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Research Impact Statement: Soybean in Texas High Plains can be irrigated at a lower total amount of irrigation application without compromising yields, thus conserving water and contributing toward lesser groundwater withdrawals.

ABSTRACT: There is an increasing need to strategize and plan irrigation systems under varied climatic conditions to support efficient irrigation practices while maintaining and improving the sustainability of groundwater systems. This study was undertaken to simulate the growth and production of soybean [*Glycine max* (L.)] under different irrigation scenarios. The objectives of this study were to calibrate and validate the CROPGRO-Soybean model under Texas High Plains' (THP) climatic conditions and to apply the calibrated model to simulate the impacts of different irrigation levels and triggers on soybean production. The methodology involved combining short-term experimental data with long-term historical weather data (1951–2012), and use of mechanistic crop growth simulation algorithms to determine optimum irrigation management strategies. Irrigation was scheduled based on five different plant extractable water levels (irrigation threshold [ITHR]) set at 20%, 35%, 50%, 65%, and 80%. The calibrated model was able to satisfactorily reproduce measured leaf area index, biomass, and evapotranspiration for soybean, indicating it can be used for investigating different strategies for irrigating soybean in the THP. Calculations of crop water productivity for biomass and yield along with irrigation water use efficiency indicated soybean can be irrigated at ITHR set at 50% or 65% with minimal yield loss as compared to 80% ITHR, thus conserving water and contributing toward lower groundwater withdrawals. ***Editor's note:*** *This paper is part of the featured series on Optimizing Ogallala Aquifer Water Use to Sustain Food Systems. See the February 2019 issue for the introduction and background to the series.*

(KEYWORDS: CROPGRO-Soybean; irrigation water use efficiency; crop water productivity; deficit irrigation; irrigation strategy.)

INTRODUCTION

Due to changing climate and inconsistent precipitation patterns, groundwater is becoming a prominent source of water in arid and semiarid regions of the world (Ruud et al. 2004; Uddameri et al. 2017). Dwindling groundwater resources pose a threat to global food security (Hanjra and Qureshi 2010) and adversely impact rural economies worldwide (Burke and Moench 2000; Wang et al. 2017). Agriculture uses approximately 80% of ground and surface water in the United States (U.S.) annually (USDA 2013). Additionally, recent decline in water availability and droughts are becoming critical factors impacting crop yield goals in the U.S. (Lobell and Field 2007). In

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recent years, sustainability of groundwater for agricultural production has received substantial attention from the research community along with development of strategies to balance crop production and optimize irrigation water requirements (Tilman 1999; Scanlon et al. 2012; Guzman et al. 2018).

In the Ogallala aquifer region comprising of Nebraska, Kansas, Texas, Oklahoma, and parts of South Dakota, Wyoming, Colorado, and New Mexico groundwater from underlying Ogallala aquifer is the primary source of irrigation for production of crops such as cotton, corn, sorghum, soybean, peanuts, and winter wheat (USDA-NASS 2017). In recent times, it has become important to improve water use efficiency (Modala et al. 2015; Dietzel et al. 2016) to sustain the use of groundwater from the Ogallala aquifer while maintaining crop water productivity (CWP) (Araya et al. 2017). Several past studies have shown that managing groundwater depletion can be achieved using deficit or limited irrigation methods that decrease irrigation input while maintaining crop production (Klocke et al. 2012; Lamm et al. 2014).

Soybean (*Glycine max* L.) is one of the main crops grown around the world and the U.S. as an important source of oil and protein for the animal feed industry. In a three-year study conducted in Nebraska (Schneekloth et al. 1991), it was found that deficit irrigation on soybean did not significantly affect yields and conserved an average 119 mm of seasonal water over full irrigation treatment. Depending on the maturity characteristics of the hybrid planted and annual weather conditions, soybean requires about 400–635 mm water in the Texas High Plains (THP) (Bean and Miller 1998). In soybean crops, reproductive and vegetative growth coexist for some duration of the growth cycle (Setiyono et al. 2007). Soybean is sensitive to water stress at all stages of growth and grain yields are usually linearly related to water use from the stage when seed yield begins to accumulate until the point of maximum yield is reached. However, soybean typically requires less irrigation as compared to other irrigated crops such as corn and water saving irrigation strategies can be useful in maintaining soybean yields (Lamm et al. 2007). Some researchers have found that the time between flowering and the beginning of seed formation is the soybean reproductive stages that are most susceptible to water stress. Water stress imposed on a soybean crop during these stages reduces vegetative growth, therefore affecting yield (Hodges and Heatherly 1983). Some studies (Spetch et al. 1989; Garcia y Garcia et al. 2010) have shown that irrigating only during reproductive stages could result in yields comparable to that under full irrigation, thus allowing for water stress during less critical growth stages. Deficit irrigation of soybean has been found to maximize CWP without significant reduction in yield by timing the irrigation applications with critical periods for water stress (Irmak et al. 2014), which might require understating the response of each growth stage of the crop to water stress (Dogan et al. 2007a, b).

The total irrigation amount is greatly affected by the decision on when to initiate the irrigation during the growing season. Among other approaches, measurements or estimates of soil available water and crop water use rates present a more reliable strategy to schedule irrigation for soybean (Rogers 2015) than growth-based scheduling. Irrigation scheduling in this form can be achieved by using either soil water measurement devices or evapotranspiration (ET)-based irrigation scheduling (Ciampitti et al. 2018). Studies have shown that scheduling irrigation for soybean by soil water depletion method (30% or 60% of plant available water) uses relatively less water (Ciampitti et al. 2018). The larger the threshold for soil water depletion, the fewer the number of irrigations that were applied. Therefore, a management approach using estimates of soil water content could help to optimize irrigation water use while not reducing soybean yields.

Given the erratic climate patterns that exist in the THP, the biggest challenge is to optimally implement deficit irrigation strategies without compromising yield and economic returns. Combining short-term field experiments with crop growth models using long-term historic climate data can be a useful tool in identifying suitable irrigation strategies (Kisekka et al. 2016). The Decision Support System for Agrotechnology Transfer (DSSAT) (Hoogenboom et al. 2015) is one of the most widely used crop simulation models for evaluating agricultural management options (Thorp et al. 2008) and to simulate crop water use and yield along with the development of management strategies for different soil and climatic conditions (McNider et al. 2015). DSSAT version 4.6 is comprised of models for more than 28 crops that simulate crop growth, development, and yield along with management strategies that involve irrigation, fertilizer application, crop rotations, and others (Sharda et al. 2017).

