Agricultural Systems 170 (2019) 49–62

Contents lists available at ScienceDirect

Agricultural Systems

journal homepage: www.elsevier.com/locate/agsy

Simulation of efficient irrigation management strategies for grain sorghum production over different climate variability classes

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ARTICLE INFO

Keywords:
Climate variability
CERES-Sorghum
CROPGRO-Cotton
Irrigation strategy
Water use efficiency

ABSTRACT

The Texas High Plains (THP) is a productive agricultural region, and it relies heavily on the exhaustible Ogallala Aquifer for irrigation water for crop production. Efficient use of irrigation water is critical for the sustainability of agriculture in the THP. Grain sorghum is one of the major crops grown in the region, and it is known for its drought tolerance and lower water requirement compared to other cereal crops such as corn. In this study, the CERES-Sorghum and CROPGRO-Cotton modules of the Decision Support System for Agrotechnology Transfer (DSSAT) were evaluated using data from cotton-sorghum rotation experiments at Halfway, Texas over a period of nine years (2006–2014). The evaluated CERES-Sorghum model was then used to identify the optimum (i) initial soil moisture at planting (ISM); (ii) threshold to start irrigation (ITH); (iii) threshold to terminate irrigation; and iv) deficit/excess (DFI) irrigation strategy for grain sorghum production based on simulated sorghum yield, irrigation water use efficiency (IWUE), and grain water use efficiency (WUE). In addition, the effect of weather conditions on simulated strategies was elucidated by dividing the long-term (1977–2016) weather data into cold, warm, wet, dry, and normal climate variability classes based on the 33rd and 66th percentiles of growing season temperature and precipitation. The DSSAT model adequately simulated the grain sorghum and seed cotton yields during calibration (average Percent Error (PE) of 1.3% (sorghum) and 3.4% (cotton)) and evaluation (average PE of −2.2% (sorghum) and −10.5% (cotton)). The results from long-term simulations indicated that weather conditions played a key role in selecting appropriate irrigation management strategies. Under normal/cold/wet weather, ISM of 75% available water holding capacity (AWC), ITH of 50%, and DFI 85% were found to be adequate for irrigated grain sorghum production. However, in warm/dry weather, ISM of 75%, ITH 60%, and DFI at 100% reduced sorghum yield loss.

1. Introduction

The semi-arid Texas High Plains (THP) is an important agricultural region in the United States with 1.8 million ha of irrigated land (Weinheimer et al., 2013). The primary source of irrigation in the THP region is the Ogallala Aquifer. Water has been withdrawn from this aquifer at a much higher rate than it has been replenished. This has resulted in a rapid decline in the groundwater levels, especially in the southern portion of the aquifer (Chaudhuri and Ale, 2014; Scanlon et al., 2012). In view of the declining groundwater resources, the Groundwater Conservation Districts in the THP have started imposing restrictions on groundwater pumping (HPWD, 2015). These restrictions are designed to achieve certain percent volumetric storage (varies within the Groundwater Management Area) available in 50 years, also known as Desired Future Conditions (Mace et al., 2008). Recent studies (Modala et al., 2017; Nielsen-Gammon, 2011) project warm and dry future climate in the region, which necessitate larger groundwater withdrawals to meet higher crop evapotranspiration requirements, and hence raise further concerns about future groundwater availability for irrigation. Therefore, it becomes imperative to adopt efficient water management practices to sustain agricultural production in this region.

Colaizzi et al. (2009) studied irrigation trends in the THP and suggested that replacing high-water demand crops with low-water demand crops could reduce groundwater withdrawals by nearly 20%. Grain

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https://doi.org/10.1016/j.agsy.2018.12.011
Received 8 June 2018; Received in revised form 26 December 2018; Accepted 27 December 2018
Available online 04 January 2019

sorghum is one of the important low-water use crops grown in the THP. Major crops grown in the THP region are cotton, wheat, corn and sorghum with planted acres equal to 52%, 25%, 12% and 8%, respectively of the total field crop acreage in the THP in 2017 (USDA-NASS, 2018). Annual planted area of grain sorghum during 1977–2016 was on average 0.5 million ha (USDA-NASS, 2018). Although the popularity of grain sorghum in the region declined after the late 1970s, there is a renewed interest in this crop in recent times due to its lower water requirement and dependable performance under varied weather patterns and ethanol production (Rooney et al., 2007). Development and evaluation of efficient irrigation strategies for sorghum production could not only assist producers in efficiently utilizing valuable groundwater resources from the Ogallala Aquifer, but also provide useful information for sorghum growers and researchers working in similar agro-climatic regions.

Previous studies in the THP, mostly field experiments, focused on studying the effects of soil water and irrigation management practices on grain sorghum yields (Hao et al., 2014; Musick and Dusek, 1971; O'Shaughnessy et al., 2014; Tolk and Howell, 2003; Unger and Baumhardt, 1999). Unger and Baumhardt (1999) performed a regression analysis between annual and growing-season rainfall, soil water content at planting, soil water use, and crop evapotranspiration (ET_c) to identify the reasons for the steady increase in dryland sorghum yields from 1939 to 1997 at Bushland in the THP. They found that an increase in soil moisture at planting, mainly due to adoption of conservation-tillage that improved crop residue retention, was the dominant factor for yield increase apart from the use of improved hybrids. In another study at Bushland, Tolk and Howell (2003) evaluated four irrigation treatments (100%, 50%, 25%, and 0% ET_c replacement) in two growing seasons (1998–1999) and concluded that irrigation water use efficiency (IWUE) decreased with increasing irrigation, and IWUE was higher in milder (lower temperature, high rainfall) climatic conditions. They have also reported that the sorghum grain yields were more susceptible to changes in environmental conditions in a Pullman clay loam soil than in Ulysses and Amarillo soils. In a more recent deficit irrigation evaluation study conducted at Bushland from 2009 to 2011, O'Shaughnessy et al. (2014) reported higher grain sorghum yields with higher irrigation amounts (80% of full replenishment of soil water depletion to field capacity in the top 1.5 m soil profile) than those reported in lower irrigation (55%, 30%, and 0% of full replenishment) treatments. However, IWUE was higher with a 55% of full replenishment irrigation when compared to 80% of full replenishment, except for the drought year of 2011. Hao et al. (2014) also noted a difference in IWUE response to irrigation under different climatic conditions at Bushland, with a general trend of higher IWUE for biomass yields in photoperiod-sensitive sorghum (bioenergy crop) in limited irrigation when compared to full and no irrigation conditions. Nearly all these field studies were conducted at the USDA-ARS Conservation and Production Research Laboratory at Bushland and they spanned over three or fewer growing seasons only.

Bordovsky et al. (2011) conducted a long-term deficit irrigation study on cotton-grain sorghum rotation at the Texas A&M AgriLife Research Station at Halfway in the THP. The treatments included both rainfed and irrigated with those having maximum irrigation capacities of $1.7\ \mathrm{mm\ d^{-1}}$ and $3.4\ \mathrm{mm\ d^{-1}}$ irrigation. Grain sorghum yields and IWUE in this experiment were generally higher for the $3.4\ \mathrm{mm\ d^{-1}}$ treatment compared to the other two treatments. Although, the study provided useful comparison of sorghum IWUE and grain yields over six growing seasons (2003–2008), it did not consider the crop yield responses to soil moisture at planting. Moreover, irrigation was supplied to fulfill cotton ET requirements first and the remainder of available water was applied to grain sorghum, resulting in non-uniform irrigation application for grain sorghum in different years of the experiment. A critical understanding of the interactive effects of climate variables and irrigation management decisions (e.g. soil water at planting, soil water threshold for initiating irrigation, deficit irrigation levels, etc.) on crop growth and yield over a longer period of time is of utmost importance for developing efficient irrigation strategies for grain sorghum production.

After a thorough calibration using field data sets, crop models can be useful complements to field experiments for quickly and inexpensively evaluating different irrigation strategies with reasonable confidence based on generally available long-term weather data. They simulate crop growth and development under numerous crop management and agro-climatic scenarios. The Decision Support System for Agrotechnology Transfer Cropping System Model (DSSAT-CSM) (Jones et al., 2003) has been successfully applied in the THP and nearby Texas Rolling Plains for simulating deficit irrigation for cotton (Modala et al., 2015), winter wheat (Attia et al., 2016), and corn (Marek et al., 2017). Although the CERES-Sorghum (Alagarswamy and Ritchie, 1991) module of DSSAT-CSM has been used by a few researchers (Carbone et al., 2003; Fu et al., 2016) to simulate the effect of different management practices and environmental conditions on sorghum production at different locations in the US, it has not been evaluated for the THP region.

The specific objectives of this study were to (i) evaluate the DSSAT CSM CERES-Sorghum module for the THP region using measured data from long-term cotton-grain sorghum rotation experiments at the Helms Farm, Halfway, TX, and (ii) use the evaluated CSM CERES-Sorghum model to determine the optimum soil moisture content at planting, identify the optimum soil moisture threshold for initiating irrigation, and suggest appropriate deficit irrigation strategies for sorghum in the THP region. Since measured data used for evaluating the CERES-Sorghum module came from a cotton-grain sorghum rotation experiment (instead of a grain sorghum monoculture experiment), a DSSAT sequential project was created and the CROPGRO-Cotton module was also evaluated simultaneously in this study. This additional step was necessary to ensure that the water and nutrient balances during the years when cotton was grown (in between two grain sorghum crops) and during the fallow periods between grain sorghum/cotton growing seasons were simulated accurately.

