GROWTH RESPONSE, PRODUCTIVITY, AND SIMULATION OF BIOMASS

SORGHUM FOR BIOENERGY PRODUCTION IN SOUTH TEXAS

A Dissertation

by

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DOCTOR OF PHILOSOPHY

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ABSTRACT

Considerable research has been conducted to evaluate the productivity of biomass sorghum hybrids for bioenergy production, but research questions were mostly focused on determining the highest yielding hybrid for a single sowing season. Considering that a bioenergy refinery requires a sustained supply of biomass, this dissertation explores the production of several varieties for various sowing seasons, soil types, water supply condition, and irrigation methods to select the most profitable practices. Therefore, the main goal of this dissertation was to investigate and evaluate the effect of weather and management conditions on growth response and productivity of biomass sorghum for bioenergy production using replicated field experiments and computer simulation. It also studied the effect of crop parameters, such as radiation use efficiency (RUE) and water use efficiency (WUE) on crop growth of several sowing dates and varieties.

A variance analysis determined that significant differences ($p < 0.05$) were observed among sorghum hybrids and sowing seasons in dry biomass (DB) production, leaf area index (LAI), and WUE. The highest DB yields, LAI values, and WUE were observed on the energy hybrids sowed between March and May. Energy hybrids also exhibited higher maximum and average crop growth rate (CGR) in the early sowing seasons of the year. They also could produce up to 66% more biomass than forage hybrids, and they also had the potential for producing as much as 33 Mg ha^{-1} with an average of 530 mm of water using drip irrigation in south Texas when sown from March to May.

Successful calibration of the Environmental Policy Integrated Climate (EPIC) model allowed to conduct simulations to determine the total DB, LAI, crop water use (CWU), the relationship between crop productivity and crop evapotranspiration (ET_c), and WUE of biomass sorghum. The most important crop parameters identified in EPIC that needed to be adjusted to achieve appropriate DB were the biomass energy-ratio (WA), potential heat units (PHU), and the Hargreaves-Samani PET equation coefficient (PARM 38), and exponent (PARM 13). The statistical parameters derived from measured versus simulated dry biomass in the calibrated model indicated that the EPIC model performed well, showing a great potential for simulating the total DB of sorghums. Thus, it was demonstrated that the EPIC model could be used for the assessment of crop water use and total DB production under limited irrigation levels, especially in semi-arid regions.

It was found that RUE depended on crop variety and sowing seasons. Higher RUE values were observed for the energy hybrids in the sowing dates from March to May. Therefore, the changing of these RUE values according to the sowing date can improve the prediction of DB in crop models. The EPIC model was parameterized using the RUE values from field experiments to enhance the effectiveness of the crop simulation model to predict the potential DB of biomass sorghum. The statistical parameters derived from measured versus simulated DB indicated that the EPIC model performed well at estimating DB with an average percent error of 11% at harvest, and an average $R^2 = 0.91$. Therefore, the identification of adequate RUE values for different sowing seasons enhanced crop simulation effectiveness in predicting sorghum growth and yield response for staggered biomass production.

DEDICATION

To Mom and Dad, for everything they did for me growing up

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All work of the dissertation was completed by the student under the advisement of professors Vijay P. Singh (Biological & Agriculture Engineering Department), Juan Enciso (Biological & Agriculture Engineering Department), Jaehak Jeong (Biological & Agriculture Engineering Department) and Nithya Rajan (Crop & Soil Science Department).

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NOMENCLATURE

°C	Celsius degree
ALMANAC	Agricultural Land Management Alternative with Numerical Assessment Criteria
ANOVA	Analysis of variance
BD	Bulk density
CCC	Calcium carbonate content
CEC	Cation-exchange capacity
CIPAR	Cumulative intercepted photosynthetically active radiation
CO2	Carbon dioxide
CRG	Crop rate growth
CWU	Crop water use
DB	Dry biomass
DB	Day
DMLA	Maximum leaf area index
DSSAT	Decision Support System for Agrotechnology Transfer
EC	Electrical conductivity
EP	Plant transpiration
EPIC	Environmental Policy Integrated Climate
ET	Evapotranspiration
ET_c	Crop evapotranspiration