The CROPGRO-Soybean model, included in DSSAT, has been used to simulate crop phenology (Salmeron and Purcell 2016) and yield along with analyzing the impact of crop management parameters on soybean growth (Dogan et al. 2007a, b; Salmeron et al. 2017) along with being used in several climate change studies (Bao et al. 2015; Battisti et al. 2017; Walikar et al. 2018). The CROPGRO-Soybean model has also been used to evaluate how various water stress environments affected the yield of soybean in Iowa (Paz et al. 1998) and Mississippi Delta Region (Guzman et al. 2018). Sincik et al. (2008) investigated the effects of deficit irrigation on soybean during field studies and found that dryland and all deficit irrigation treatments significantly decreased biomass and yield. However, relatively few studies have been conducted in semiarid environments (Garside et al. 1992). Since there are multiple factors that could affect soybean growth and yields for a region, it is imperative that modeling approaches be implemented to strategize irrigation for sustainable use of limited groundwater resources at a regional level. Therefore, this study was designed with an overall goal to identify irrigation management strategies that optimize yield and maximize irrigation water use efficiency (IWUE) while maximizing CWP in the THP. The specific objectives of this study were to (1) calibrate and validate the DSSAT-CROPGRO-Soybean model for simulating soybean growth and yield in the THP and (2) identify and evaluate different deficit irrigation strategies that conserve water while providing optimum crop yields.

METHODOLOGY

Study Area

Soybean was grown under sprinkler irrigation at the U.S. Department of Agriculture/Agricultural Research Service (USDA-ARS) Conservation and Production Research Laboratory (CPRL) near Bushland, Texas (35°11.N, 102°6.W, 1170 m elevation above mean sea level) in the THP. This region has semiarid climate with an annual precipitation of approximately 460 mm (Marek et al. 2017), with nearly 325 mm of precipitation falling from May to September. The region experiences high diurnal temperature variability with a mean temperature during soybean growing season of approximately 24°C. The soil at the study site is Pullman silty clay loam (fine, mixed, thermic Torrertic Paleustoll). The experiment site was a nearly square field of nearly 20 ha that was subdivided into four 4.73 ha plots, each having a large weighing lysimeter (built and managed by the USDA-ARS CPRL) located in its center (Figure 1). The fields slope to the east at ~0.15% and are usually furrow diked to reduce runoff. The four fields were designated according to the cardinal points as the NE, SE, NW, and SW fields. The NE and SE lysimeter fields were irrigated with a 10-span, 457 m lateral move irrigation system equipped with mid-elevation spray application sprinkler drops (~1.5 m height).

Experimental Data

Hybrid soybean variety Pioneer 94B73RR was grown in 2003 and 2004 in both NE and SE lysimeter fields (Figure 1). Soybeans were inoculated with Nitragin granular at 5.6 kg/ha in-furrow. Daily ET values were measured using precision large weighing lysimeters located at the center of each field. A neutron probe measured weekly soil water content (to a depth of 1.5 m) using two access tubes installed in the lysimeters (Marek et al. 2017). Based on the information obtained from the neutron probes, irrigations were scheduled in a way that the soil water content can be maintained at a level to prevent water stress (Marek et al. 2017).

The sowing dates for soybean were May 19 and May 12 in 2003 and 2004, respectively, with a population of 46 plants/m^2 planted at a depth of 3 cm in rows 0.76 m apart. Nitrogen (10 kg/ha) was applied four days before planting and 63-14-48 kg/ha N-P-K was applied 68 days after planting. Plant samples were collected at different growth stages and plant height, leaf area, above ground dry matter, and yield were recorded. In season, plant sampling was done from the surrounding field and no destructive sampling was performed on the lysimeters until harvest, at which time all biomass and yield was collected from the lysimeter. Recommended pesticides were used to control weeds, diseases, and insects. The soybean management conditions used in this field study are assumed to be representative for the THP.

DSSAT Description

The DSSAT-CROPGRO-Soybean (version 4.6) (Boote et al. 1998; Hoogenboom et al. 2015) was used to simulate soybean yields with a variety of climate inputs over a 62-year period (1951–2012) in seasonal analysis mode (Thorton and Hoogenboom 1994). Seasonal analysis helps in comparing the crop performance variability based on different management practices and weather conditions over a range of years.

CROPGRO-Soybean. CROPGRO-soybean uses differential sensibility of growth stages to environmental factors such as temperature, photoperiod, along with water and nutrient stress to simulate soybean phenology (Boote et al. 1998). CROPGRO calculates crop water demand at a daily time step by combining a tipping bucket-type soil water movement model with a root water uptake model (Ritchie et al. 1998). Factors like soil water availability, drained upper limit and lower limit, and root density, control the water uptake rate by roots (Mercau et al. 2007).

DSSAT Input Data. Long-term daily weather data for a 62-year period (1951–2012) were compiled from the Texas High Plains Evapotranspiration Network (Porter