2. Material and methods

2.1. Study area/experiment site

In this study, field data from cotton-sorghum rotation experiments (TALR, 2016) conducted at Halfway, TX (34° 9′ N, 101° 57′ W, 1071 m above mean sea level, Fig. 1), from 2006 to 2014, were used for the evaluation of CERES-Sorghum and CROPGRO-Cotton (Boote et al., 1998) modules. Sorghum was grown after two years of cotton in two adjacent sections of a Low Energy Precision Application (LEPA) center pivot irrigation system, namely plots 5b and 5f (Fig. 1). Irrigation was applied at three levels, i.e., base, high, and low levels. These three variable irrigation rates were replicated in four spans of the center pivot. The base water level approximately matched 80% of the crop evapotranspiration rate (ET_c) from 2006 to 2009, and 60% of the ET_c from 2010 to 2014. The high and low irrigation levels were kept at ± 20% of the base level in the year 2006, and ± 50% of the base level from 2007 to 2014. The sequence of crops and the irrigation amounts applied for the three treatments in this study are summarized in Table 1. The climate at the study site is semi-arid and the soil is deep well-developed Pullman Clay Loam (Fine, mixed, superactive, thermic Torrertic Paleustolls). Additional information about climate, soil, and cropping system at the study area is provided in the model input section.

2.2. DSSAT-CSM description

The DSSAT-CSM (Jones et al., 2003) simulates crop growth and yield as well as soil water, carbon, and nitrogen processes over time based on weather, soils, crop management, and crop cultivar data. The

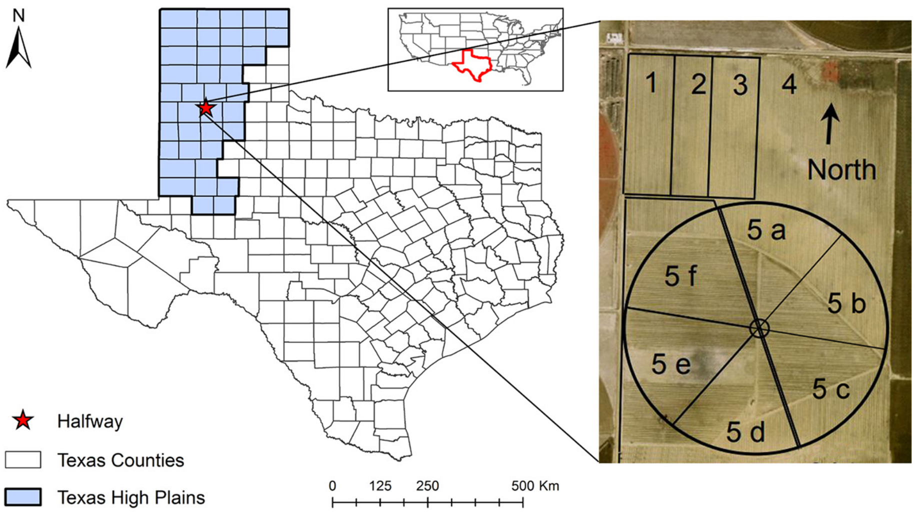

Fig. 1. Location of Helms Farm near Halfway in the Texas High Plains (left). Layout of the center pivot system at the farm (right) (TALR, 2016).

Table 1
Summary of growing season irrigation amounts applied, and rainfall received during cotton-sorghum rotation experiments at Halfway.

Plot	Year	Crop	Irrigation during growing season (mm)			Seasonal rain (mm)
			High	Base / Medium	Low	
5b	2006	Cotton	429	389	332	278
	2007	Sorghum	330	218	112	335
	2008	Cotton	449	307	171	232
	2009	Cotton	276	187	104	316
	2010	Sorghum	229	162	104	292
	2011	Cotton	492	342	191	68
	2012	Cotton	395	275	151	236
	2013	Sorghum	299	200	86	263
5f	2011	Cotton	451	300	150	68
	2012	Sorghum	367	255	138	236
	2013	Cotton	319	226	130	263
	2014	Cotton	92	63	36	483

latest DSSAT 4.6.1 version (Hoogenboom et al., 2015) contains over 42 different crop growth simulation models including models for cereals, legumes, fruit, fiber, oil, sugar, vegetables, and forage crops.

The DSSAT-CSM provides five methods for simulating irrigation, out of which two methods are available for automatic irrigation: (i) automatic when required and (ii) fixed amount automatic. Amount of irrigation water applied through automatic irrigation (auto-irrigation) is estimated based on the soil available water content (AWC), which is equal to the difference between the field capacity (SDUL) and wilting point (SLLL) soil water contents. Auto-irrigation is triggered when the soil moisture drops to the irrigation lower limit and ends once the water is replenished up to upper limit of auto-irrigation. The “Automatic when required” method allows setting the lower limit as percent of maximum AWC while keeping the upper limit as constant at 100%, whereas in the “fixed amount automatic” method, in addition to lower limit, the amount of irrigation to be applied (in mm) to refill soil profile can be specified. In this study, the “automatic when required” option was used for determining optimum soil moisture at planting and threshold to start irrigation, and the “fixed amount automatic” option was used for creating deficit irrigation scenarios.

A sequence analysis was initially carried out in this study during the model evaluation to mimic cotton-sorghum rotation field experiments at Halfway, and then seasonal analysis was conducted to run long-term (1977–2016) sorghum monoculture scenarios.

2.3. Model input data

2.3.1. Weather data

The weather data for this study was obtained from the Texas High Plains Evapotranspiration Network (TXHPET) (Porter et al., 2005) weather station at Halfway, TX for the period from 1977 to 2016. The climate variables included minimum and maximum air temperature (°C), precipitation (mm), solar radiation (MJ m^{-2}), wind speed (m s^{-1}), and relative humidity (%). Missing values were filled with the data obtained from the National Oceanic and Atmospheric Administration (NOAA, 2017), Agricultural Modern-Era Retrospective Analysis for Research and Applications (AgMERRA) (Ruane et al., 2015) and NASA's Prediction of Worldwide Energy Resource (Stackhouse, 2006). The average annual precipitation at Halfway over the period from 1977 to 2016 was about 463 mm, and the daily mean temperature varied from −15 °C to 32 °C. A summary of annual rainfall and sorghum growing period (May–October) rainfall and average temperature is presented in Fig. 2.

2.3.2. Weather data classification

Long-term weather data at Halfway was classified into nine different climate variability classes based on growing season air temperature and precipitation (Fig. 2). The years with growing season precipitation below the 33rd percentile (272 mm) were considered “dry” years, and those with precipitation above the 66th percentile (356 mm) were considered “wet” years. Similarly, the years with average growing season temperature below 33rd percentile (21.2 °C) and above 66th percentile (21.8 °C) were classified as “cold” and “warm” years, respectively (Fig.3). The years that did not fall under any of the above four categories were considered “normal” years. The thresholds chosen in this study were intermediate to the 25th and 75th percentiles used by Chmielewski and Potts (1995) and the 40th and 60th percentiles used by Auer and Böhm (1994). Based on these five categories of years, nine climate variability classes were defined, and the years falling within each climate variability class are listed in Table 2.

2.3.3. Crop management data

The crop management data for cotton-sorghum rotation experiments at Halfway were obtained from Helms Farm Annual Reports, which are available on the Texas A&M AgriLife Research website (TALR, 2016). Data from a total of 36 treatments from 8 cotton and 4 sorghum growing seasons in combination with three irrigation levels were used in this study. Seeds were planted at a 3.8 cm depth in circular rows 1.02 m apart using a John Deere MaxEmerge™ Planter. One or more crop varieties were planted within each irrigation treatment in a

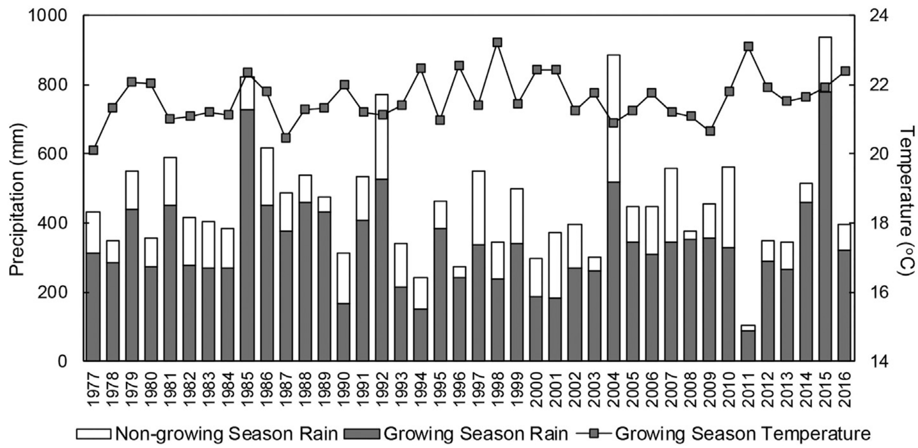

Fig. 2. Annual and growing season (May–October) precipitation and growing season average air temperature at Halfway, TX from 1977 to 2016.

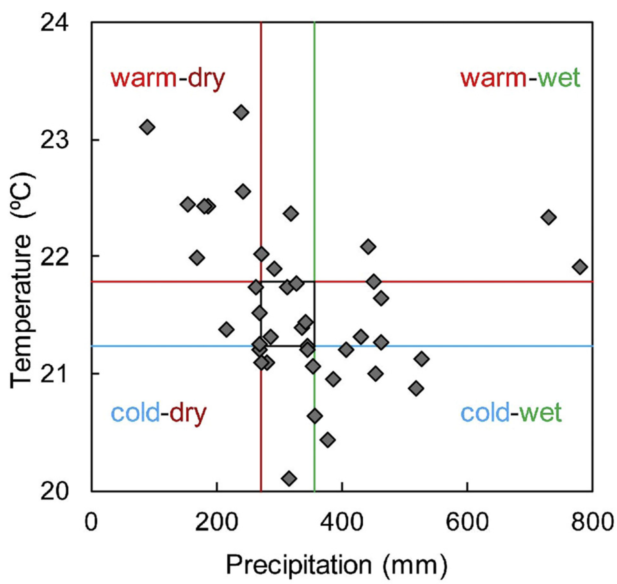

Fig. 3. Classification of long-term weather data at Halfway, TX based on 33rd and 66th percentiles of air temperature and precipitation.

Table 2
Climate variability classes defined for climate variability impact assessment.

