS Conservation and Production Laboratory site.

The P_e values for SWC determined at different days of the growing season for validation simulations ranged from -17 to 4% in fully irrigated, -3 to 10% in limited irrigated and -16 to 25% in dryland treatments. The P_e for the calibration simulation varied from -2 to 4% and the RMSE was 0.01 $m^3 m^{-3}$. The RMSEs ranged from 0.01 to 0.04 $m^3 m^{-3}$ for the validation simulations (Figure 4.3). The normalized RMSE expressed as a percentage of the average of all measured SWC for this study was 9%. Mkhabela and Bullock (2012) found similar RMSE values ranging from 0.03 to 0.05 $m^3 m^{-3}$ for soil water content simulated for grain wheat, with a normalized value of 12%. Mebane, Day, Hamlett, Watson, and Roth (2013) found RMSE values ranging from 0.02 to 0.10 $m^3 m^{-3}$ for SWC simulations for a dryland maize crop, and a study by Ahmadi et al. (2015) determined a range between 0.01 and 0.04 $m^3 m^{-3}$ for irrigated maize under different irrigation levels. Therefore, the accuracy of simulated SWC determined from this study seemed satisfactory, and in agreement with results reported in the literature.

Although a low R^2 (0.56) was achieved for the calibration simulation, high R^2 values ranging from 0.77 to 0.97, were attained for SWC during the validation period for full and limited irrigated treatments, respectively, an indication that the model could explain well the variance in measured SWC. The dryland treatment for the 1998 season had a relatively high R^2 (0.74). However, the 2007 dryland had the least R^2 of 0.17. Overall, the validation results from irrigation treatments were better than those reported in Mkhabela and Bullock (2012), who achieved R^2 values ranging from 0.51 to 0.86. These results further suggest that the AquaCrop model could be utilized for forecasting soil water extraction for irrigated crops, which is key in irrigation scheduling.

4.4.3 Evapotranspiration

The AquaCrop model tended to overestimate daily ET for 1993/50%, especially in the early stages of the growing season (Figure 4.4). However, the measured and simulated daily ET followed a close trend in both of the 2005 Full irrigation treatments throughout the growing season. Whilst 2007/Dryland treatment had a combination of under and overestimation of daily ET, the 1998/Dryland treatment overestimated daily ET in most parts of the growing season. ET temporal trends in the dryland treatments appeared to follow rainfall distribution and overestimation of CC, with more ET after rainfall events. The RMSE for daily ET was 1.5 mm d^{-1} for both full irrigation treatments, 1.9 mm d^{-1} for the limited irrigation (50%) treatment, and 2.6 and 1.9 mm d^{-1} for the 1998 and 2007 dryland treatments, respectively.

In the study by Mebane et al. (2013), ET overestimation by the AquaCrop model was attributed to errors in estimating soil hydraulic parameters including field capacity and wilting point. Soil hydraulic parameters used in this study for the CPRL site were obtained from field measurements reported by Heng et al. (2009), but their representativeness and measurement errors were not reported. These parameters were assumed uniform for all the CPRL fields and could have partly resulted in ET simulation errors. Thus, the argument by Mebane et al. (2013) underscores the need to use accurate soil parameters as these could have an impact on the simulated ET. Heng et al. (2009) found similar trends in ET when the AquaCrop model was applied for simulating maize ET at the CPRL site. They attributed the initial daily ET peaks to the high input temperature and wind data used, which was argued to result in high atmospheric evaporative demand. These climatic parameters are used as input in the model for estimating reference ET. In this study, the soil water content at planting was close to field capacity for all the simulations. It therefore seems likely that a combination of high atmospheric evaporative demand and high SWC could have caused the high ET in the initial phases of the growing season. This argument concurs with the results by Marek et al. (2016b) that used the Soil and Water Assessment Tool (SWAT) model for the same site. They attributed overestimation of ET earlier in the growing season to increased available water content due to occurrence of rainfall events in some years.