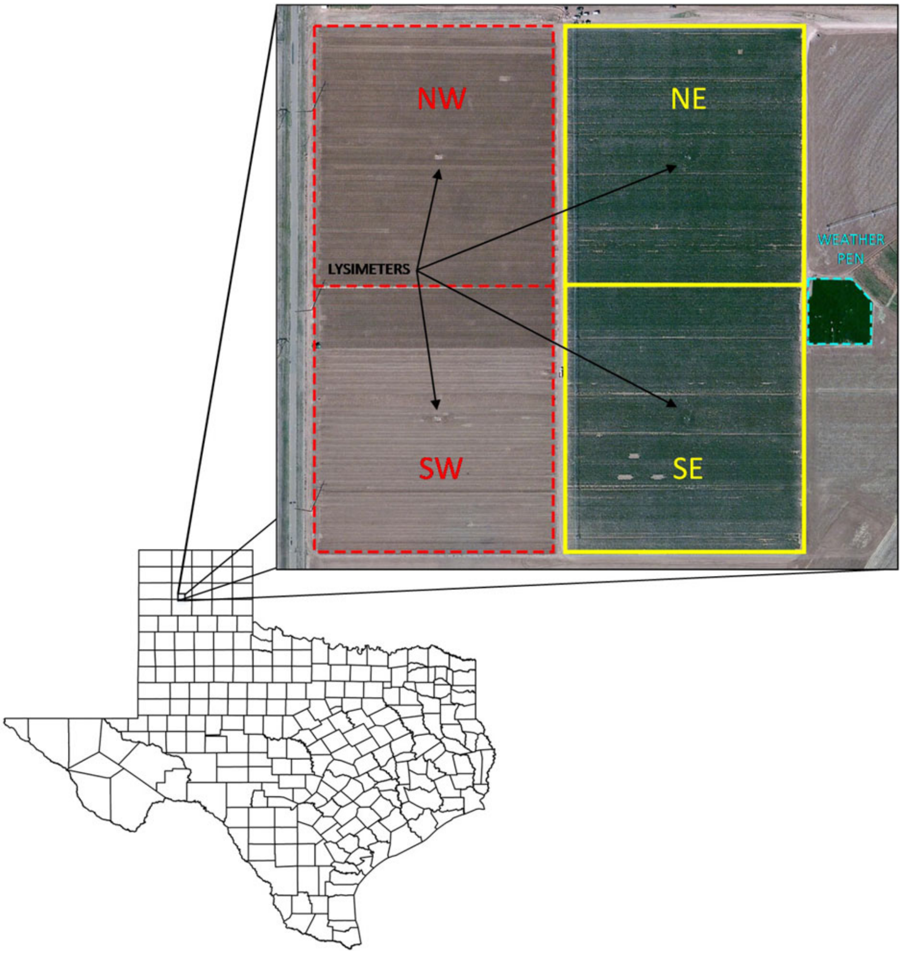


FIGURE 1. The site of field experiment for soybean (thick boundary, NE and SE fields) at the United States Department of Agriculture/Agricultural Research Service (USDA-ARS) Conservation and Production Research Laboratory (CPRL) near Bushland, Texas. Figure adapted from Marek et al. (2016).

et al. 2012), and National Climate Data Center (NCDC 2012) data from around Bushland. The variables include maximum and minimum air temperature, precipitation, and solar radiation. Soil Survey Geographic database (NCSS 2013) was used to download the soil profile for study area and was then converted to a DSSAT soil profile using the methodology given in Sharda et al. (2017). The soil parameters required by the model are given in Table 1 and the profile of Pullman silty clay loam soil for the study area are presented in Figure 2.

Cultivar Calibration — LAI, Biomass, and ET

Yield and phenology in CROPGRO-Soybean are determined by 18 genetic coefficients, and the purpose of calibration was to obtain reasonable estimates of these coefficients by comparing simulated data with observed data. The simulated occurrence dates of different phenological stages are important parameters for planning farm management actions, while the adjusted cultivar (CUL) coefficients (Table 2) are vital in simulating the growth and development of soybean, and to compare the observed and simulated yield (Talacuece et al. 2016). ET is a very significant portion of the water budget in semiarid environments. It is an important component in estimation of resulting irrigation demand for improved understanding of impacts of irrigation practices on groundwater resources (Marek et al. 2016). The model input data were prepared as per DSSAT file formats to be included in CROPGRO-Soybean model for calibration (Hoogenboom et al. 2015). The model was calibrated with soils, weather, and actual crop management data from both NE and SE fields (Figure 1) using experimental data and observed values of leaf area index (LAI), biomass, and ET from the 2003 growing season. The crop management data used were the actual dates of planting, application of fertilizer (dates, amount, and depth), irrigation, and harvest at both the field locations.

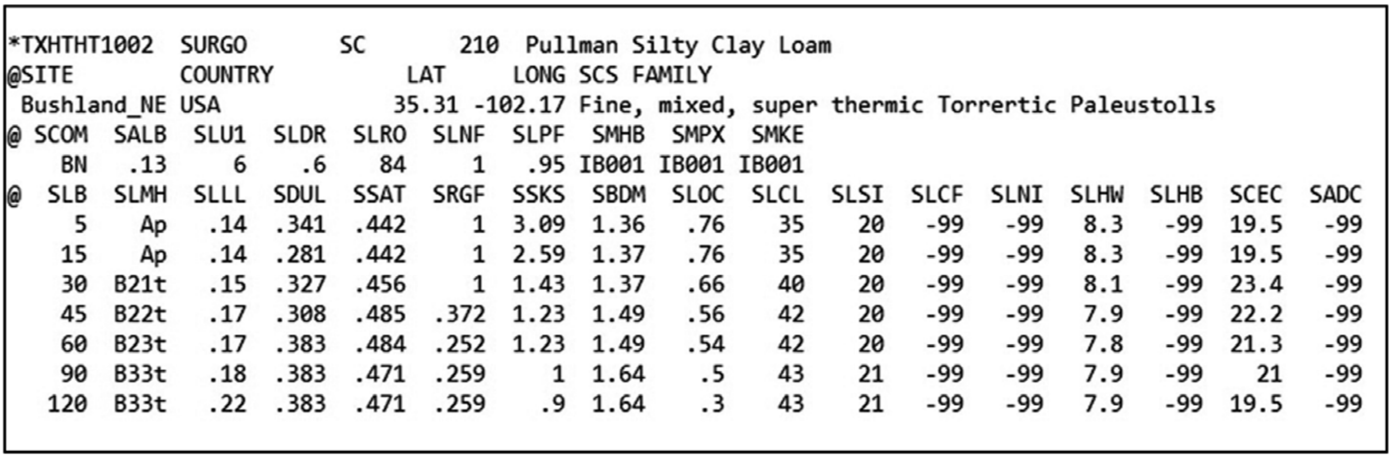
The methods used to simulate various processes in the model include the FAO 56 (Allen et al. 1998) and the Suleiman–Ritchie (Suleiman and Ritchie 2003) options for estimating reference ET and soil evaporation, respectively, and the Soil Conservation Service option for estimating infiltration. When calibrating the model, the beginning soybean genetic coefficients were selected from a default soybean maturity group IV CUL (Bean et al. 2001) within the DSSAT database. Generalized likelihood uncertainty estimation (GLUE) (Beven and Binle 1992) was used to modify the genetic coefficients to reduce the difference between simulated and observed parameters being adjusted. The sensitive model parameters were further manually adjusted to compare simulated and observed values of LAI, biomass, and ET until these closely matched each other while simultaneously evaluating the model performance statistics. According to DSSAT calibration guidelines, first the sensitive parameters affecting crop growth were adjusted with reasonable values until a satisfactory match between simulated and observed LAI was achieved. Thereafter, the parameters affecting biomass and ET were adjusted until the predicted and observed results matched well (Table 2).

TABLE 1. Soil properties available from NCSS (2013) database required for Decision Support System for Agrotechnology Transfer (DSSAT) (adapted from Wu et al. 2010).