ET_o	Reference evapotranspiration
FAO	Food and Agriculture Organization
FC	Field capacity
g	Gram
GDD	Growing degree days
h	Hour
ha	Hectare
HI	Harvest index
HMX	Maximum crop height
HSD	Honestly significance difference
I	In-season irrigation
I_0	Solar radiation above the canopy
I_i	Solar radiation under the canopy
IPAR	Intercepted photosynthetically active radiation
J	Joule
K	Canopy extinction coefficient
K_c	Crop coefficient
$K_{c\ end}$	End crop coefficient
$K_{c\ ini}$	Initial crop coefficient
$K_{c\ mid}$	Middle crop coefficient
kg	Kilogram
L	Liter

LAI	Leaf area index
ln	Natural logarithm
LSD	Least significant difference
m	Meter
m^2	Square meter
Mg	Mega gram
MJ	Mega joule
mm	Millimeter
N	Nitrogen
nm	nanometer
NRCS	National Resources Conservation Service
NSE	Nash-Sutcliffe efficiency
OCC	Organic carbon concentration
PAR	Photosynthetically active radiation
PBIAS	Percent bias
PET	Potential evapotranspiration
PHU	Potential heat units
r	Correlation coefficient
R	In-season effective rainfall
R^2	Coefficient of determination
RCBD	Randomized complete block design
RMSE	Root mean square error

Rs	Solar radiation
RUE	Radiation use efficiency
s	Second
sd	Standard deviation
SE	Standard error
SSURGO	Soil Survey Geographic Database
STWP	South Texas Weather Program
SW	Soil water
t_{base}	Base temperature
TOP	Optimum temperature
UAN	Urea and ammonium nitrate
USA	United States of America
USDA	United States Department of Agriculture
WA	Biomass to energy ratio
WL	Water loss
WP	Wilting point
WUE	Water use efficiency
τ	Transmittance

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1. INTRODUCTION

Biomass sorghum is one of the most attractive alternatives for producing energy in many regions of the world because of the high biomass obtained in a short period, high efficiency at producing structural carbohydrates, high water use efficiency, drought-tolerance, and high salt tolerance. The potential growth of biomass sorghum is a function of photosynthetically active radiation and its interception, and its biomass productivity is constrained by stresses, such as temperature, water, and nutrients. However, as a C4 plant, biomass sorghum utilizes many inputs, such as water and nutrients, to satisfy their needs and achieve their production potential. To evaluate the yield potential of biomass sorghum, crop simulation models are suitable as a decision support tool for assessing the management, crop growth, and crop production under different spatial and climatic conditions.

1.1. Problem statement

Critical information in the literature relates to the use of high biomass sorghum for annual production. Many farmlands in Texas' production region remain idle every year due to high crop production costs and low crop return margins, high water delivery costs, and limited water supplies. Hence, the introduction of alternative biomass crops, such as sorghum for bioenergy production, has become a focus of researchers, agronomists, and plant breeders as an option to improve local agricultural economies. Therefore, it is essential to explore the biomass yield potential of different feedstocks and varieties and study the efficiency in converting solar energy into biomass, and its water use efficiency.

Another gap in the current knowledge, according to the literature, is limited information regarding the response of these biomass crops on solar energy use. This information is important to assess the physiological ability of biomass sorghum to produce dry biomass under the effect of different climate conditions. Since many of those biomass crops are highly sensitive to climatic conditions, the monitoring of radiation use efficiency at several sowing seasons would provide an extensive understanding of biomass sorghum's physiological ability to produce biomass under different climate conditions, such as temperature and photoperiod.

Additionally, in recent years, agriculture has been facing challenges in water supply that are critical for increasing agricultural production. Some of these problems are high water-delivery costs, high water pumping costs, and limited water availability. Therefore, it is essential to investigate the biomass productivity of biomass feedstocks under different irrigation scenarios to identify appropriate irrigation strategies, such as deficit irrigation, to improve crop water use. An alternative may be to take advantage of drought tolerant crops, such as sorghum in South Texas' water-limiting areas. It is also necessary to conduct field experiments and evaluate sorghum's biomass productivity under different irrigation levels so the best strategy can be proposed.

Another challenge is the lack of crop models suitable for simulating energy sorghums to help producers evaluate the impact of environment and crop management practices in producing biomass sorghum. Although field experimentation is necessary to provide valuable data, crop simulation models can be a useful tool to obtain information on possible outcomes without conducting extensive field experiments. The availability of reliable data from field experiments is essential to feed crop simulation models. Once the crop models are calibrated and validated, it is necessary to explore the potential growth and productivity of biomass sorghum and to explore the opportunities of growing biomass sorghum under stress constrictions, such as temperature, water, and nitrogen.