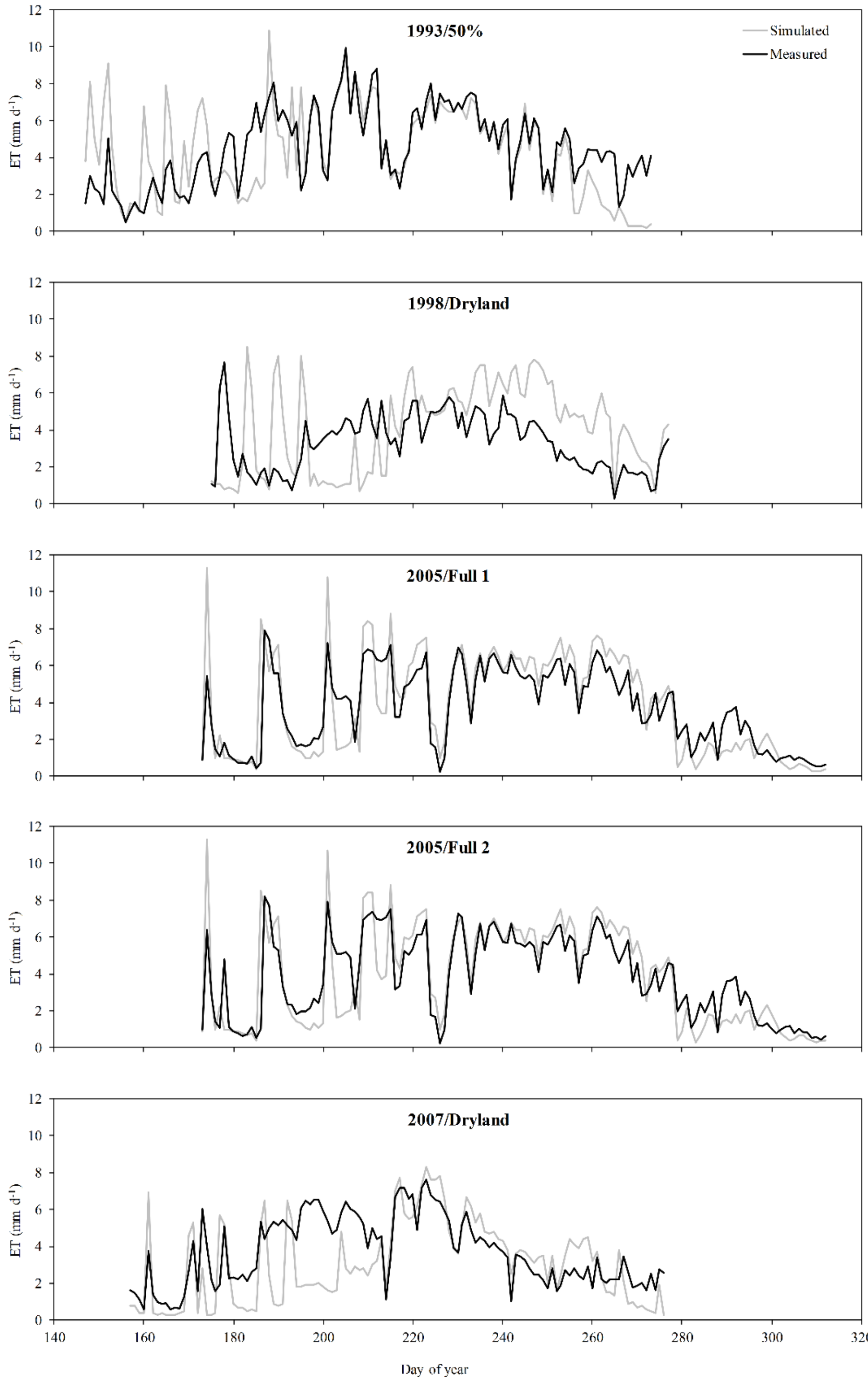


Figure 4.4. Simulated and measured daily ET at the at USDA-ARS Conservation and Production Laboratory site.

The simulated seasonal ET in the irrigated treatments closely approximated the measured values. The P_e values for irrigated treatments used in validation varied from -5 to 4% (Table 4.7).

Table 4.7. Measured and simulated seasonal ET with model prediction errors.