DSSAT soil variable	Definition	Units
SITE	Site name	—
COUNTRY	Country name	—
LAT	Latitude	Degrees
LONG	Longitude	Degrees
SLSOURCE	Soils data source	—
SLTX	Soil texture	—
SLDESCRIP	Soil description	—
SCSFAM	Soil family	—
SLDP	Soil depth	cm
SLDR	Soil drainage rate	Fraction per day
SLRO	Runoff curve number	—
SLPF	Soil fertility factor	0–1
SLB	Depth until base of layer	cm
SLCL	Clay	%
SLSI	Silt	%
SLOC	Soil organic carbon concentration	%
SLHW	pH in water	—
SCEC	Soil cation exchange capacity	cmol(+) per kg

Initially, with default maturity group IV soybean CUL, the DSSAT underpredicted LAI across all growth stages for both years at both the sites. To reduce the error between observed and simulated values, model parameters related to soil conditions (SLPF, soil fertility factor) were adjusted for both the sites and years of the study. After using GLUE to get an initial set of CUL coefficients, parameters such as LFMAX (maximum leaf photosynthesis rate at 30°C, 350 vpm CO_2, and high light (mg CO^2/m^2-s)), SLAVR (specific leaf area of CUL under standard growth conditions (cm^2/g)), SIZLF (maximum size of full leaf (three leaflets; cm^2)), and FL-SH (time between first flower and first pod (R3) (photothermal days)) were adjusted to obtain satisfactory simulations of LAI, ET, and biomass.

Statistical parameters, including the coefficient of determination (R^2) (Legates and McCabe 1999), root-mean-square error (RMSE), and coefficient of agreement (d) (Wilmott 1981) were used to check the goodness of fit. The target variables for model validation were grain yield, end of the growing season biomass, LAI, and ET for year 2004. The aim of calibration



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*TXHTHT1002  SURGO      SC      210  Pullman Silty Clay Loam
@SITE        COUNTRY          LAT     LONG SCS FAMILY
 Bushland_NE USA            35.31 -102.17 Fine, mixed, super thermic Torrertic Paleustolls
@ SCOM  SALB  SLU1  SLDR  SLRO  SLNF  SLPF  SMHB  SMPX  SMKE
    BN   .13     6    .6    84     1   .95 IB001 IB001 IB001
@  SLB  SLMH  SLLL  SDUL  SSAT  SRGF  SSKS  SBDM  SLOC  SLCL  SLSI  SLCF  SLNI  SLHW  SLHB  SCEC  SADC
     5    Ap   .14  .341  .442     1  3.09  1.36   .76    35    20   -99   -99   8.3   -99  19.5   -99
    15    Ap   .14  .281  .442     1  2.59  1.37   .76    35    20   -99   -99   8.3   -99  19.5   -99
    30  B21t   .15  .327  .456     1  1.43  1.37   .66    40    20   -99   -99   8.1   -99  23.4   -99
    45  B22t   .17  .308  .485  .372  1.23  1.49   .56    42    20   -99   -99   7.9   -99  22.2   -99
    60  B23t   .17  .383  .484  .252  1.23  1.49   .54    42    20   -99   -99   7.8   -99  21.3   -99
    90  B33t   .18  .383  .471  .259     1  1.64    .5    43    21   -99   -99   7.9   -99    21   -99
   120  B33t   .22  .383  .471  .259    .9  1.64    .3    43    21   -99   -99   7.9   -99  19.5   -99
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FIGURE 2. DSSAT soil profile for Pullman silty clay loam at site of field experiment for soybean at the USDA-ARS CPRL near Bushland, Texas.

TABLE 2. CROPGRO-Soybean genetic coefficients calibrated for cultivar (CUL) Pioneer 94B73RR.

CUL coefficient	Description	Initial value	Calibrated value
CSDL	Critical Short-Day Length below which reproductive development progresses with no day length effect (for short-day plants) (hour)	13.09	13.06
PPSEN	Slope of the relative response of development to photoperiod with time (positive for short-day plants) (1/hour)	0.294	0.291
EM-FL	Time between plant emergence and flower appearance (R1) (photothermal days)	19.4	17.93
FL-SH	Time between first flower and first pod (R3) (photothermal days)	7.0	7.3
FL-SD	Time between first flower and first seed (R5) (photothermal days)	15.0	12.50
SD-PM	Time between first seed (R5) and physiological maturity (R7) (photothermal days)	34.00	35.75
FL-LF	Time between first flower (R1) and end of leaf expansion (photothermal days)	26.00	30.00
LFMAX	Maximum leaf photosynthesis rate at 30°C, 350 vpm CO_2, and high light (mg CO_2/m^2-s)	1.030	1.197
SLAVR	Specific leaf area of CUL under standard growth conditions (cm^2/g)	375.0	250.0
SIZLF	Maximum size of full leaf (three leaflets) (cm^2)	180.0	152.6
XFRT	Maximum fraction of daily growth that is partitioned to seed + shell	1.00	1.00
WTPSD	Maximum weight per seed (g)	0.19	0.17
SFDUR	Seed filling duration for pod cohort at standard growth conditions (photothermal days)	23.0	17.26
SDPDV	Average seed per pod under standard growing conditions (#/pod)	2.20	1.799
PODUR	Time required for CUL to reach final pod load under optimal conditions (photothermal days)	10.0	10.0
THRSH	Threshing percentage. The maximum ratio of (seed/(seed + shell)) at maturity. Causes seeds to stop growing as their dry weight increases until shells are filled in a cohort.	77.0	77.0
SDPRO	Fraction protein in seeds (g(protein)/g(seed))	0.405	0.405
SDLIP	Fraction oil in seeds (g(oil)/g(seed))	0.205	0.205

procedure was to achieve a resultant CUL so that the coefficient of determination (R^2) was high (>0.70), RMSE was low, and the coefficient of agreement (d) was high (>0.80). The calibrated values for soybean CUL Pioneer 94B73RR were copied into DSSAT CUL file to further simulate soybean and evaluate the results.

Irrigation Management Strategies

After the model was satisfactorily evaluated using field experiment data, it was used to simulate soybean yields and study the impact of different irrigation management strategies using long-term historic climatic data (1951–2012). The seasonal analysis program (Tsuji et al. 1998) was used to run the simulation for comparing variability associated with crop performance based on management options over a number of years.

DSSAT uses water thresholds called irrigation threshold (ITHR) to define different levels of plant extractable water for crop growth. This available water is the difference between field capacity and permanent wilting point. Plant extractable soil water for a specific irrigation depth defined by the user is checked by the model at a daily time step based on comprehensive calculations of the soil water balance. Irrigation periods in DSSAT can be activated or deactivated using ITHR values while setting up the simulation control module.