Climate variability class	Code	Number of years	Years
Warm-Wet	WW	4	1979, 1985, 1986, 2015
Warm-Dry	WD	8	1980, 1990, 1994, 1996, 1998, 2000, 2001, 2011
Cold-Wet	CW	7	1981, 1987, 1991, 1992, 1995, 2004, 2009
Cold-Dry	CD	2	1983, 1984
Warm-Normal	WN	2	2012, 2016
Cold-Normal	CN	5	1977, 1982, 2005, 2007, 2008
Normal-Normal	NN	5	1978, 1997, 1999, 2006, 2010
Normal-Dry	ND	4	1993, 2002, 2003, 2013
Normal-Wet	NW	3	1988, 1989, 2014

year, and the varieties changed over time depending on availability. The DSSAT evaluation was performed based on field data collected for the early-maturity cotton cultivars (Sharma et al., 2015; Snowden et al., 2014; Speed et al., 2008) including DP 104B2RF, FM 9180 B2F and FM 2011 GT, and medium-maturity grain sorghum cultivars (Schnell et al., 2015), DKS 44-20 and DKS 49-45. The aim of the calibration effort in this study was to develop a generic set of cultivar parameters for a medium-maturity grain sorghum and an early-maturity cotton, which would reasonably simulate phenology and crop yield over the 9-year period, and eventually use those calibrated parameters for suggesting efficient irrigation strategies for grain sorghum over a variety of climate classes. The hypothesis behind this methodology was that the parameters developed from a wide range of seasonal conditions would be more robust than those developed from a single season (He et al., 2017; Timsina and Humphreys, 2006).

The details of planting and fertilizer application are presented in Table 3. For the long-term (1977–2016) irrigated and dryland sorghum simulations, crop management-related model inputs were specified based on the actual practices adopted in the Halfway experiments and common cultural practices followed for sorghum production in the THP region as outlined in the High Plains Production Handbook (McClure et al., 2010) (Table 3). For the auto-irrigation used in the long-term simulations, a management depth of 0.3 m of topsoil (default) and an irrigation efficiency of 90% were considered to represent the Low Energy Precision Application (LEPA) center-pivot irrigation system used at the location (Bordovsky and Lyle, 1996; Colaizzi et al., 2009).

2.3.4. Soil data

Some of the soil input parameters were directly obtained from soil sample analysis results from the study site (Adhikari et al., 2016), and the remaining parameters were generated using the SBuild tool distributed with the DSSAT model (Uryasev et al., 2004). The parameters taken from soil sample tests include percentages of clay, silt, organic carbon and total nitrogen, pH and cation exchange capacity (cmol kg^{-1}). The parameters generated using these values in the SBuild were saturated hydraulic conductivity (cm h^{-1}), soil water lower limit (cm cm^{-1}), drained upper limit (cm cm^{-1}), soil water at saturation (cm cm^{-1}), soil bulk density (g cm^{-3}), and soil root growth factor (Table 4). The simulated plant available water content of 21.3 cm in the top 200 cm profile was close to the values reported for Halfway in a previous study, which varied between 17.5 cm and 21.0 cm (Clouse, 2006). The lower and upper soil water limits and saturated hydraulic conductivity used in this study were also within the range of values estimated using pedotransfer functions by Nelson et al. (2013) for this study site.

2.4. Model calibration and evaluation

The CERES-Sorghum and CROPGRO-cotton modules of the DSSAT-CSM were calibrated against the measured data from the "High" irrigation treatments, because it is recommended to calibrate the DSSAT CSM under no-stress conditions (Boote, 1999). Measured data from the "Base" and "Low" irrigation treatments were then used for model evaluation. New sorghum and cotton cultivars, "DK Halfway" and

Table 3
Crop management related inputs used in the DSSAT CSM.

	Halfway, TX sorghum production year[a]				Sorghum long-term simulations[b]
	2007	2010	2012	2013	1977–2016
Cultivar:	DKS 37-07	DKS 44-20	DKS 44-20	DKS 49-45	
Planting data:					
Planting date	May 19	May 26	May 31	June 4	June 1
Seeding density, seeds/m^2	24$^{(H)}$, 19$^{(B)}$, 14$^{(L)}$	17$^{(H)(B)(L)}$	24$^{(H)}$, 19$^{(B)}$, 14$^{(L)}$	19$^{(H)(B)(L)}$	18$^{(irrigated)}$, 6$^{(dryland)}$
Fertilizer data:					
Total nitrogen applied, N kg/ha	272$^{(H)}$, 222$^{(B)}$, 173$^{(L)}$	156$^{(H)(B)(L)}$	187$^{(H)}$, 111$^{(B)}$, 60$^{(L)}$	175$^{(H)}$, 128$^{(B)}$, 90$^{(L)}$	150$^{(irrigated)}$, 60$^{(dryland)}$
Timing, month/day	7/3, 7/19, 7/25, 7/28, 8/1	4/1, 6/17	3/5, 6/22	3/20, 7/3	6/20, 7/10

	Halfway, TX cotton production year[a]						
	2006	2008	2009	2011	2012	2013	2014
Cultivar:	FM960B2R	DP104B2RF	DP104B2RF	FM9180B2F	FM9180B2F	FM2011GT	FM2011GT
Planting data:							
Planting date	May 10	May 14	May 13	May 11	May 8	May 14	June 4
Seeding density, seeds/m^2	13	13	13	13.3	13	13	12.8
Fertilizer data:							
Total nitrogen applied, N kg/ha	175$^{(H)}$, 170$^{(B)}$, 150$^{(L)}$	168$^{(H)(B)(L)}$	180$^{(H)}$, 142$^{(B)}$, 105$^{(L)}$	125$^{(H)}$, 78$^{(B)(L)}$	187$^{(H)}$, 111$^{(B)}$, 60$^{(L)}$	175$^{(H)}$, 128$^{(B)}$, 90$^{(L)}$	217$^{(H)}$, 179$^{(B)}$, 135$^{(L)}$
Timing, month/day	4/7–10, 5/23, 6/28–29, 7/12–27	3/19, 7/7, 8/1	3/2, 7/21–23, 8/3–6	3/14, 3/21, 6/16	3/5, 6/25	4/3, 6/26, 6/28	2/7, 3/27–28, 4/1, 7/22

$^{(H), (B), (L)}$ correspond to the irrigation levels, high, base, and low, respectively as described in Table 1 (TALR, 2016).
[a] Helms Research Farm, Halfway actual planting and fertilizer methods used for DSSAT evaluation.
[b] Common practices in the THP used to create long-term (1977–2016) sorghum dryland and irrigated scenarios (McClure et al., 2010).

"FiberMax Halfway TX", respectively were added to the DSSAT cultivar database to represent the medium maturity sorghum and early maturity cotton varieties used in the field experiments. A step-wise manual calibration was carried out in three phases by changing one cultivar or ecotype parameter at a time.

Initially, sorghum cultivar parameters were adjusted to get a reasonable match between simulated and generally observed dates of onset of crop growth stages, followed by adjusting several other parameters to match simulated yields with measured sorghum yields. After obtaining a satisfactory calibration for sorghum, cotton parameters were adjusted first according to the dates of onset of crop growth stages and then seed cotton yields. Lastly, both cotton and sorghum cultivar parameters and initial field moisture and nitrogen concentration were fine-tuned simultaneously to get an overall good match of crop yields with the measured data. Measured data on initial soil conditions (soil water and nitrogen contents at the beginning of first growing season in the cropping sequence) were not available and therefore they were decided during the model calibration. Simulation start date was set at about 50 days before the planting date and this spin-up period allowed stabilization of soil water and nutrient contents as a result of rainfall received and irrigation water applied before planting, and thereby reduced the effect of bias resulting from defining initial soil conditions (Müller and Robertson, 2013). The measured seed cotton and grain sorghum yields were reported at 8% and 13% seed and grain moisture content, respectively. Therefore, measured seed cotton and grain sorghum yields were reduced by 8% and 13%, respectively, since DSSAT simulates dry weight (Araya et al., 2017).

For grain sorghum, additional evaluation for seasonal irrigation water use efficiency (IWUE, Eq. (1)) was performed. For calculating IWUE, dryland grain sorghum yields were simulated by mimicking dryland experiments conducted at Halfway. The planting density was equal to that of the "low" irrigation treatment. Fertilizer amounts were average of those applied at Halfway during the 2001–2008 period (Bordovsky et al., 2011).

$$\mathrm{IWUE} = \left[\frac{\textit{Irrigated Yield} - \textit{Dryland Yield}}{\textit{Seasonal Irrigation}}\right] \tag{1}$$

2.5. Performance statistics

Model performance during the calibration and evaluation was evaluated using four quantitative statistical performance indicators

Table 4
Soil hydraulic and physical properties used in the DSSAT simulations.

Depth (cm)	SLLL (cm^3 cm^{-3})	SDUL (cm^3 cm^{-3})	SSAT (cm^3 cm^{-3})	SBDM (g cm^{-3})	SSKS (m s^{-1})	SRGF
0–5	0.13	0.23	0.41	1.48	7.2×10^{-6}	1.0
5–15	0.13	0.23	0.41	1.48	7.2×10^{-6}	1.0
15–30	0.17	0.29	0.43	1.44	1.2×10^{-6}	0.6
30–45	0.20	0.31	0.43	1.44	6.4×10^{-7}	0.5
45–60	0.22	0.34	0.43	1.44	6.4×10^{-7}	0.4
60–90	0.21	0.32	0.43	1.45	6.4×10^{-7}	0.2
90–120	0.20	0.31	0.42	1.48	6.4×10^{-7}	0.1
120–150	0.20	0.30	0.41	1.51	6.4×10^{-7}	0.1
150–180	0.20	0.30	0.41	1.51	6.4×10^{-7}	0.0
180–210	0.20	0.30	0.41	1.51	6.4×10^{-7}	0.0

SLLL = soil water lower limit, SDUL = drainable upper limit, SSAT = saturation, SBDM = bulk density, SSKS = saturated hydraulic conductivity, SRGF = soil root growth factor

Table 5
Parameters adjusted during CSM-CERES-Sorghum model calibration.