Site name	Growing season	Irrigation Treatment	Seasonal ET (mm) Measured	Seasonal ET (mm) Simulated	P_e (%)
CPRL	1993	Full	634	564	-11
	1993	50%	570	547	-5
	1998	Dryland	341	420	24
	2005	Full 1	516	539	4
	2005	Full 2	542	539	-1
	2007	Dryland	441	368	-17

The error in simulated seasonal ET was larger under dryland conditions in this study with P_e values of 24 and -17% for the 1998 and 2007 growing seasons, respectively. These findings agree with earlier studies which found low accuracy with the AquaCrop model when simulating severe water-stress treatments (Katerji, Campi, & Mastrorilli, 2013; Paredes, de Melo-Abreu, Alves, & Pereira, 2014; Ahmadi et al., 2015). As previously explained, the AquaCrop model simulates transpiration and soil evaporation as a function of CC. Paredes et al. (2014) reported the lack of emphasis by model developers to highlight the importance of CC parameterization as a requisite for accurate simulations. Pereira, Paredes, Rodrigues, and Neves (2015), similarly, recognized the importance of accurate parameterization of CC in the model to achieve accurate estimates of ET, SWC, biomass and yield. However, sufficient LAI measurements were not available for severely stressed treatments for rigorous CC parameterization in this study. This could have had a negative impact on the ET simulation results especially for the dryland treatments where crop growth depended on availability of soil moisture from rainfall events.

Despite the relatively large deviation of simulated seasonal ET under dryland conditions, overall, the RMSE and NSE for seasonal ET with all validation simulations was 51 mm and 0.63, which indicated that the model results were acceptable. The RMSE expressed as a percentage of the measured seasonal average ET was 11%, and this falls within the good performance category (Ahmadi et al., 2015). The coefficient of determination (R^2) between the measured and simulated seasonal ET was relatively high (0.68) as displayed by the one to one plot (Figure 4.5). The seasonal ET simulation results from this study indicated that the AquaCrop model can be useful for making irrigation management and water conservation decisions, as water resource managers and decision makers are more interested in the seasonal crop water use (as opposed to daily ET) for planning purposes.

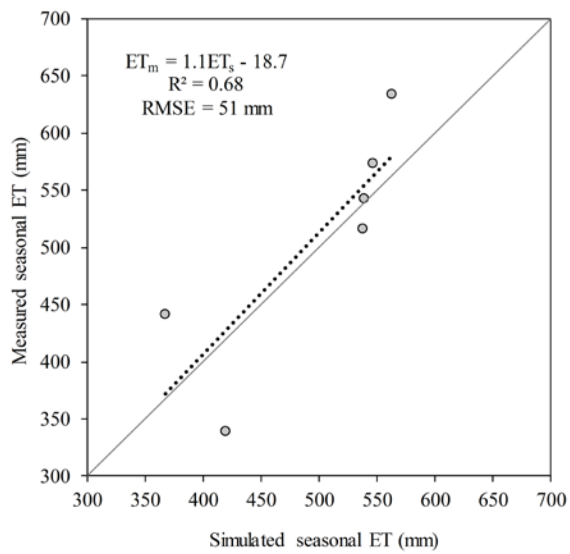


Figure 4.5. A 1:1 plot of the simulated and measured seasonal evapotranspiration for the USDA-ARS Conservation and Production Research Laboratory site.

4.4.4 Grain Yield

The measured and simulated grain yield data are presented in Table 4.8 along with their respective P_e values for each growing season and treatment. Total estimates of ET_o and applied water from irrigation (I) and precipitation (P), simulated seasonal ET and simulated transpiration (T) during the growing season are also provided to assist with analyzing yield variabilities.

Table 4.8. Measured and simulated sorghum grain yield with model prediction errors.

Site name	Growing season	Irrigation Treatment	ET_o (mm)	I+P (mm)	ET (mm)	T (mm)	Yield ($Mg\ ha^{-1}$)		P_e (%)
							Measured	Simulated	
CPRL	1993	Full	780	642	564	367	8.68	8.41	-3
	1993	50%	780	437	547	351	8.26	8.01	-3
	1998	Dryland	855	422	420	286	4.65	5.09	9
	2005	Full 1	843	384	539	348	7.03	7.85	12
	2005	Full 2	843	383	539	348	7.02	7.88	12
	2007	Dryland	713	192	367	236	5.31	6.19	17
OPREC	2014	Full	891	654	612	464	9.66	8.92	-8
	2014	75%	891	558	594	451	9.44	8.91	-6
	2014	50%	891	463	545	418	7.70	8.24	7
	2015	Full	800	616	517	427	10.32	9.31	-10
	2015	75%	800	533	505	421	10.30	9.23	-10
	2015	50%	800	456	488	410	10.29	9.08	-12
	2016	Full	886	522	558	434	8.88	8.80	-1
	2016	75%	886	451	540	425	9.26	9.01	-3
	2016	50%	886	380	489	388	8.51	8.39	-1