Seven irrigation treatments were set up for seasonal analysis in the DSSAT model. To study the effect of irrigation amounts and timing on yield and water productivity, ITHR was set to rainfed, 20%, 35%, 50%, 65%, and 80% levels. For all management strategies, a fixed amount of 25 mm was applied whenever irrigation was necessary based on the ITHR settings. The application of a fixed amount matched the widely used center pivot or linear irrigation systems in the THP. Irrigation efficiency was set at 80%, assuming an efficient irrigation system. To investigate the effect of different irrigation treatments on crop yield, biomass, and ET, each of the irrigation scenarios was used to calculate CWP (Zwart and Bastiaansen 2004) using Equations (1 and 2)

$$\mathrm{CWP}_y = \frac{Y}{\mathrm{E}T} \tag{1}$$

$$\mathrm{CWP}_b = \frac{B}{\mathrm{E}T}, \tag{2}$$

where Y is crop yield (kg/ha), ET is evapotranspiration (mm), and B is biomass (kg/ha). Both yield and biomass are end of the season values on dry matter basis. Another parameter evaluated was IWUE (kg/m^3) which was calculated (Howell 2001) using the following Equation (3):

$$\mathrm{IWUE} = \frac{Y_i - Y_0}{W}, \tag{3}$$

where Y_i represents the irrigated yield (kg/ha), Y_0 is the nonirrigated yield (kg/ha), and W (mm) is the amount of water used for irrigation during the season in the irrigated treatment.

RESULTS AND DISCUSSION

CUL Calibration — LAI, Biomass, and ET

The final values of calibrated CUL coefficients are given in Table 2. The close agreement between the observed and simulated values for days of emergence, anthesis, appearance of first pod, and maturity dates (Table 3) indicated that phenological CUL coefficients were calibrated well. The deviation between observed and simulated phenological phases varied between −2.0% and 14.0% (Table 3). In general, it was observed that the soybean CUL grown was satisfactorily represented by the genetic coefficients presented in Table 2.

The CROPGRO-Soybean model was evaluated by comparing observed and simulated data of temporal changes in LAI, biomass, and ET. The temporal changes in LAI for year 2003 in both the experimental sites are presented in Figure 3a. It was found that the simulated LAI values closely agreed with the observed data during most of the vegetative and reproductive soybean growth cycle. Upon careful examination of Figure 3a, it can be seen that during the early exponential rise phase of LAI development, the model overpredicted LAI, and under predicted the maximum LAI. This may be partly due to earlier simulation of maximum LAI than the observed date. The plausible explanation to this lies in the phenomenon of progressive senescence of green leaves in a soybean plant which can cause reduction in LAI. It was observed that the field data on rate of leaf area expansion was high in the mid-vegetative stage, and the simulated maximum LAI was lower than the observed (Figure 3b). These results are in close agreement with several studies that have used CROPGRO-Soybean to simulate soybean growth in other parts of the country (Boote et al. 1997; Alagarswamy et al. 2000; Nielsen et al. 2002; Wang et al. 2003).

Similar results were obtained for biomass simulations as well (Figures 4a,4b) with biomass predictions being very close to the observed values during the reproductive growth stage of soybean plants. It is not surprising as biomass is calculated using the simulated LAI. CROPGRO-Soybean simulated time series

TABLE 3. A comparison of observed and simulated values and percentage difference in the phenological development stages of soybean at two experimental sites (NE and SE) for calibration and validation.

	NE (calibration)			NE (validation)		
Phenological stage	**Measured**	**Simulated**	**%Deviation**	**Measured**	**Simulated**	**%Deviation**
Emergence day (dap)	9	8	11	7	6	14
Anthesis day (dap)	50	50	0	48	49	−2
First pod (dap)	65	66	−1	70	65	7
Physiological maturity day (dap)	122	121	1	118	119	−1
	SE (calibration)			**SE (validation)**		
	Measured	**Simulated**	**%Deviation**	**Measured**	**Simulated**	**%Deviation**
Emergence day (dap)	9	8	11	7	6	14
Anthesis day (dap)	50	50	0	48	49	−2
First pod (dap)	65	66	−1	70	65	7
Physiological maturity day (dap)	122	120	2	118	120	−2

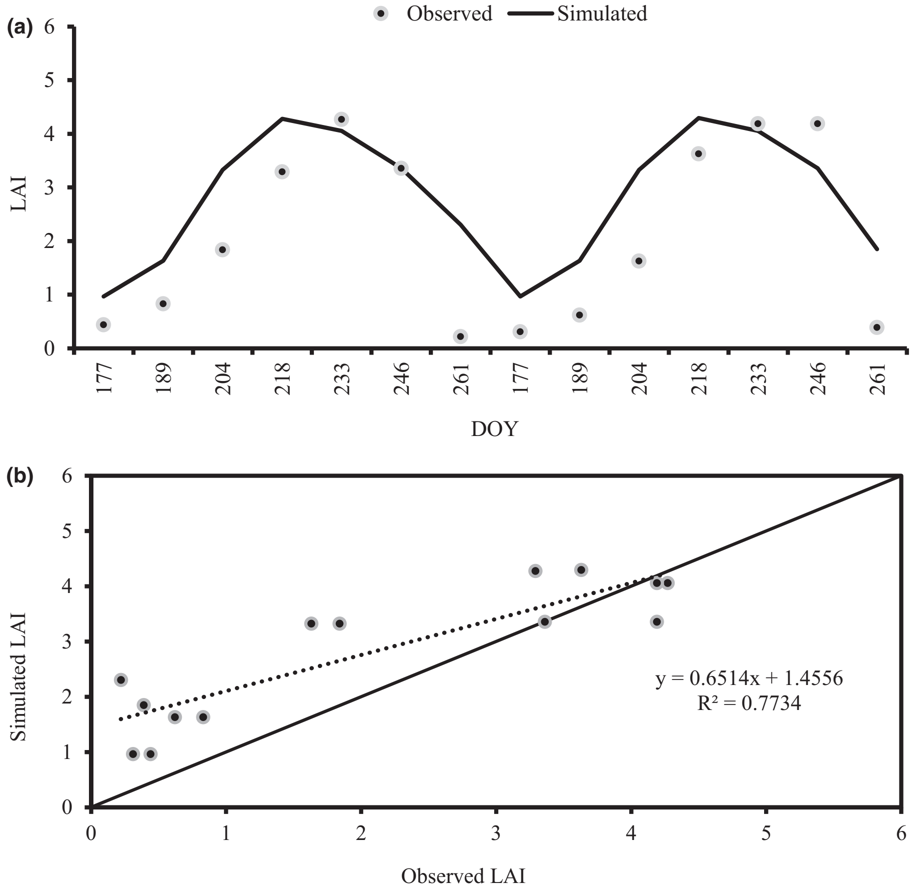

FIGURE 3. Comparison of simulated and observed leaf area index (LAI) of soybean during model calibration at the NE and SE fields at CPRL, Bushland, Texas. (a) LAI over the growing season and (b) observed vs. simulated LAI.

of biomass accumulation fairly well for both the experiment sites during calibration and validation periods.