1.2. Objectives and hypothesis

Considering the information that exists from weather and 3-year field experiments conducted for biomass sorghum in south Texas, this work will have the following objectives:

1.2.1. General objective

Investigate and evaluate the effect of climate and management conditions on growth response and productivity of biomass sorghum for bioenergy production using replicated field experiments and computer simulation.

1.2.1.1. Specific objectives

i. To evaluate the effects of variable timed sowing dates of three biomass sorghum hybrids on dry biomass productivity, crop growth rate, and crop water use efficiency. Biomass sorghum is widely recognized among many species by its high biomass yield potential and high efficiency in water use. Therefore, it could be an excellent substitute for traditional food/feed crops grown in South Texas. Besides, to supply future biorefineries, there is a need to sustainably intensify biomass production on current agricultural land (Manevski et al., 2017) to obtain sufficient feedstock and achieve sufficient annual production rates to run biorefineries.

ii. To calibrate and evaluate the EPIC model and evaluate the production of biomass sorghum under different irrigation levels. Water availability has been one of the most critical factors for crop production. To help offset the reduced availability of water in agriculture, cropping patterns may need to adapt to irrigation water availability and climate variability to sustain agricultural production. The model will be used to simulate dry biomass productivity and crop water use to identify appropriate irrigation strategies.

iii. To determine the RUE and evaluate the EPIC model for biomass sorghum production under variable timed sowing dates of three sorghum hybrids. Plant dry matter, grown under optimal conditions, depends basically on the quantity of radiation absorbed by the crop canopy (Kiniry et al., 1989). Thus, the estimation of RUE at several sowing dates under optimal growth conditions provides a deep understanding of sorghum hybrids' physiological ability to producing dry biomass under the effect of weather conditions, such as temperature and photoperiod. Therefore, simulation of the EPIC model using the RUE results will help identify appropriate strategies for annual biomass production.

1.2.2. Hypothesis

i. Dry biomass productivity, crop growth rate, and water use efficiency of biomass sorghum are affected by sowing dates.

ii. The EPIC model is capable of simulating dry biomass productivity of biomass sorghum under different irrigation levels.

iii. RUE is a crop parameter that varies over time and cannot be used as a constant parameter in crop models for simulation.

The study area chosen for this study was the experimental fields of the Texas A&M AgriLife Research Center at Weslaco, Texas, US. during the 2013, 2015 and 2016 growing seasons. The research center is in the Lower Rio Grande Valley, which is in the south along the border between the United States and Mexico. It has a semi-arid climate. This environment was chosen so as to evaluate the performance of three biomass sorghum hybrids sown under different dates, different irrigation systems and irrigation levels.

The biomass yield potential of three sorghum hybrids and their efficiency in converting solar energy into biomass was studied in the South Texas' environment for different management practices. One forage sorghum hybrid from Pioneer, Pioneer 877F, and two energy sorghum hybrids from Blade Energy Crops, Blade ES 5140 (photoperiod-insensitive hybrid) and Blade ES 5200 (photoperiod-sensitive hybrid) were selected for field experiments conducted in this study. These three hybrids are recognized to be highly efficient in water use, perform well in marginal lands and marginal conditions. Energy hybrids have a high yield biomass in as few as 90 to 100 days in many areas and grow higher plants that reach up to 6 m. the field experiments consisted basically of evaluating the biomass yield responses, leaf area index, and both radiation and water use efficiency. The experimental design used for each of the experiments during the growing seasons was a randomized complete block design with four replications. The irrigation practices evaluated were biomass production grown under optimal conditions and different water-stress levels. For the 2013 growing season, it was established two experimental sites. One of them was prepared to be irrigated under deep irrigation and the other was prepared to be irrigated under furrow irrigation. For the 2015 growing season, the experimental site was prepared to be irrigated under furrow irrigation. Finally, for the 2016 growing season, the experimental site was prepared to be irrigated under deep irrigation.

1.3. Structure of the dissertation

The objectives formulated in this research were addressed through three chapters.