At the CPRL site, the 1993/50% achieved an equally high yield as the 1993/Full treatment. This can be explained by a relatively low evaporative demand in the 1993 season as seen by the ET_o in Table 4.8. Additionally, relatively high seasonal rainfall was received in that year, which increased the total water supply in both full and deficit irrigation treatments. Musick and Sletten (1966) reported that grain sorghum required between 508 and 610 mm of water supply to attain maximum yields on a Pullman soil. Similarly, Tolk and Howell (2008) reported an optimized yield-ET relationship at a total water supply of 500 mm in all the soils found in the study area including the Pullman soils. Furthermore, New (2004) reported an average water supply (rainfall + irrigation + initial soil water) of 528 mm to attain optimum yields for grain sorghum in the Texas High Plains. The water supply (rainfall + irrigation) was 642 and 437 mm for the 1993/Full and 1993/50% treatments, respectively. The deficit irrigation treatment received water only slightly lower than previously stated rates, which might be the reason it also attained high yields. Possibilities are that the total water supply for the deficit irrigation treatment was within the water supply range to obtain maximum yields, if the initial available soil water content was added to the sum of rainfall and irrigation applications. Howell et al. (1997) reported seasonal ET for fully irrigated sorghum from different studies, ranging between 549 to 619 mm. The full and 50% irrigation treatments for the 1993 season had measured seasonal ET values of 634 and 570 mm respectively. These values are within the range that results in optimum yield for a fully irrigated crop.

The two 2005/Full treatments had lower yields compared to that of 1993. The 2005 growing season was characterized by significantly higher evaporative demand, yet the crop received less water than in 1993. This might have contributed to the lower yield achieved in 2005. The two dryland treatments in 1998 and 2007 had the smallest yields at CPRL. However, these yield measurements were close or above the upper limit of 5 Mg ha^{-1}, reported by Wade and Douglas (1990) under dryland conditions and similar plant densities.

At the OPREC site in 2014, the yield for the full and 75% irrigation treatments were similar but significantly different from the 50% treatment. Both the 2014/Full and 2014/75% treatments received water supply well above the reported requirement for optimum yield. However, water application for the 2014/50% was less than reported ranges considering the high ET_o in that year. In addition, the timing of rainfall could have played a role in achieving lower yield. Most of the 2014 rainfall was received earlier in the season, followed by a dry period around the middle of the season. The earlier rainfall resulted in pronounced vegetative growth (anecdotal records), which exacerbated the negative impact of the short dry period on yield. The AquaCrop model managed to simulate mild water stress during the dry period for the 2014/50% treatment. However, this mild stress did not result in a significant yield reduction and the simulated value was similar to that of the other two treatments. Based on the relative higher yield in the 2014/50% treatment, it appears that the mid-season mild stress enhanced HI, and this resulted in a higher simulated yield than expected.

In the 2015 season at OPREC, differences in the irrigation water supply had no impact on yield. In addition, the largest measured and simulated yields were achieved in this year, possibly because of the low evaporative demand and more in-season rainfall. In the 2016 season, the 50%, 75% and full irrigation treatments attained similar grain yield despite the differences in water supply. It is likely that the sorghum variety that was grown in 2016 was more tolerant to water stress, hence the attained high yield.

Steduto et al. (2012) reported that prediction of yield with less than 15-20% error is reasonable. In this study, the range of P_e for grain sorghum yield was -3 to 17% for the CPRL site and -12 to 7% for the OPREC site. These results are comparable to others found in literature. For instance, Araya et al. (2016) achieved P_e values ranging from -16 to 18% for grain sorghum yield using AquaCrop. In a malt barley study using AquaCrop for two contrasting rainfall years, Pereira et al. (2015) attained P_e values of -3% and +17% for dry and wet years, respectively. Bello and Walker (2016) obtained P_e values that varied between -10 and 16% under dryland, moderate, and full irrigation for pearl millet. The yield prediction accuracy in the current study was better than the results by Iqbal et al. (2014), who obtained a P_e of -43.2% in their dryland simulations of winter wheat yield.