Parameter	Description	Testing range	Calibrated value
Cultivar parameters			
P1	Thermal time from seedling emergence to the end of the juvenile phase (expressed in degree days above TBASE, i.e., 8 °C)	317–495	334
P2	Thermal time from the end of the juvenile stage to tassel initiation under short days (degree days above TBASE)	80–102	102
P2O	Critical photoperiod or the longest day length (in hours) at which development occurs at a maximum rate	14.5–15.5	15.2
P2R	Extent to which phasic development leading to panicle initiation (expressed in degree days) is delayed for each hour increase in photoperiod above P2O	1–40	40
PANTH	Thermal time from the end of tassel initiation to anthesis (degree days above TBASE)	585–875	617.5
P3	Thermal time from to end of flag leaf expansion to anthesis (degree days above TBASE)	152.5–200	152.5
P4	Thermal time from anthesis to beginning grain filling (degree days above TBASE)	81.5–190	81.5
P5	Thermal time from beginning of grain filling to physiological maturity (degree days above TBASE)	350–670	575
PHINT	Phylochron interval; the interval in thermal time between successive leaf tip appearances (degree days)	49–65	49
G1	Scaler for relative leaf size	0–22	3.5
G2	Scaler for partitioning of assimilates to the panicle (head)	6–8	7

(Adhikari et al., 2016) and graphical techniques. The statistical indicators used are percent error (*PE*), percent root mean square error (*%RMSE*), coefficient of determination (R^2), and index of agreement (*d*) as given in Eqs. 2–5:

$$PE = \left(\frac{\hat{\bar{Y}} - \bar{Y}}{\bar{Y}}\right) \times 100 \quad (2)$$

$$\%RMSE = \sqrt{\frac{\sum_{i=1}^{N} (\hat{Y}_i - Y_i)^2}{N}} \times \frac{100}{\bar{Y}} \quad (3)$$

$$R^2 = \frac{\left\{ \sum_{i=1}^{N} [(Y_i - \bar{Y}) \times (\hat{Y}_i - \hat{\bar{Y}})] \right\}^2}{[\sum_{i=1}^{N} (Y_i - \bar{Y})^2] \times [\sum_{i=1}^{N} (\hat{Y}_i - \hat{\bar{Y}})^2]} \quad (4)$$

$$d = 1 - \frac{\sum_{i=1}^{N} (\hat{Y}_i - Y_i)^2}{\sum_{i=1}^{N} (|\hat{Y}_i - \bar{Y}| + |Y_i - \bar{Y}|)^2} \quad (5)$$

where $\hat{Y}_i$ and Y_i are the ith simulated and measured values, respectively, with i varying from 1 to N. N is number of observations, and $\hat{\bar{Y}}$ and $\bar{Y}$ are the averages of simulated and measured crop yields, respectively.

PE varies between −100 to ∞. *%RMSE* ranges from 0 to ∞, and it indicates the average magnitude of the difference between measured and simulated values. A value of *PE* and *%RMSE* closer to zero indicates a better fit. Model performance in this study was considered as excellent, if %RMSE < 10; good, if 10 < %RMSE < 20; fair, if 20 < %RMSE < 30; and poor, if %RMSE > 30 (Bannayan and Hoogenboom, 2009; Jamieson et al., 1991). We have aimed to achieve good model performance during both calibration and evaluation periods. R^2 varies from 0 to 1 with a value of 1 representing a perfect fit between two series. The *d* ranges between 0 and 1 with 1 representing a perfect agreement between the two series. Model calibration was carried out until *PE* and *%RMSE* between measured and simulated yield were < 15%, and *d* was > 0.5.

2.6. Irrigation management scenarios

A seasonal project was created with the evaluated DSSAT-CSM CERES-Sorghum model to study the effects of variability in historical climate and deficit irrigation strategies on grain sorghum yield and water use, and to determine optimum soil moisture at planting and optimum soil moisture threshold for initiating irrigation. A total of four volumetric soil water contents at planting, 25%, 50%, 75%, and 100% of AWC in the top 2.1 m soil profile were considered in the simulations. Irrigated yield, dryland yield, total irrigation water applied, irrigation water use efficiency (IWUE, Eq. (1)), and grain water use efficiency (WUE, Eq. (6)) were computed for each scenario. These initial soil moisture (ISM) scenarios were referred to as ISM 25, ISM 50, ISM 75, and ISM 100 with the numeric value representing percent of AWC.

$$WUE = \left[\frac{\textit{Irrigated Yield}}{\textit{Seasonal Evapotranspiration}}\right] \quad (6)$$

After deciding an optimum ISM based on yields, irrigation water use, IWUE, and WUE, the effects of soil moisture threshold for initiating auto-irrigation (ITH) were analyzed by keeping the ISM at the selected optimum value. In these simulations, the ITH was varied by varying the soil water lower limit and keeping the soil water upper limit constant at 100% of AWC. The ITHs tested include 30%, 40%, 50%, 60%, 70%, and 80% of AWC, similar to the approach followed by Kisekka et al. (2016) for corn. For example, the ITH 30 scenario indicates that auto-irrigation was triggered when water in the soil profile was depleted to 30% AWC and refilled to 100% AWC. Finally, various deficit/excess irrigation strategies to replenish soil water up to 55%, 70%, 85%, 100%, 115%, and 130% of AWC were simulated by keeping the ITH and ISM at the optimum values determined in preceding steps. These scenarios were designated as DFI followed by a numeral that represents the targeted final percent of AWC (DFI 55 to DFI 130). These scenarios were created by first determining the "average daily" irrigation water (~21 mm) required to fill the soil profile from the optimum ITH to 100% AWC (DFI 100) using the "automatic when required" auto-irrigation option. The estimated DFI 100 average daily irrigation depth was then increased/decreased proportionately for other DFI scenarios, and applied using the "fixed amount automatic" auto-irrigation option.

3. Results and discussion

3.1. Model calibration and evaluation

3.1.1. Phenological stages

Parameters adjusted during the calibration of CERES-Sorghum and CROPGRO-Cotton modules are shown in Tables 5 and 6, respectively. The simulated dates of onset of cotton and sorghum growth stages during the calibration and evaluation were close to the observed dates for cotton (Adhikari et al., 2016; Kerns et al., 2009) and sorghum (Gerik et al., 2003; McClure et al., 2010) in the THP region (Table 7). In 2014, cotton did not reach physiological maturity, as it was planted late (i.e., it was replanted after the first cotton stand was damaged during heavy rains), and freezing temperatures (< 0 °C) were encountered during the reproductive growth stage (data not shown). Nonetheless, the freezing date was close to the actual harvest date at Halfway, TX.

3.1.2. Crop yields

There was an acceptable agreement between simulated and measured crop yields at Halfway (Fig. 4) as indicated by average *PE* of 1.3% and 3.4% for sorghum and cotton, respectively, during calibration (Table 8). The maximum *PE* for grain sorghum yield was 15% in the year 2007, which substantially lowered R^2 value during the calibration period. Higher *PE* was obtained in 2007 because a medium-early

Table 6
Parameters adjusted during CSM-CROPGRO-Cotton model calibration.

Parameter	Description	Testing range	Calibrated value
Cultivar parameters			
EM-FL	Time between plant emergence and flower appearance (photothermal days)	34–44	38
FL-SH	Time between first flower and first pod (photothermal days)	3–8	5
FL-SD	Time between first flower and first seed (photothermal days)	6–13	12
SD-PM	Time between first seed and physiological maturity (photothermal days)	38–50	40
FL-LF	Time between first flower and end of leaf expansion (photothermal days)	55–75	65
LFMAX	Maximum leaf photosynthesis rate at 30C, 350 vpm CO2, and high light (mg CO_2 m^{-2} s^{-1})	1.1–1.7	1.3
SLAVR	Specific leaf area of cultivar under standard growth conditions (cm^2 g^{-1})	160–175	170
SIZLF	Maximum size of full leaf (three leaflets) (cm^2)	250–320	250
XFRT	Maximum fraction of daily growth that is partitioned to seed + shell	0.7–0.9	0.8
SFDUR	Seed filling duration for pod cohort at standard growth conditions (photothermal days)	24–35	29
PODUR	Time required for cultivar to reach final pod load under optimal conditions (photothermal days)	8–12	8
THRSH	Threshing percentage. The maximum ratio of (seed/(seed + shell)) at maturity	65–70	70
Ecotype parameters			
RWDTH	Relative width of this ecotype in comparison to the standard width per node	0.8–1	0.9
RHGHT	Relative height of this ecotype in comparison to the standard height per node	0.85–0.95	0.9
FL-VS	Time from first flower to last leaf on main stem (photothermal days)	40–65	65
LNGSH	Time required for growth of individual shells (photothermal days)	6–12	9
TRIFL	Rate of appearance of leaves on the mainstem (leaves per thermal day)	0.20–0.25	0.25

Table 7
Comparison of simulated and generally observed sorghum and cotton phenological stages during calibration and evaluation.

Phenological stage	Observed (days after planting)	Simulated (days after planting)			
		Calibration (high water treatment)		Evaluation (base and low water treatments)	
SORGHUM		Range	Average	Range	Average
Emergence[a]	5–10	5–7	6	5–7	6
Panicle Initiation[a]	35–40	29–35	31	29–35	31
End Leaf Growth[b]	59	57–65	60	57–65	60
Anthesis[a]	64–70	65–74	69	65–74	69
Physiological Maturity[a]	101–115	107–117	111	107–117	111
COTTON					
Emergence[c]	4–9	6–12	8	6–12	8
First Leaf[d]	11–25	12–18	14	12–18	15
Anthesis[c]	60–70	58–64	61	58–65	61
Physiological Maturity[c]	130–160	133–167	148	129–160	144
Harvest[e]	151–188	143–177	158	139–170	154

[a](Gerik et al., 2003); [b](McClure et al., 2010); [c](Adhikari et al., 2016); [d](Kerns et al., 2009); [e](TALR, 2016).

Table 8
Model performance statistics during the DSSAT CSM Evaluation for crop yield simulation.