It has been reported (Kisekka et al. 2016) that DSSAT is unable to relate soil water stress factors to phenological development in water stress environment. Since water stress factors are related to biomass accumulation, this could have resulted in overestimation of biomass during certain stages of growth. Model evaluation response for soybean at a temporal scale for both LAI and biomass during calibration and validation period showed that the model performed well statistically during growing seasons for the CUL used at both the experimental sites at CPRL (Table 4). The goodness-of-fit statistics calculated for model validation (2004) showed that the model was able to simulate the parameters adequately with high index of agreement (>0.84) and R^2 values (0.73–0.90) (Table 4).

The ET of soybean was simulated with a RMSE of 0.8 and index of agreement of 0.94 for calibration period (Table 4). Similar results were also observed for the validation period (Table 4). Upon careful study of Figure 5b, it can be seen that there was a period of overestimation of ET later in the growing season. Marek et al. (2016) found comparable results for ET estimation in the THP along with studies conducted in other parts of the world (Nielsen et al. 2002; Dogan et al. 2007a, b) reporting similar findings. Despite the overestimation of ET during later part of the soybean growing season, based on the statistical parameters, it can be said that the ET of the experimental CUL was satisfactorily simulated.

Overall, the statistical evaluation showed that the model simulated the LAI, biomass, and ET of soybean very well and can be used to assess the impact of irrigation treatments on crop productivity of soybean to determine best limited irrigation scenarios for THP using long-term historical weather data (1951–2012).

Irrigation Management Strategies

Average of all the ITHRs simulated over the years exhibited that higher irrigation amounts increased soybean yield in the THP (Figure 6) with the average yields varying between 2,200 and 5,400 kg/ha. These

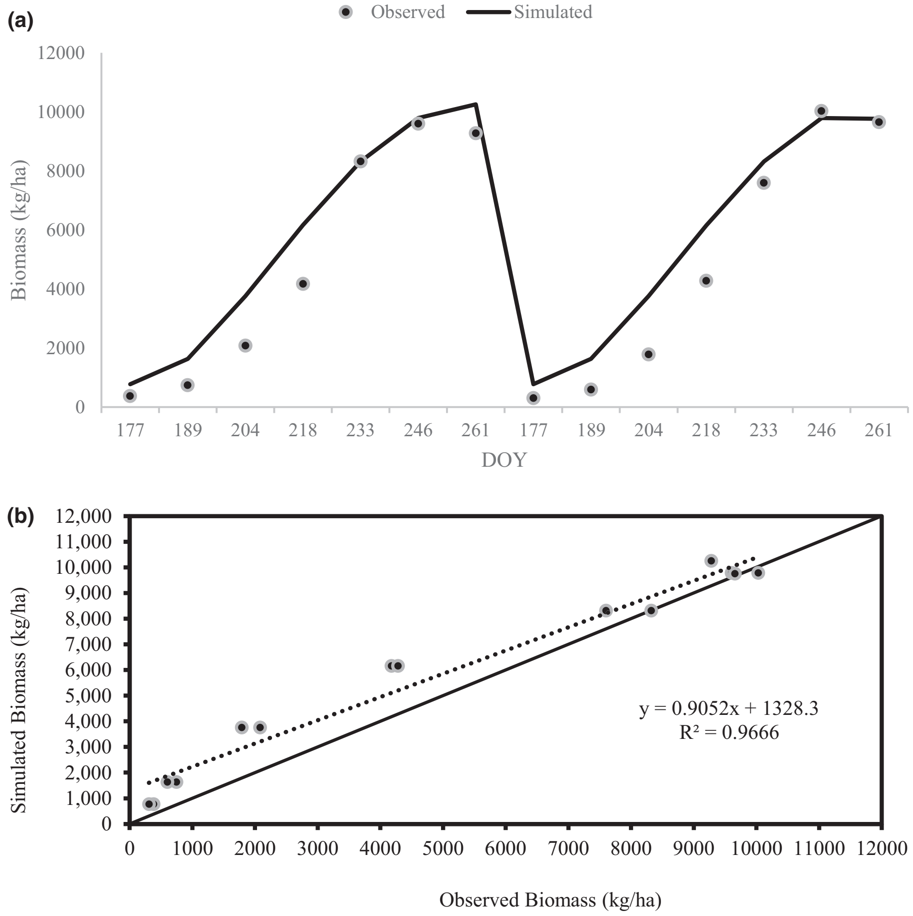

FIGURE 4. Comparison of simulated and observed LAI of soybean during model calibration at the NE and SE fields at CPRL, Bushland, Texas. (a) Biomass over the growing season and (b) observed vs. simulated biomass.

TABLE 4. Goodness-of-fit statistics for observed and simulated growth parameters and evapotranspiration (ET) during calibration and validation for soybean at CPRL, Bushland, Texas.

	Calibration			Validation		
Parameter	R^2	**RMSE**	*d*	R^2	**RMSE**	*d*
LAI	0.77	0.85	0.86	0.90	0.50	0.95
Biomass	0.97	1,135.5	0.98	0.81	2,439.7	0.84
ET	0.81	0.68	0.94	0.80	0.73	0.94

results are in agreement with another soybean study conducted in the High Plains Region that found that irrigated soybean increased by 38 kg/ha as compared to 24 kg/ha for dryland soybean over 25 years (Ciampitti et al. 2018). However, it was also concluded in the same study that the maximum soybean yield occurred using a 50% ITHR criterion, which used less water than other higher application treatments. Nevertheless, the challenge is to find an optimum ITHR scenario that can produce significantly higher yield as compared to rainfed conditions, while sustaining the available groundwater resources.