Chapter two focuses on the study of the potential for biomass sorghum production in staggered production. Dry biomass productivity, leaf area index, and water use efficiency were analyzed by analysis of variance for every sowing season to determine whether there were significant differences among hybrids through the sowing seasons. The accumulated dry biomass was modeled against time using the logistic regression to determine the rate at which sorghum grew at each sowing season and the duration of the phenological phases of the crop. This analysis defined the crop's phenological phases, which are essential to know to determine when the crop needs an adequate amount of water and nutrients to maintain its potential growth. An analysis of the differences in water use efficiency was conducted for the sorghum hybrid at each sowing season to identify water losses and their possible causes to formulate crop management strategies to improve water efficiencies.

Chapter three focuses on modeling assessments of the productivity of biomass sorghum under different irrigation scenarios. Sensitive crop parameters involved in the accumulation of dry biomass for biomass sorghum were assessed. Calibration was performed by comparing experimental field data to the EPIC simulated data. The data used for calibration was obtained from a full irrigation plot for one of the seasons, considering that it reached the potential dry biomass productivity. The calibrated model was then validated by comparing measured data to simulated data at the rest of the experimental plots. For evaluating the crop model performance, statistical indices were calculated and evaluated according to the ranges suggested by Wang et al. (2012) for satisfactory water and crop yield.

Chapter four focuses on the study of the RUE of three biomass sorghum hybrids across the sowing seasons. First, it analyzed the capacity of the sorghum to convert solar irradiance into biomass for different growing seasons. RUE was estimated by the linear regression of the accumulated dry biomass productivity against the sowing season's accumulated IPAR. For IPAR estimation, the canopy extinction coefficient was calculated, which is a parameter that combines all the factors affecting the interception of solar irradiance in the canopy. The accumulated IPAR across sowing seasons is a function of the canopy extinction coefficient and leaf area index and environmental factors, such as temperature and solar radiation. The RUE values obtained for sorghum at each sowing season was used to parameterize the EPIC model. Then, the EPIC model was evaluated to demonstrate its capability of simulating dry biomass of sorghum sown under different sowing dates.

Finally, in chapter five, the main research conclusions are articulated, and also, more essential recommendations are stated.

2. AGRONOMIC PERFORMANCE OF POTENTIAL BIOMASS SORGHUM PRODUCTION FOR STAGGERED SOWING DATES [1]

2.1. Synopsis

Biomass sorghum [*Sorghum bicolor* (L.) Moench] is widely recognized, among many others, by its high biomass yield potential, high efficiency in converting solar energy into biomass, and high efficiency in water use. Therefore, it could be an excellent substitute for traditional food/feed crops grown in south Texas. The objectives of this chapter were to evaluate the effects of variable timed sowing dates of three biomass sorghum hybrids on (i) dry biomass productivity, (ii) crop growth rate, and (iii) crop water use efficiency. Experiments were conducted at the Texas A&M AgriLife Research Center in Weslaco, Texas, during the 2013 and 2016 growing seasons. Significant differences were observed among sorghum hybrids and sowing seasons in dry biomass production (DB), leaf area index (LAI), crop growth rate (CGR), and water use efficiency (WUE). The sorghum DB ranged as expected from 12.57 to 32.77 Mg ha^{-1}. The highest DB values were observed when the sowing took place between March and May, while the lowest DB wase observed on the sowings of August and September. Higher LAI values were observed on the energy hybrids (LAI > 4.0 m^2 m^{-2}). CGR ranged from 0.108 to 0.309 Mg ha^{-1} d^{-1} for the three hybrids during all sowing seasons. There were significant differences among

[1] Part of this section is reprinted with permission from "Growth Response and Productivity of Sorghum for Bioenergy Production in South Texas" by Chavez J.C., Enciso J., Ganjegunte G., Rajan N., Jifon J., Singh V.P. Transactions of the ASABE Vol.62(5): 1207-1218. https://doi.org/10.13031/trans.13317. Copyright 2019 American Society of Agricultural and Biological Engineers.

hybrids during the two years in dry biomass, LAI, and WUE. The highest productivities and efficiencies were observed in the energy hybrids. WUE is used for some crop models as a crucial crop parameter used to predict the potential dry matter accumulation. WUE varied from 3.626 to 7.042 kg m^{-3}. Among sowing seasons, higher WUE values were observed from the energy sorghums sown in March, April, and May. The results of this chapter show that biomass hybrids can produce up to 66% more biomass than forage hybrids, and they also have the potential for producing as much as 33 Mg ha^{-1} with 530 mm of water using drip irrigation in south Texas.