Criteria	Calibration (high water)	Evaluation (base and low water)
Sorghum		
Number of observations	4	8
Average PE	1.3	−2.2
%RMSE	7.6	16.3
d	0.82	0.96
Cotton		
Number of observations	8	16
Average PE	3.4	−10.5
%RMSE	15.5	25.9
d	0.90	0.94

PE = percent error, RMSE = root mean square error, d = index of agreement.

maturity variety, DKS 37-07 (Schnell et al., 2015) was planted in that year as opposed to the medium maturity varieties that were planted in other years and targeted during calibration. Differences in sorghum yields between these two varieties have also been reported in sorghum variety trials in Texas (TALR, 2014), Virginia (Balota et al., 2013), and New Mexico (Marsalis et al., 2015). The over-prediction of seed cotton

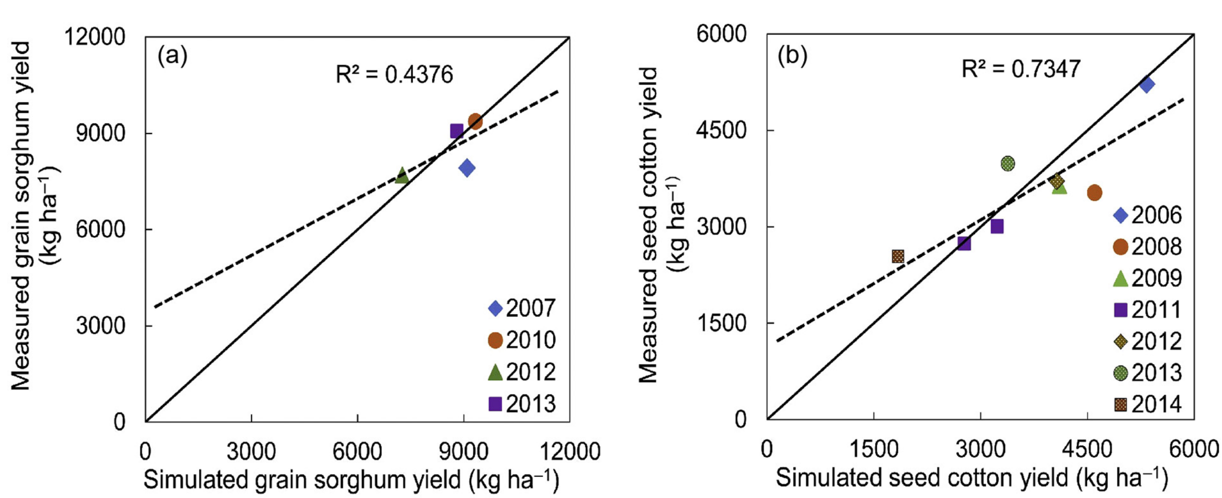

Fig. 4. Comparison of measured and simulated (a) grain sorghum and (b) seed cotton yields at Halfway during model calibration for the “High” water treatment. The solid line is 1:1 line and the dashed line is ordinary least-squares linear regression line.

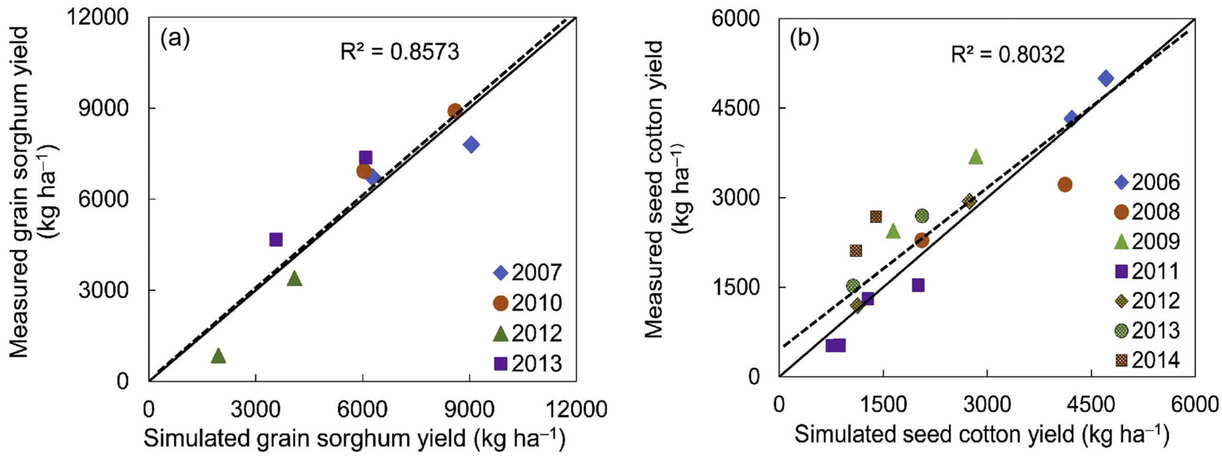

Fig. 5. Comparison of measured and simulated (a) sorghum and (b) seed cotton yields at the Helms Farm during the model evaluation for the "Base" and "Low" water treatments.

yield in 2008 could be due to the carry-over effect from the previous year. Over-prediction of sorghum residue in the previous year most likely resulted in overestimation of soil organic carbon (SOC) (Soler et al., 2011) and soil nitrogen (N) (Havlin et al., 1990). Higher SOC is generally associated with higher seed cotton yields (Mitchell and Entry, 1998). On the other hand, sorghum is reported to uptake high N and thereby reduce soil nitrate-N levels (Booker et al., 2007), which is consistent with this study. The depleted nitrate-N during the growing seasons was stabilized by fertilization, and no nitrogen stress was simulated in any cotton years (data not shown). The underestimation of seed cotton yield in 2014 could be explained due to the freeze damage. The average measured and simulated dry grain sorghum yields during the calibration were 8513 kg ha^{-1} and 8623 kg ha^{-1}, respectively. The average measured and simulated seed cotton yields during the calibration were 3546 kg ha^{-1} and 3666 kg ha^{-1}, respectively.

Although the model performance during the calibration (high water treatment) was good, results were not as good for cotton under water-limiting conditions during evaluation and resulted in an average *PE* of −10.5% (Fig. 5 and Table 8). This is similar to previous studies (Modala et al., 2015; Nouna et al., 2000; Thorp et al., 2014), which reported unsatisfactory model performance under dry conditions. Nouna et al. (2000) have also reported an underestimation in maize yields under water-stress conditions largely due to inadequate simulation of soil water deficits and leaf area, using the CERES-Maize model. More recently, some other researchers (DeJonge et al., 2012; Thorp et al., 2014) have also reported unsatisfactory performance of the ET routines currently available in the DSSAT-CSM under water stress conditions. ET was calculated using the FAO-56 method (Allen et al., 1998) option available in DSSAT. Leaf area, soil moisture, biomass and ET were not measured during the field experiments, hence their simulation accuracy could not be evaluated. The simulated maximum leaf area index (LAI) for grain sorghum (5.56 $m^2\,m^{-2}$) and cotton (3.33 $m^2\,m^{-2}$) were within the range of reported values in the THP region (Adhikari et al., 2017; Howell et al., 2008). The CERES-Sorghum model performance was markedly poor in the year 2012 for low irrigation treatment during evaluation, which was preceded by a severe drought year in 2011. In general, there is a potential for error propagation in the "sequence" analysis due to continuous long-term simulation of soil processes (Bowen et al., 1998). Relatively poor model performance during the model evaluation suggests that error propagation was more prominent under resource-limiting conditions. Additional performance statistics that indicate the robustness of the model evaluation (Willmott, 1981) are reported in Table 8.

As absolute values of sorghum yields were much higher as compared to seed cotton yields, *PE* is not an appropriate measure for comparing performances of CERES-Sorghum and CROPGRO-Cotton modules of DSSAT. In addition, *PE* is sensitive to the large error values, therefore, normalized RMSE (*%RMSE*) values were also calculated to assess model performance. Further, the *d*-statistic was estimated between measured and simulated yields to assess overall model performance, as it is widely used to report crop model performance (Palosuo et al., 2011; Sau et al., 2004; Timsina et al., 2008).

The *%RMSE* in simulation of crop yield was the lowest (7.6%) during sorghum calibration and the highest (25.9%) during cotton evaluation (Table 8). In contrast, *d*-statistic during sorghum calibration was found to be lowest (0.82) among both cotton and sorghum evaluations. This was due to the limited number of observations and higher magnitude of error in sorghum yield simulation in the year 2007 during calibration. Overall, based on model performance statistics, it can be concluded that the DSSAT cotton and sorghum modules simulated crop yields with reasonable accuracy in well-watered conditions.

3.1.3. Irrigation water use efficiency (IWUE)

The simulated IWUEs for grain sorghum were close to the measured values (except for the year 2007) with an average *PE* of 7.4% (Fig. 6). A larger difference in maturity and yield traits of the variety used in 2007 compared to the remaining three years was most likely the reason due to the poor model performance in 2007. This limits the extrapolation of current results to other grain sorghum varieties that are different from the medium maturity varieties (DKS 44-20 and DKS 49-45) simulated in this study. The underestimation of IWUE in the year 2010, especially under base and low irrigation treatments, is likely due to over-prediction of dryland grain sorghum yield in 2010 (data not shown).

Although the DSSAT model was successfully evaluated against phenology, crop yield, and IWUE data available from three irrigation treatments over four sorghum and eight cotton growing seasons, non-availability of in-season data such as LAI, soil moisture, biomass and ET for model evaluation is one of the major limitations of this study. As suggested by He et al. (2017), evaluation of crop growth models against in-season data on crop growth and soil processes in addition to the end-of-the-season data such as crop yield is desirable to enhance confidence in model application, and hence future calibration efforts should focus on overcoming this limitation.