The NSE was 0.83, indicating that the model performance in simulating grain yield was acceptable. The RMSE was 0.70 Mg ha^{-1}. Bello and Walker (2016) found a similar RMSE of 0.51 Mg ha^{-1} for pearl millet using the AquaCrop model. Xie et al. (2001) achieved RMSEs of 0.36 and 0.71 Mg ha^{-1} for grain sorghum yield using the ALMANAC and SORKAM models, respectively. RMSE less than 0.8 Mg ha^{-1} was considered acceptable and indicated that the model could be used for yield prediction (Xie et al., 2001). Kiniry and Bockholt (1998) obtained a mean RMSE of 0.73 Mg ha^{-1} using the ALMANAC model for several Texas environments. The one to one plot shown in Figure 4.6 indicates that the model closely simulated the grain yield with acceptable accuracy. The R^2 of 0.91 with a slope and intercept of 1.42 and -3.33, respectively, showed a good agreement between the simulated and measured yield. Overall, the model produced fair to good results in simulating grain yield as compared with past studies (Kiniry & Bockholt, 1998; Xie et al., 2001).

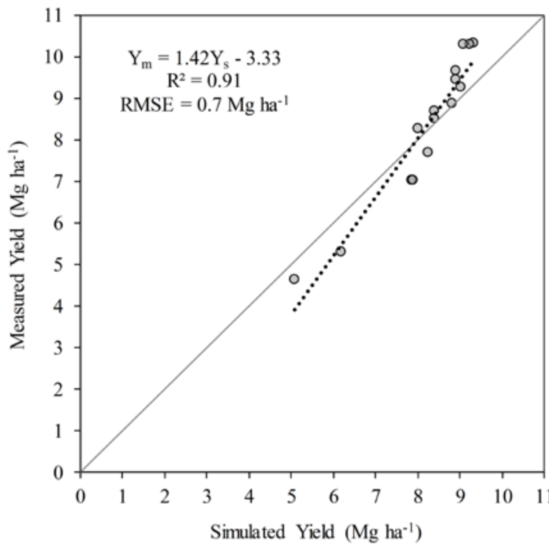


Figure 4.6. Simulated and measured grain yield for all the study years at the two sites.

4.4.5 AquaCrop Model Application

The calibrated AquaCrop model was applied to run scenarios of variable planting dates and planting densities to assess their impacts on grain yield and irrigation requirement. The scenario analysis results showed no significant interaction between planting date and planting density over the 21-year study period. The planting density had no significant effect on grain yield or seasonal irrigation requirement at a significance level of 0.05. The 21-year average grain yield was 7.6, 7.8 and 7.9 Mg ha^{-1} for planting densities of 135,908, 160,618 and 185,329 seeds ha^{-1}, respectively. The average seasonal irrigation requirement ranged between 389 and 403 mm, an indication that no significant water savings may be achieved by considering only planting densities within the range used in this study. However, by adopting the 135,908 seeds ha^{-1} density, producers may benefit from cutting the cost of seed. On the other hand, significant differences were observed in grain yield and seasonal irrigation requirement for different planting dates. This was clearly seen across the simulated strategies, as presented in Figures 4.7 and 4.8 below.