2.2. Introduction

Production of fuel ethanol from high biomass crops can be a sustainable alternative for energy production. Some crops such as sugarcane [*Saccaharum officinarum* L.], corn or maize [*Zea mays* L.], sorghum [*Sorghum bicolor* (L.) Moench], and miscanthus [*Miscanthus spp*.] are warm-season C4 plants that achieve high biomass. Plants that use the C4 photosynthetic pathway are more efficient than C3 crops in converting solar energy into biomass (Zhu et al., 2008). They fix CO_2 into a compound containing four carbon atoms before entering the Calvin cycle of photosynthesis, making them highly efficient in converting solar energy to biomass. However, some C4 plant species require a considerable amount of input, such as water and nutrients, to satisfy their needs and achieve their production potential.

Forage and energy sorghums have been identified as important biomass feedstock crops because of their high biomass production, drought tolerance, short growing cycle, and high water-use efficiency (Monge et al., 2014; Sharma et al., 2017). Forage sorghum, which includes both Sudan grass and silage sorghum, is primarily used for grazing and silage production. Photoperiod-sensitive hybrids of forage sorghum offer higher biomass yield potential compared to other sorghum cultivars and continue growing until the day lengths are less than 12:20 h (Rooney et al., 2007). These are considered dual-purpose because these hybrids are used for both energy and forage production (Shoemaker and Bransby, 2010). Energy sorghums have more significant biomass potential than forage sorghums; however, they differ in forage quality and harvest timings because of their delayed flowering (Maughan et al., 2012; Rooney and Aydin, 1999). Energy sorghum has several advantages compared to conventional energy crops. They are more tolerant of water stress, have higher efficiency in producing structural carbohydrates, have higher biomass potential and water use efficiency, and have the potential for genetic improvement using both traditional and genomic approaches (Enciso et al., 2013; Enciso et al., 2015b; Rooney et al., 2007). Other distinctive characteristics of energy sorghums are that they can remain in the vegetative growth phase throughout the growing season at most latitudes and can grow for more than 200 days in subtropical regions (Marsalis et al., 2010). Therefore, with crop genetic improvements, better cultural practices, and efficient use of irrigation water, sustained production of energy sorghums could be achieved in subtropical regions.

Information about staggered sowing for sorghum is limited in scope, and very few studies exist in the literature. Almodares and Darany (2006) and Balole (2001) reported that late sweet sorghum typically had lower yields of stalks and sugar than earlier sowings. Hipp et al. (1970) evaluated the influence of sowing dates and solar radiation on sweet sorghum in the Rio Grande Valley. They observed that the highest sugar yield was found in crops sown in May. The plants' solar radiation received during the period between boot and early seed formation accounted for about 75% of the variation in yield. There is a little information about staggered sowing, probably because farmers looked at optimal production in a single crop cycle. The need for continuous feedstock supplies for biorefineries makes it necessary to understand better the yield response under different sowing seasons and environmental factors such as solar irradiance and temperature, influencing canopy development, and biomass production.

Water is essential in rainfed agriculture, critically crucial in semiarid dryland agriculture, and explicitly important in irrigated agriculture (Howell, 2001). One of the most important indices used to evaluate crop's response to specific climatic conditions or crop management is the water use efficiency (WUE). The WUE of a biomass crop is generally defined in agronomy (Viets, 1962) as the amount of total biomass yield produced divided by the amount of water used by the plant to produce the yield. WUE is used by practitioners as an indicator in specific regions to identify differences between irrigation methods and irrigation management. Hsiao (1993) reported that a correlation between the above-ground DB and water used tends to remain linear in both well-watered and water deficit conditions. Increasing biomass production and reducing crop water consumption trigger substantial improvements in WUE (Chavez et al., 2018). Some management strategies can increase WUE, such as irrigation scheduling to reduce water losses during the periods of stress (Enciso et al., 2009), reducing the number of irrigation events (Enciso-Medina et al., 1998), or improving the uniformity of the irrigation system (Rajan et al., 2015). Hao et al. (2014) conducted field experiments to improve biomass yield and maximize the WUE in photoperiod-sensitive sorghum in the Texas High Plains. They found that higher WUE was due to increased biomass rather than reduced ET, which indicates that photoperiod-sensitive sorghum may achieve high biomass yield under deficit irrigation.