3.2. Model application

3.2.1. Crop response to soil moisture at planting

Irrigated grain sorghum yields under different ISM scenarios were comparable except for the ISM 25 scenario (Fig. 8a). This suggests that irrigated sorghum yields were not substantially affected by soil moisture at planting of ≥50% AWC. However, initial soil water content of ≤25% AWC (or 75% or more soil water depletion) could be

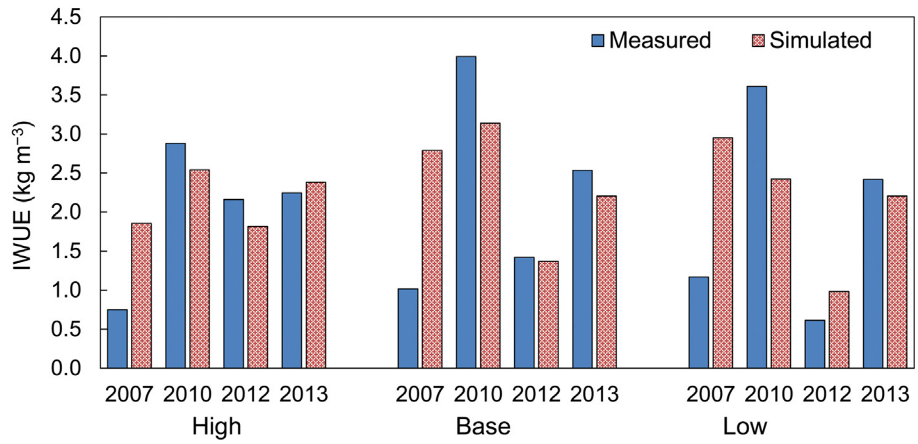

Fig. 6. Comparison of measured and simulated grain sorghum irrigation water use efficiency (IWUE) under different irrigation treatments; High, Base, and Low, over four years.

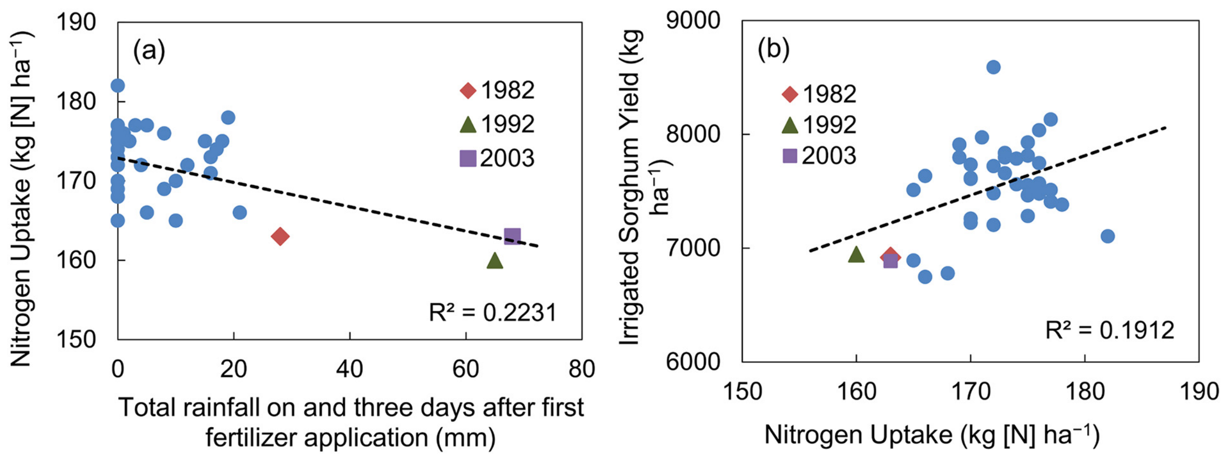

Fig. 7. Relation between seasonal nitrogen uptake and (a) total rainfall occurring on and three days after the first fertilizer application, and (b) irrigated grain sorghum yield, for the ISM 100 treatment. The dots represent years from 1977 to 2016, and years with heavy rainfall after fertilizer application are highlighted.

detrimental to sorghum yields, especially during dry years. Under the ISM 25 scenario, 14% more irrigation water was applied and the grain sorghum yields were 6% and 2% lower when compared to the ISM 100 in dry and wet years, respectively. Simulated grain sorghum yields were the lowest under ISM 25 scenario, but the highest ISM did not result in the highest irrigated sorghum yields among all climate variability classes. Simulated sorghum yields were high under ISM 75 scenario in wet years (CW, NW, and WW) and under ISM 100 scenario in the remaining climate variability classes. The probable reasons for differences in irrigated grain sorghum yields across climate variability classes were rainfall distribution pattern over the growing season and differences in length of the growing season (data not shown). The rainfall distribution over time affected irrigated grain sorghum yields by influencing nitrogen (N) leaching and N uptake by the plant. In the years 1982, 1992, and 2003, heavy rainfall events shortly after fertilizer application led to N leaching, which reduced simulated N uptake and hence simulated grain sorghum yields (Fig. 7). This is consistent with the findings of Gérardeaux et al. (2013), who found that N uptake was the main driver of cotton yields simulated using the CROPGRO-Cotton model, and the negative correlation between excessive rainfall and cotton yields was attributed to N leaching. Although, there were no measurements at the field to confirm this relation, similar pattern has been reported in a field study (Errebhi et al., 1998) at Becker, MN, where heavy rainfall and subsequent N leaching events reduced N recovery and the marketable potato yield. In warm-dry years (1980, 1998, 2001, and 2011), the crop matured about 12 days earlier than the average growing season. The shortening of growing season is known to reduce grain sorghum yields (Singh et al., 2014).

Simulated dryland grain sorghum yields were about 10% (in WD) to 39% (in CW) of the irrigated sorghum yields (Fig. 8b). As expected, the dryland sorghum yields decreased as the soil water at planting decreased. Dryland grain sorghum yields under ISM 25 scenario were about 55% lower than those under ISM 100 scenario. Dryland grain sorghum yields were 48% lower in normal years and 50% lower in dry years when compared to wet years. Cold weather was found to be more favorable for dryland sorghum than normal and warm temperatures. Dryland grain sorghum yields in warm years were 36% and 50% of that in cold years during dry and normal rainfall years, respectively. In wet growing seasons, simulated dryland grain sorghum yields were relatively stable among all temperature classes.

In general, sorghum IWUE was the highest under ISM 75 scenario (or 75% AWC) followed by ISM 50 (Fig. 8c). IWUE was the lowest under ISM 100 in wet years (CW, NW, and WW), due to smaller difference between the irrigated and dryland sorghum yields in those years (resulting in smaller numerator in Eq. (5)). In the remaining climate variability classes, IWUE was the lowest under ISM 25 mainly due to higher irrigation applied compared to other ISM scenarios. Among climate variability classes, IWUE varied between 1.11 kg m^{-3} (CW) and 1.58 kg m^{-3} (CD). The comparatively higher than average IWUE in CD class is attributed to the low irrigation water applied (11% less than the average climate variability class). Although the irrigation applied is about the same (365 mm) in the CW class, it has a lower IWUE due to

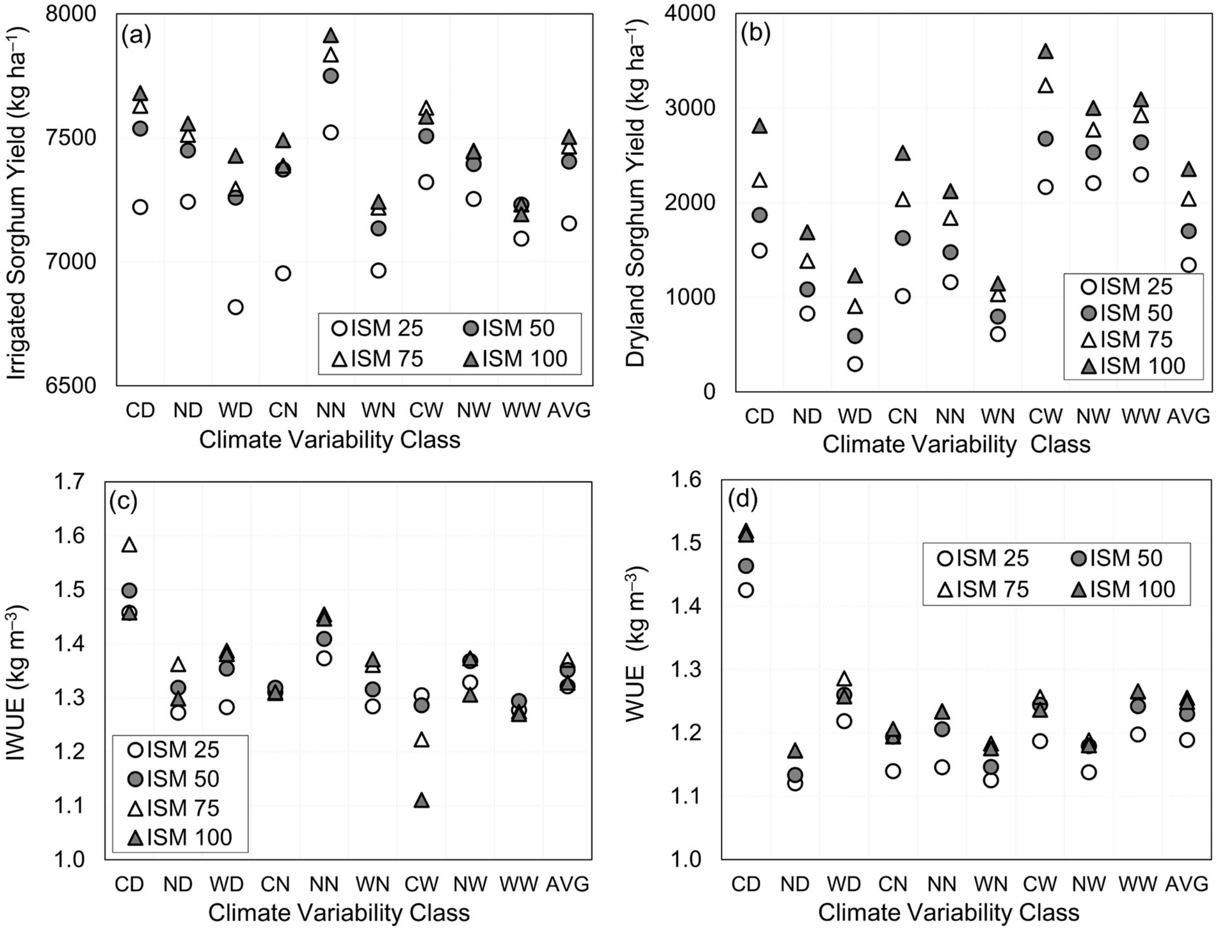

Fig. 8. Grain sorghum (a) irrigated yields, (b) dryland yields, (c) irrigation water use efficiency, and (d) water use efficiency under different initial soil moisture (ISM) and weather conditions.

high dryland grain sorghum yields resulting in a smaller difference between irrigated and dryland sorghum yields. This is also true for other wet climate variability classes (NW and WW).