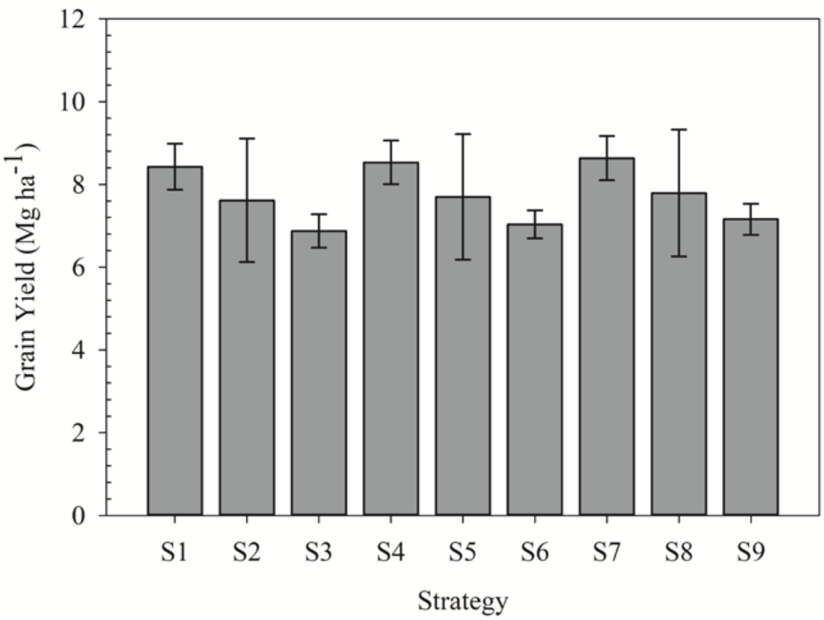


Figure 4.7. Grain yield achieved by each strategy.

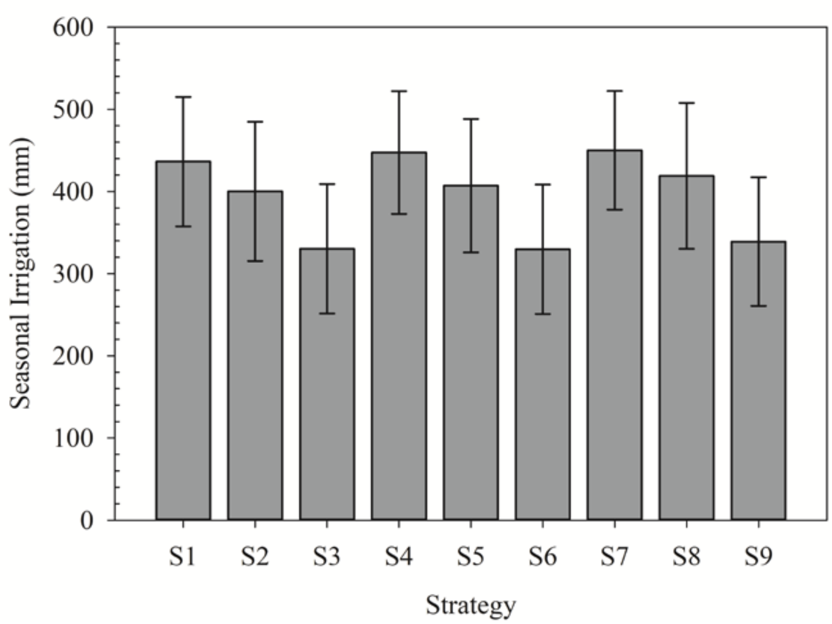


Figure 4.8. Seasonal irrigation requirement achieved by each strategy.

Grain yield declined for later planting dates. The 21-year average grain yield was 8.5, 7.7 and 7.0 Mg ha^{-1} for the 25-May, 10-June and 25-June planting dates, respectively, and this difference was statistically significant ($p < 0.001$). Baumhardt and Howell (2006) reported similar findings and their results showed attainment of greater yields in early-planted grain sorghum grown under full irrigation. The average seasonal irrigation followed the same trend as the grain yield. The respective average seasonal irrigation requirement for the 25-May, 10-June and 25-June planting dates was 445, 409 and 333 mm and the difference among treatments was statistically significant ($p < 0.001$). These results are consistent with those reported by Araya et al. (2016), who also reported lower irrigation requirements and higher water productivity with late planting for grain sorghum in Kansas. These results present an opportunity for producers in the study area to choose appropriate planting dates for grain sorghum that can work with their respective well capacities. However, future studies in the area should include economic analysis of each strategy so that producers are informed of the costs and benefits of each strategy.

4.5 Conclusion

The AquaCrop model was calibrated and validated for simulating evapotranspiration (ET), soil water content (SWC), and yield of variably irrigated grain sorghum, grown at two sites in the Central and Southern High Plains. The model produced better results for simulating daily and seasonal ET under irrigated as compared to dryland conditions. The model's ability to simulate seasonal ET highlighted its potential for use in irrigation planning and formulating deficit strategies. For SWC, the model again performed better in irrigated treatments as compared to dryland treatments, particularly during the mid-season. AquaCrop underestimated SWC in fully irrigated treatments late in the season, and it generally overestimated under dryland conditions until mid-season. The model predicted grain yield with acceptable accuracy for all irrigation and dryland treatments, with errors similar to or smaller than those reported in previous studies. Overall, the model performed well considering the limited measured datasets that were used for calibration. Therefore, the AquaCrop model can be used as a tool for evaluating the effects of different irrigation managements in the semi-arid and arid regions. The calibrated model was used to evaluate the effects of planting date and density on grain yield and seasonal irrigation requirements in the study area. Both grain yield and seasonal irrigation requirement were reduced significantly due to late planting but were not affected by planting density in the range that was used.