Production of bioenergy in a bio-refinery requires a continuous supply of feedstock during the year, and consequently, a plan to staggered sowing dates. Most bioenergy experiments involving sorghum are conducted to determine an optimum sowing date, seeking maximum biomass yields with minimum use of inputs such as water and fertilizers. However, there is a need to continuously supply feedstock to biorefineries, which require strategically distribute sowing dates to maximize sorghum dry biomass production during a year. Therefore, it is essential to investigate the biomass sorghum's crop growth rate, and its water productivity with staggered sowing dates under optimal growth conditions. The objective of this chapter is to evaluate the effects of variable timed sowing dates of three biomass sorghum hybrids on (i) dry biomass productivity, (ii) crop growth rate, and (iii) crop water use efficiency. The results obtained in this chapter may allow crop modelers to increase the ability to determine the optimal crop parameters for a more precise prediction of dry biomass productivity of biomass sorghums in staggered production systems.

2.3. Material and methods

2.3.1. Description of field experiments

Field experiments were conducted during the 2013 and 2016 growing seasons at the Texas A&M AgriLife Research Center in Weslaco, Texas (latitude 26° 09' 26'' N, longitude 97° 57' 32'' W; elevation 24 m above sea level) (Figure 2.1). The study area has a semi-arid climate with an average annual precipitation of 558 mm. According to the SSURGO database (USDA, 2013), the soil type is a Hidalgo silt clay loam.

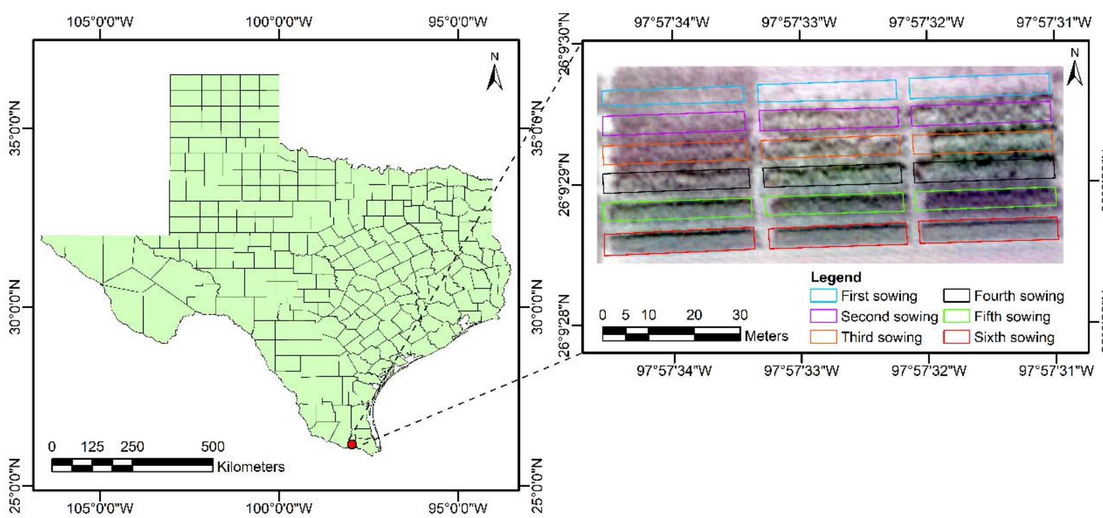

Figure 2.1 Map of Texas showing the location where the experiment was located.

Two biomass sorghum hybrids from Blade® Energy Crops (Blade ES 5140 and Blade ES 5200) and one forage sorghum hybrid from Pioneer® (Pioneer 877F) were sown in 1.02 m wide rows oriented north to south. The plots used for experiments were 4.1 m wide and 91.4 m long. The plant density in all plots was approximately 140,000 seeds per hectare, with a sowing depth of 30 to 45 mm. The plant density after emergence showed no differences among the sowing seasons.

A subsurface drip irrigation system was installed to assure uniform germination and better control in measuring water inputs (Henggeler et al., 2002). Drip tape with 15 mm thickness was placed in the center of each bed. Drip emitters were spaced 0.60 m apart laterally with a nominal discharge of 1.5 L h^{-1} per emitter, resulting in a water application rate of 2.5 mm h^{-1}. Urea ammonium nitrate (UAN; 32% mass fraction of N) was applied through the drip irrigation system in two equal split applications at a rate of 100 kg ha^{-1}. The same total fertilizer was applied to all experimental units.