It was observed that there was a strong relation between yield and total amount of water (rainfall + irrigation) received for all the irrigation treatments with some inherent variability, with the rainfed treatment being the most variable (Figure 7). The results indicate that increase in supplemental irrigation increased the yield and these results agreed with previous soybean irrigation studies

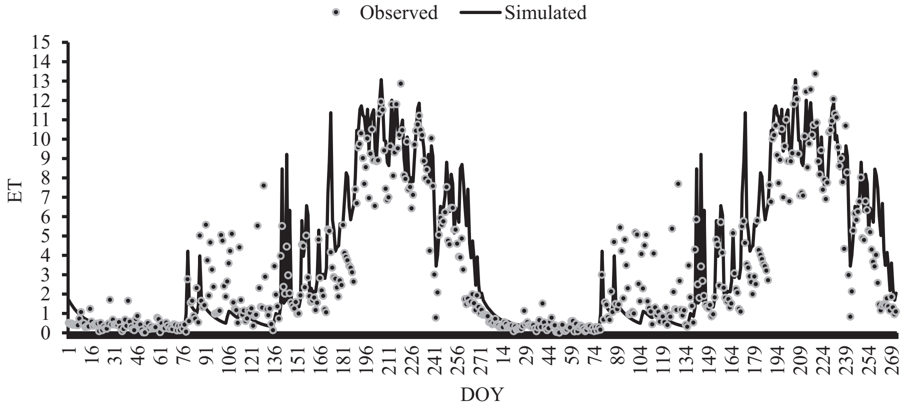

FIGURE 5. Simulated vs. observed ET for soybean grown at both the study sites at USDA-ARS CPRL near Bushland, Texas. (a) ET over the growing season and (b) observed vs. simulated ET.

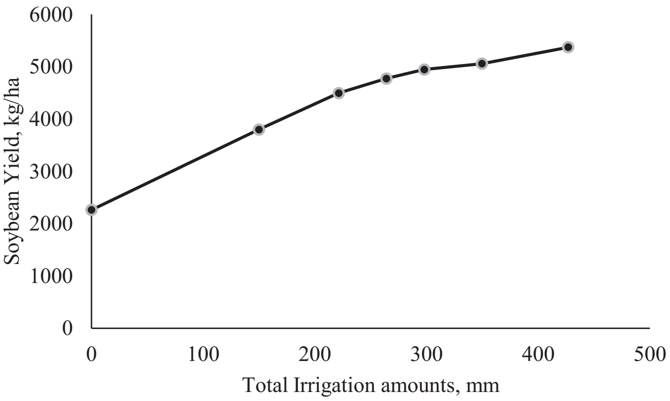

FIGURE 6. Simulated average crop yields for soybean and its response to total irrigation amount at USDA-ARS CPRL near Bushland, Texas for 62 years (1951–2012) at an application efficiency of 80%.

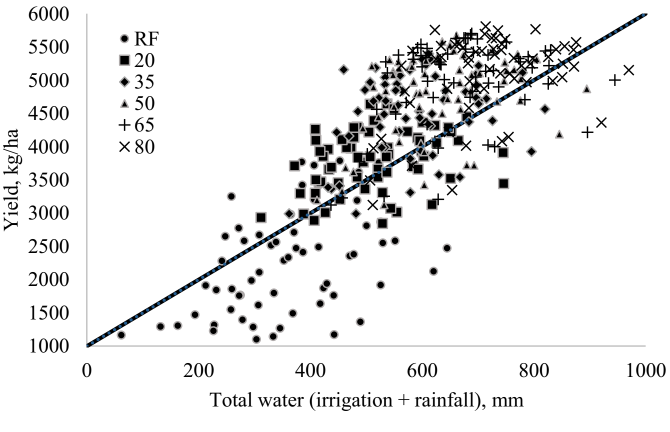

FIGURE 7. Relationship between soybean yield (kg/ha) and total amount of water applied (irrigation + rainfall) during the growing season for years 1951–2012 for rainfed (RF) conditions and different irrigation thresholds (ITHR).

conducted around the U.S. (Sweeney et al. 2003; Garcia y Garcia et al. 2010).

Mean soybean yield averaged over the 62 growing seasons for different ITHRs (Table 5) indicates that there was a significant difference ($p < 0.05$) between yields in ITHRs of 20%, 35%, 50%, 65%, and 80%, and the rainfed treatment. As expected, the yield increased as more water was available during the growing season. These results differ from some studies conducted in other parts of the country (Guzman et al. 2018) that found little or no change in yield (33.6 kg/ha) with increased application of irrigation but are similar to the findings of Garcia y Garcia et al. (2010) who found that the yield increased at a rate of 7.2 kg/mm of water applied. It is important to note that over the length of the study period and the irrigation treatments, total rainfall, total number of irrigation applications, and amount of irrigations varied due to difference of the vegetative and reproductive growth stages of the crop. On an average, the 20% ITHR received six irrigation applications for a total of 150 mm, ITHR 35% received nine irrigation applications while ITHR 50% and 65% received 11 and 12 irrigations, respectively, while ITHR 80% irrigation treatment received 14 irrigation applications for a total of 350 mm. It has been reported (Garside et al. 1992) that for every mm of accumulation of pan evaporation between irrigation applications, 6–8 kg/ha of soybean seed yield is lost. Garside et al. (1992) also reported that for soybean, more frequent irrigation enhances the growth rates of all plant components in a semiarid environment of Australia.

Similar results were obtained for biomass, whose values tended to increase with irrigation, with mean simulated biomass of 4,457 kg/ha for rainfed treatment and 9,864 kg/ha for the irrigation treatment where ITHR was set to 80% (Figure 7). These results were in agreement with Mercau et al. (2007); Dogan

TABLE 5. Mean soybean yields for different ITHR treatments averaged over 62 years (1951–2012) of historic weather data at CPRL, Bushland, Texas.

ITHR treatment	Mean yield (kg/ha)	SD (kg/ha)
RF	2,261	785.36
20%	3,797	463.85
35%	4,496	595.96
50%	4,773	636.43
65%	4,946	668.93
80%	5,057	629.44

TABLE 6. Mean crop water productivity (CWP) for soybean yields (*y*) and biomass (*b*) for different ITHR treatments averaged over 62 years (1951–2012) of historic weather data at CPRL, Bushland, Texas.

ITHR treatment	CWP_y (kg/m^3)	CPW_b (kg/m^3)
RF	4.62	9.10
20%	6.66	11.89
35%	7.41	13.51
50%	7.64	14.38
65%	7.75	14.88
80%	7.59	14.80

et al. (2007a, b); Rogers (2015); and Ciampitti et al. (2018) and showed that soybean biomass responds well to irrigation.