CHAPTER V

CONCLUSIONS

Water scarcity continues to be a threat for sustainable agricultural production and regional economies in many arid and semi-arid regions. There is an increasing need to strategize irrigation management under various climatic and environmental conditions to optimize water use in agriculture. To advance this vision, the present research used field monitoring and crop modeling to evaluate irrigation and crop management strategies for cotton and grain sorghum in the southern Great Plains of the U.S. The objectives of the research were to (1) investigate the impacts of irrigation termination date on cotton yield and irrigation requirement, (2) calibrate and validate a crop model for cotton and to apply the model to study the impact of irrigation capacity and seasonal weather conditions on cotton yield at a site that relies on the Ogallala aquifer for irrigation supply, and (3) calibrate and validate a crop model for variably irrigated grain sorghum by simulating soil water content, evapotranspiration and yield, and to apply the model to evaluate the performance of key water management scenarios.

In the first study (Chapter 2), evaluation of the effects of irrigation termination timings for cotton showed a general increase in cotton yields by delaying irrigation termination, and minimal effects were found for most of the fiber quality parameters. Additionally, the study revealed significant reductions in irrigation requirement with earlier termination dates. However, this water conservation caused considerable declines in cotton yield and fiber micronaire. This study recommended additional research to investigate the economic trade-offs between revenue losses from declined cotton lint value and reductions in water and energy expenses when implementing earlier irrigation termination of cotton. Furthermore, the study showed that monitoring technologies such as soil moisture sensors could be used as important decision-making tools for irrigation management and in implementing water conservation efforts. However, due to the cost of sensors and relative high sensor requirements per unit area under variable field conditions, the potential water savings and yield improvements may not offset the cost of these technologies. Thus, there is a need for further research towards the development of cost effective monitoring technologies to increase adoption by producers.

In the second study (Chapter 3), the results showed satisfactory performance by the AquaCrop model for simulating cotton production in the southern Great Plains. When the calibrated model was applied to evaluate the effects of irrigation capacity and seasonal weather conditions at a site that relies on the Ogallala aquifer for irrigation supply, the results showed significant year-to-year variability of cotton yields across all the studied irrigation capacities (0 to 0.6 $l\ s^{-1}\ ha^{-1}$). Yield variability appeared to be a result of the differences in accumulated seasonal heat units. Furthermore, the results revealed no significant increase in cotton yields at irrigation capacities higher than 0.3 $l\ s^{-1}\ ha^{-1}$ in the Ogallala aquifer region. This study recommended the use of available weather platforms and data when making irrigation and crop management decisions. This is particularly important for the southern Great Plains region, where growing season conditions, including rainfall and temperature are highly variable.

In the simulation study for grain sorghum (Chapter 4), the results indicated that the AquaCrop model could be used as an effective tool for evaluating the impacts of variable crop and irrigation managements on the production of grain sorghum in the Central and Southern High Plains of the Ogallala Aquifer region. Scenario analyses revealed a significant impact of planting date on grain sorghum yield and irrigation requirements but the impact of planting density was minimal. These findings are important for producers as this gives them valuable information of the key variables to focus on when making irrigation and crop management decisions. This study demonstrated the potential of incorporating short-term field experiments with crop simulation models using long-term historic climate data as a useful tool in ascertaining suitable irrigation management strategies.

Overall, the three studies in this dissertation have shown the potential for enhancing water conservation in the southern Great Plains region through strategic crop and irrigation managements. However, the success of these strategies may depend on the uptake and adoption by the producers in the southern Great Plains region. There is need to find ways that increase adoption of irrigation management strategies by producers to enhance water conservation. Thus, further research is needed to explain the factors that influence producers' adoption of water conservation practices. Such research may include investigating the socio-economic factors that impede the adoption of water management tools and technologies. This would require integrated management approaches through collaborations from all stakeholders in the water sector. Lastly, it is necessary to translate the results presented in this research in ways that make them policy relevant and useful to producers using appropriate language.

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