Grain sorghum WUE was the lowest under ISM 25 in all climate variability classes (Fig. 8d). The WUE was the highest under ISM 100 in ND, CN, and WW climate variability classes, and under ISM 75 in the remaining climate variability classes. Like IWUE, sorghum grain WUE was also high in cold-dry (CD) years compared to other climate variability classes, this was due to substantially low ET (15% lower than average climate) compared to other climate variability classes. In a typical year in a climate variability class, ET did not change substantially (< 14 mm) under different ISM scenarios; therefore, the changes in WUE within ISM scenarios were due to the differences in irrigated grain sorghum yield. On the other hand, among the climate scenarios considered, ET varied from −91 mm (−15%) to +42 mm (+7%) from the average. Therefore, changes in WUE were due to the combined effect of differences in ET and grain sorghum yield.

Overall, maintaining ISM at 75% AWC optimized irrigation water use without lowering grain sorghum yields substantially. In wet years, however, ISM at 50% is also an acceptable option. Soil water depletion below 25% AWC can negatively impact sorghum yields, especially in drought years. For dryland sorghum production, yield loss should be expected if ISM is < 75% AWC. Different conservation practices such as conservation tillage and residue management that enhance soil water retention can help maintain adequate soil moisture at planting (Baumhardt and Jones, 2002). Conservation tillage has been estimated to increase available soil water around planting by 25 mm in the THP (Colaizzi et al., 2009). Unger (1978) reported over 20 cm increases in plant available soil moisture within the upper 1.8 m of soil profile by using straw mulch residue in Bushland, TX.

3.2.2. Crop response to the threshold to start irrigation

Among the six irrigation trigger thresholds studied, irrigated grain sorghum yields were low under the lowest ITH scenarios (ITH 30 and ITH 40) except in CD climate (Fig. 9a). Although the simulated grain sorghum yields under ITH ≥50 scenarios were about the same (average difference 144 kg ha^{-1}) in a climate variability class, the ITH 70 scenario was found to be slightly better on average. The difference in simulated irrigated grain sorghum yield between the best and the least ITH scenarios was smaller in cold years (103 kg ha^{-1} in CN) compared to warm years (812 kg ha^{-1} in WD), suggesting that ITH decisions are critical in warmer years. Between ITH 50 and 60, the average difference in irrigated grain sorghum yields and applied irrigation was 80 kg ha^{-1} and 16 mm, respectively. In WD years, the irrigated sorghum yield difference between ITH 50 and 60 increased up to 466 kg ha^{-1} and additional 51 mm irrigation was required. In general, the effect of ITH on grain sorghum yield was much less when compared to that of soil moisture at planting (ISM) and hence ISM should be a key factor in the identification of optimum irrigation strategies.

Simulated irrigation amount required to maintain soil water at a minimum of 80%, 70%, 60%, 50%, 40%, and 30% of AWC in the top 30 cm soil profile was found to be 462, 436, 416, 402, 377 and 347 mm, respectively. Considering the annual groundwater pumping limit of 460 mm specified by the High Plains Water District (HPWD, 2015), ITH 80 does not seem practical for the THP region. The IWUE decreased as the amount of irrigation increased (Fig. 9b), and this result is in accordance with the previous studies (Colaizzi et al., 2009; Hao et al., 2014; Tolk and Howell, 2003). In a climate variability class between

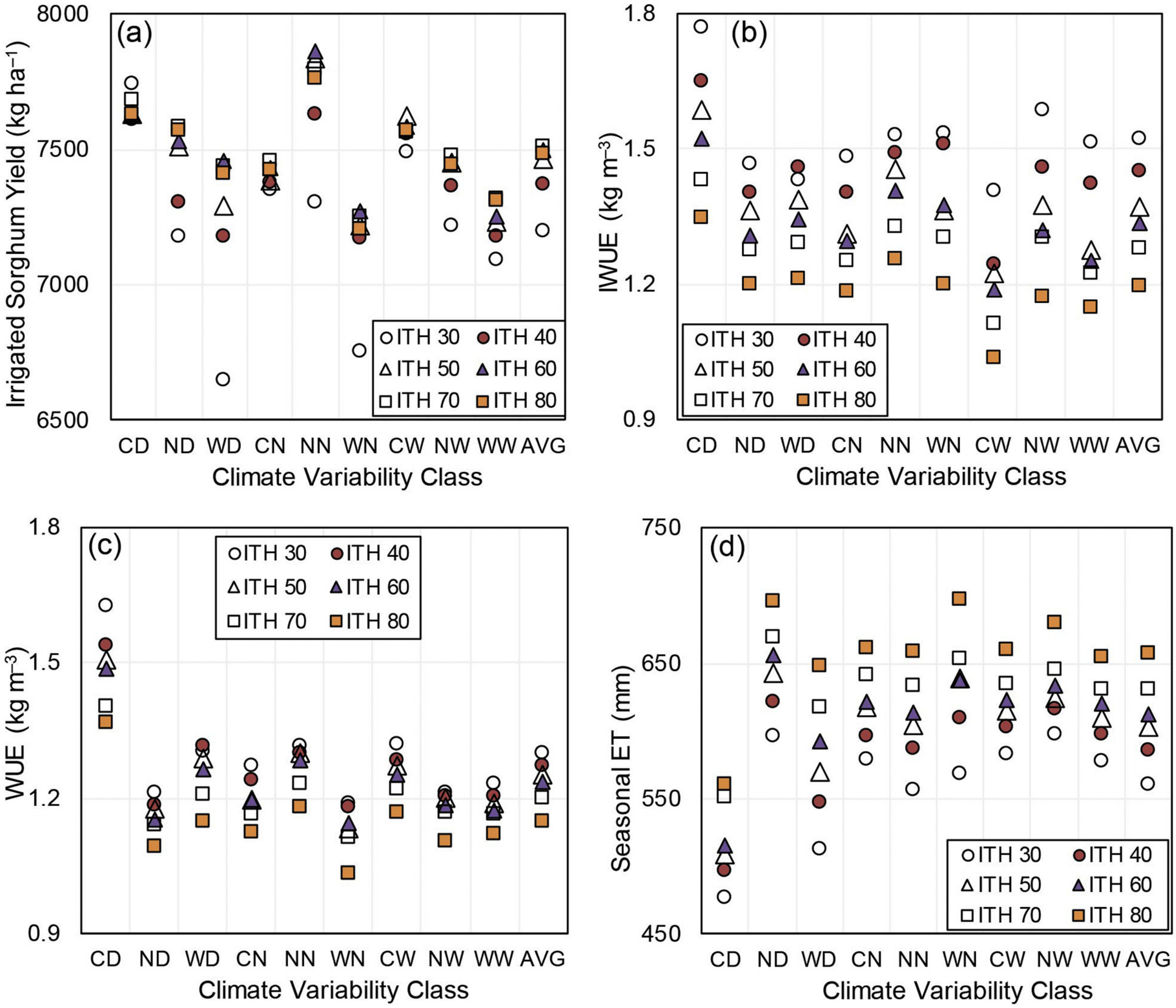

Fig. 9. Grain sorghum (a) irrigated yields, (b) IWUE, (c) WUE, and (d) seasonal ET under different thresholds to start irrigation (ITH) and climate variability classes.

ITH scenarios, the IWUE was consistently lower under ITH 70 (average 1.27 kg m^{-3}) and ITH 80 (average 1.19 kg m^{-3}) scenarios, suggesting that maintaining soil profile at ≥70% AWC is not efficient in terms of irrigation water use. The IWUE was highest under ITH 30 (average 1.52 kg m^{-3}) in all climate variability classes except WD, this was due to low irrigated sorghum yields under ITH 30 in WD climate. When grain sorghum IWUE were compared between climate variability classes, the highest and the lowest IWUE were simulated under CD (average 1.55 kg m^{-3}) and CW (average 1.20 kg m^{-3}) classes, respectively.

Similar to IWUE, the simulated grain sorghum WUE decreased as the amount of irrigation increased (Fig. 9c). Irrigated grain sorghum yields and seasonal ET varied within 11% and 23% of the average between irrigation scenarios, respectively. This suggests that variation in WUE could be explained due to changes in ET. This result is consistent with Tolk and Howell (2003), who had also attributed increases in WUE in milder climates to the reduction in ET rather than the increase in sorghum yield. Simulated ET was the lowest in the cold-dry (CD) weather and hence the WUE for this climate variability class was the highest (Fig. 9c–d).

Overall, based on the simulated sorghum yield, IWUE and WUE, ITH 50 and ITH 60 were found to be appropriate thresholds for triggering irrigation in normal/cold/wet weather conditions (CD, ND, CN, NN, WN, CW, NW, and WW) and warm-dry years (WD), respectively. Although the IWUE and WUE for ITH 30 and ITH 40 were higher under most weather conditions, those two thresholds were not recommended due to poor/low irrigated sorghum yields. In the subsequent deficit irrigation simulations, a better threshold of ITH 50 was used.