Though above results establish that soybean responds well to irrigation applications, numerous research studies across the High Plains have confirmed that there is a beneficial timing and allowable soil water depletion level for irrigation applications to conserve water without compromising on yield. Extension agents at Kansas State University (Rogers 2015), after several multiyear experiments on irrigated soybeans, have concluded that using a criteria of 50%–60% depletion allows for maximum water use efficiency. Based on simulations using CROPGRO-Soybean, it was found that ITHR of 65% applied only one more irrigation as compared to ITHR 50% and had an average yield benefit of 173 kg/ha. Over the course of the simulation period, average 55 mm in irrigation amounts resulted in only 315 kg/ha simulated yield reduction. Therefore, to achieve a 7% increase in soybean yield, about 20% of additional irrigation water was needed. These trends are similar to those found by Bronson et al. (2001) for cotton in the THP.

The highest CWP_y and CPW_b were obtained for 65% ITHR treatment and there were differences in biomass and yield water productivities among different levels of irrigation (Table 6). The results of ITHR 65% and 50% for both yield and biomass productivity were not substantially different. These results showed that either 65% ITHR or 50% ITHR irrigation treatment were more productive than higher irrigation level treatments (ITHR 80%). These trends in the water productivity were similar to those reported in Adeboye et al. (2015) and Irmak et al. (2014) who found that water productivity may be increased by skipping irrigation during certain growth stages of soybeans.

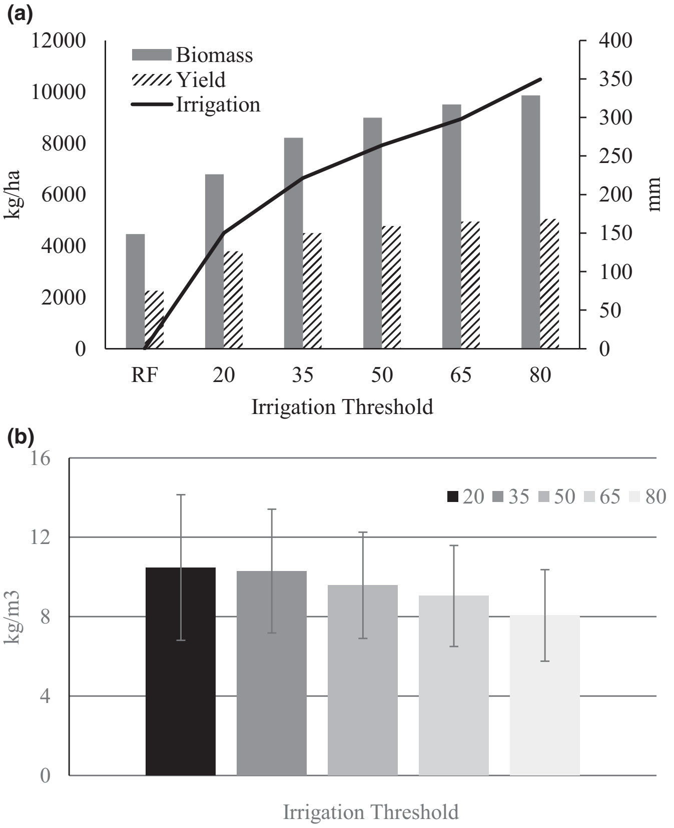

FIGURE 8. (a) Aboveground biomass (kg/ha), yield (kg/ha), and seasonal irrigation (mm) amount of soybean under various ITHRs and (b) irrigation water use efficiency at different ITHR levels for soybean simulations averaged over 1951–2012 along with standard deviation error bars at CPRL, Bushland, Texas.

IWUE ranged between 8 and 10.5 kg/m^3 (Figure 8) with IWUE for 50% and 65% ITHR being 9.6 and 9 kg/m^3, respectively. The simulated IWUE decreased with increased irrigation amounts, a trend that has been observed in other field and modeling studies (Sincik et al. 2008; Modala et al. 2015; Lopez et al. 2017). The ITHR 80% irrigation treatment had lowest irrigation water use efficiency with the possible explanation that the soil water levels were high, which did not allow to capture and store rainfall during the growing season.

These results enforce the argument that irrigation applications scheduled based on soil water depletion may be the best management practice for improving the utilization of groundwater resources in the THP. Irrigation scheduling in this form can be accomplished using either soil water measurement devices or ET-based irrigation scheduling. It is important to note that the utilization of deficit irrigation strategies to maximize CWP could, however, be impacted by several crop management factors like weather (amount of precipitation received), CUL characteristics, planting date, soil type, and antecedent soil moisture condition.

SUMMARY AND CONCLUSIONS

As producer interest in soybean production broadens in the THP, and supplies of irrigation water dwindle due to hydrological or other constraints, producers and water managers in the region face production and economic risks. This uncertainty and risk can be mitigated with the use of improved management tools. This study used DSSAT-CROP-GRO-Soybean v 4.6 crop simulation model to study irrigation strategies for effectively managing the applications in a way to conserve water while not compromising on the seed yield of soybeans and aiding in the sustainability of diminishing groundwater resources in the semiarid THP. The model was calibrated and validated using experimental data from the USDA-ARS CPRL near Bushland, Texas and then applied to simulate biomass production and yield, and to calculate water productivity and IWUE to determine irrigation management strategies based on long-term historic weather data (1951–2012).

The study demonstrated the implementation of conservative irrigation management by selecting an ITHR that can provide reasonable yields as compared to higher ITHRs. It was found that a lower total amount of irrigation can be applied without compromising soybean yields. The ITHRs between 50% and 65% present a reasonable alternative as compared to initiating irrigation at a higher soil water content (i.e., lower depletion). This strategy could potentially lower the total volume of groundwater withdrawn and provide a decision-making tool to weigh alternatives for irrigation management and groundwater withdrawal and could be useful for other semiarid regions where water for irrigation is limited. Water is, and will remain a major factor limiting soybean production. Under limited water resources, efficient use of water could be achieved through the use of new irrigation strategies (Rosadi et al. 2005) such as those investigated in this study.

As it is in most modeling studies, this investigation is based on assumptions of optimum environmental conditions, i.e., no effects of pest, disease, and weeds on the crop simulated, which may set apart the simulation results obtained from true field situations. However, this is a compromise that the scientific community is willing to make based on the benefits of studies like this and the foresight these tools provide to face the challenges that the crop production community faces today due to erratic climate patterns and dwindling natural resources.

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