3.2.3. Crop response to deficit/excess irrigation

The DFI 115 and 130 scenarios resulted in the highest grain sorghum yield in the majority of climate variability classes, suggesting that replenishing the soil profile up to 15 to 30% more than field capacity would result in slightly higher grain sorghum yields when compared to deficit irrigation (< DFI 100) strategies (Fig. 10a). Direct comparison of the simulated results with results from field studies was a challenge because the highest amount of irrigation water applied in most of the field experiments in the THP (Kiniry and Bockholt, 1998; Porter et al., 1960; Schneider and Howell, 2000; O'Shaughnessy et al., 2014; Marek et al., 2016) was to replenish water to field capacity. An exception to this practice, to our knowledge, was a field study at Halfway in which researchers (Bordovsky and Lyle, 1996) tested deficit to excess irrigation strategies including 40%, 70%, 100%, and 130% of grain sorghum ET_c replacement over three years period, and they found that grain yields for irrigation treatments ≥70% ET_c were not significantly different. The simulated irrigated grain sorghum yields varied within a range of 39 to 240 kg ha^{-1} (1 to 3% of the DFI average) among the different DFI scenarios within a climate variability class. One of the reasons behind simulating smaller differences in sorghum yields across different DFI scenarios within a climate variability class could be the assumption of higher threshold of 50% to trigger irrigation (i.e. soil water content was maintained at 50% AWC or higher at all times, which

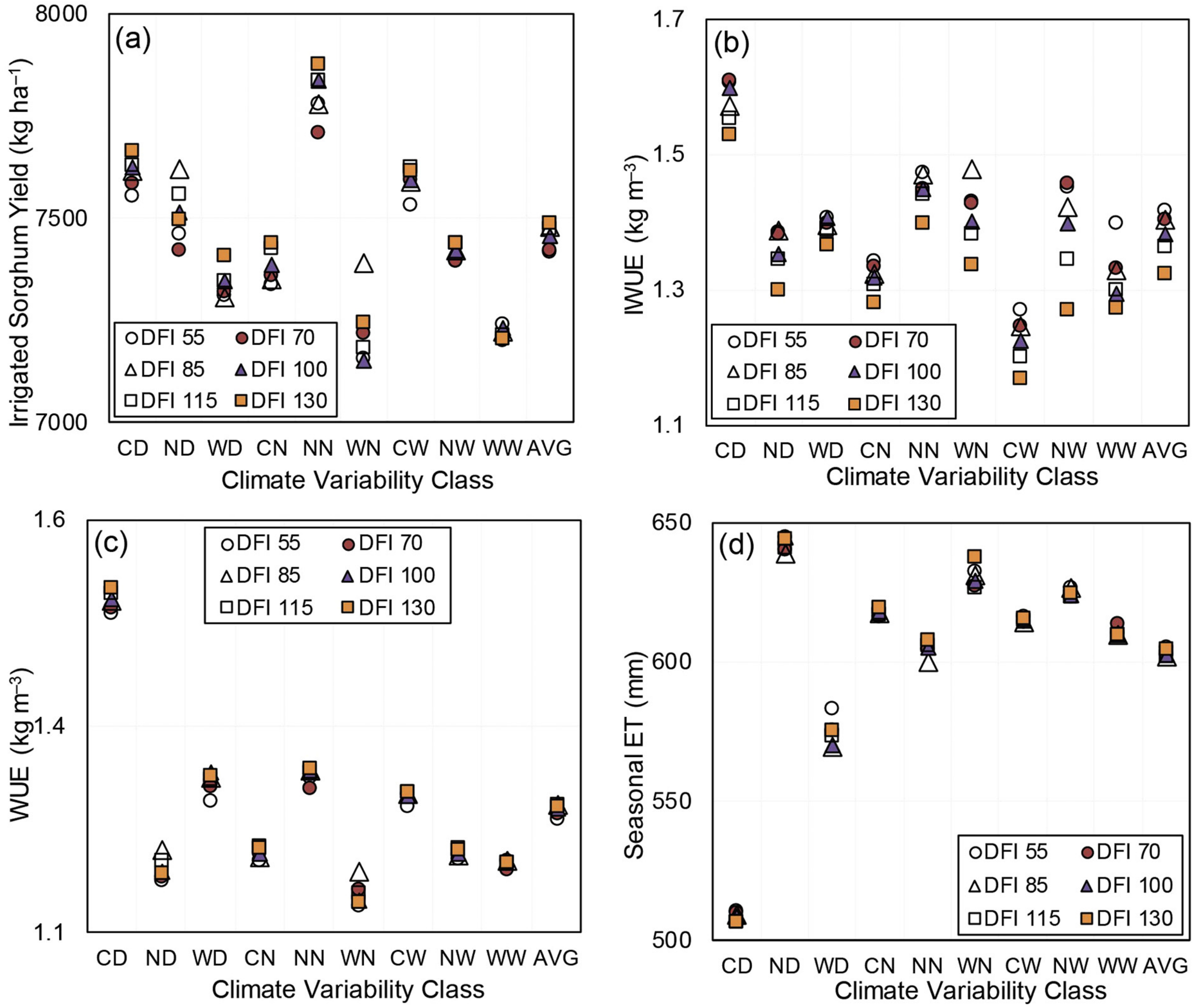

Fig. 10. Grain sorghum (a) irrigated yields, (b) IWUE, (c) WUE, and (d) seasonal ET under different thresholds to terminate auto-irrigation (DFI) and weather conditions.

avoided any severe water stress). However, the maximum difference in simulated irrigated sorghum yield across all climate variability classes was found to be 585 kg ha^{-1} (8% of the average sorghum yield) between NN (highest) and WW (lowest) climate variability classes. The differences in simulated sorghum yield across DFI scenarios were primarily due to water stress especially during the reproductive growth stage of sorghum.

In general, IWUE decreased as irrigation water use increased, and this trend was consistent with previous studies (O'Shaughnessy et al., 2014; Hao et al., 2014; Tolk and Howell, 2003). Simulated IWUE was the least and second least under DFI 130 and DFI 115 under all weather conditions, respectively (Fig. 10b). The simulated IWUE was higher for DFI ≤ 85 than those in DFI > 85 strategies by 6% (0.07 kg m^{-3}), 3% (0.05 kg m^{-3}), and 2% (0.03 kg m^{-3}) in wet, normal, and dry climate variability classes, respectively. However, the decreasing IWUE trend with increasing irrigation was not true for all the years simulated, especially the extreme dry years. This is likely due to reduced irrigated sorghum yields in DFI < 85 scenarios, consistent with O'Shaughnessy et al. (2014), who have also reported higher IWUE when soil water was replenished to 55% of field capacity than when it was replenished to 80% of field capacity (the highest irrigation level tested), except in the drought year of 2011. The low IWUE under DFI ≥115 scenarios was due to excess irrigation water use, which did not always result in proportionate sorghum yield gains (Fig. 10a). Among the nine climate variability classes, the simulated IWUE was the highest and the lowest in CD and CW climate variability classes, respectively. The average IWUE of dry and wet years was 1.41 kg m^{-3} and 1.29 kg m^{-3}, respectively. This supports the results of Musick and Dusek (1971), who reported higher IWUE when irrigation was applied in dry years.

Simulated WUE generally increased as irrigation amount increased (Fig. 10c). The WUE was the least for DFI 55 in most climate variability classes. There was no systematic increasing or decreasing trend in IWUE from DFI 85 to DFI 130 in any climate variability class. The WUE was highest for different irrigation strategies under different climate variability classes: DFI 130 in case of CD and NN years; DFI 115 in CN, CW, and NW years; DFI 100 in WD and WW years; and DFI 85 in ND, and WN years. This could be attributed to the smaller difference in simulated irrigated grain sorghum yields and ET. Irrigated sorghum yields varied within 7% (498 kg ha^{-1}) and ET varied within 6% (36 mm) between the DFI strategies (Fig. 10d). Simulated WUE among climate variability classes ranged between 1.18 kg m^{-3} (in ND) and 1.50 kg m^{-3} (in CD). A substantially higher WUE in CD years was due to low seasonal ET, which was 95 mm (16%) lower than the average ET.

Simulated average grain sorghum yields, IWUE, and WUE were the highest under DFI 130 and DFI 55, and DFI 85 strategies, respectively. During WD years, IWUE of DFI 100 was highest. Nonetheless, the DFI 85 strategy saved up to 22% irrigation water with a maximum of 6% yield loss compared to the DFI 130 strategy. In general, a DFI 85 scenario or replenishment of soil profile up to 85% AWC utilized irrigation water efficiently without substantially reducing grain sorghum yields.

The DFI 85 strategy was therefore found to be an appropriate irrigation strategy during normal and wet years, and the DFI 100 during warm-dry years.

4. Conclusions

The CERES-Sorghum and CROPGRO-Cotton modules distributed with the DSSAT model were successfully evaluated using experimental data from a cotton-sorghum rotation at Halfway in the THP. Several irrigation management scenarios were then simulated to suggest optimum irrigation management decisions for grain sorghum production in the THP region. The differences in grain sorghum yield, IWUE, and WUE were greater across climate variability classes than between irrigation scenarios, suggesting that grain sorghum production is highly susceptible to changes in climatic conditions. Simulated IWUE and WUE were consistently higher in cold-dry (CD) years, indicating that the most efficient use of applied irrigation water was achieved under CD conditions that are associated with less ET and smaller amount of excess water.

An initial soil water content (ISM) of 75% AWC was found to be optimum for irrigated sorghum production in the THP. For dryland sorghum production, ISM of < 100% AWC (in normal to dry years) or 75% (in wet years) is expected to result in yield reduction. A threshold of 60% AWC to trigger irrigation is advisable in warmer and drier years, while a 50% AWC threshold is adequate in normal, cold and wet years. Applying irrigation water to refill the soil profile up to 85% AWC was found to be sufficient in normal and wet years, however, it would be desirable to replenish soil profile to field capacity or 100% AWC in warm and dry years. The recommendations on irrigation management made in this study were based on the magnitude and distribution of seasonal rainfall and temperature during the simulation period, and the effects of days with extreme hot/cold temperatures were not investigated. In addition, irrigation water was applied regularly to maintain soil water content at appropriate levels throughout the season, and hence the effect of water stress during critical growth stages (e.g. panicle initiation and boot stage) was not investigated. Our future efforts will focus on addressing these important issues. The methodology developed in this study is not site-specific, and it can be applied to other crops and geographical regions to design water-use-efficient irrigation schemes with some modifications.

Acknowledgements

The authors would like to acknowledge the funding support provided by the College of Agriculture and Life Sciences, Texas A&M University, and the Ogallala Aquifer Program, a consortium between USDA Agricultural Research Service, Kansas State University, Texas A&M AgriLife Research, Texas A&M AgriLife Extension Service, Texas Tech University, and West Texas A&M University. We would like to thank two anonymous reviewers for their valuable comments and suggestions, which were very helpful in improving the manuscript.

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