The field experiments were arranged in a randomized complete block design (RCBD) with three sorghum hybrid levels and four replications. Full irrigation was applied in all experimental plots. It was achieved by replacing water used by the crop, which was calculated using the Sudan grass crop coefficients suggested by FAO 56 and using the Penman-Monteith equation for reference evapotranspiration (ET_o) (Allen et al., 1998). The actual evapotranspiration (ET_c) requirement for sorghum is estimated based on a linear relationship for a well-watered reference grass using the equation:

$$ET_c = K_c \times ET_o \tag{1}$$

where K_c is the crop coefficient (Enciso and Wiedenfeld, 2005). The standard $K_{c\ ini}$, $K_{c\ mid}$, and $K_{c\ end}$ values of 0.15, 1.15, and 1.1, respectively, were applied to ET_o to calculate ET_c

using the Penman-Monteith approach (Rajan et al., 2015). Soil water content was measured using gravimetric methods at the beginning and end of each sowing season. The South Texas Weather Program (STWP), which is an internet-based program developed by Texas A&M AgriLife Research, http://southtexasweather.tamu.edu/ (Enciso et al., 2015), was used to create an irrigation schedule for each sowing season. This program calculates the number of irrigation events during each sowing season and the timing and amount of irrigation water required using a predetermined allowable depletion level of 90%. The irrigation system was assumed to have a 100% efficiency. Weather data used for ET calculations were collected at a weather station (model ET106, Campbell Scientific, Logan, Utah) located 100 m away from the experimental plots. The weather station is equipped with a tipping bucket rain gauge (model TE525, Texas Electronics, USA) for measuring rainfall; a temperature sensor (model CS500, Vaisala, Helsinki, Finland) for measuring maximum and minimum air temperature, and relative humidity; a pyranometer (model LI200X, LI-COR Biosciences, Lincoln, Nebraska) for measuring total solar radiation; and a wind set (model 034A Campbell Scientific, Logan, Utah) for measuring average wind speed. All weather data were recorded hourly using a CR10X data logger.

2.3.2. Field data measurement

Table 2.1 shows the agronomic data on dates in which crop development was monitored. This study used the same plant sampling methodology as described by Meki et al. (2017) who evaluated the performance of biomass sorghum in Hawaii and Texas. Measured plant variables were fresh and dry weight, plant height, stalk diameter, and green LAI. Plant sampling was conducted on each of the experimental units four to five times throughout the sowing season if weather conditions were favorable. Plant height measurements were performed before each biomass harvest by randomly selecting three plants to measure them from the ground to the tip of the longest leaf. Actual LAI and biomass were determined using destructive sampling. The destructive samples were randomly collected from 1 m^2 area at the center of each plot to avoid the border effects. Dry biomass and tissue moisture content percentage were determined after drying all plant materials in a forced-air oven at 60°C until the material reached a constant mass (approximately 72 h). After the end of each sowing season, field plots were harvested using a forage harvester (model Jaguar 940, Claas, Herzerbrock, Germany).

Table 2.1 Agronomic data of sorghum at the Texas A&M AgriLife Research Center at Weslaco, TX. in 2013 and 2016 growing seasons.

Activity	2013		2016					
Sowing date	23 Apr	1 Sep	1 Mar	4 Apr	11 May	15 June	14 July	25 Aug
Harvest date	8 Aug	15 Dec	29 June	2 Aug	8 Sep	13 Oct	11 Nov	23 Dec
Length of sowing season	107 days	105 days	120 days	120 days	120 days	120 days	120 days	120 days
Sampling dates	29 May, 8 July, 25 July, and 13 Aug.	11 Sep., 30 Oct., 20 Nov., and 15 Dec.	11 Apr., 9 May, 9 June, and 29 June	6 May, 7 June, 26 July, and 2 Aug.	2 June, 10 July, 8 Aug., and 8 Sep.	11 July, 30 Aug., 27 Sep., and 13 Oct.	8 Aug., 30 Sep., 4 Nov., and 11 Nov.	28 Sep., 8 Nov., 28 Nov., and 23 Dec.
Mean minimum T°	23.4°C	17.6°C	21.3°C	23.7°C	25.1°C	24.9°C	23.6°C	19.0°C
Mean maximum T°	33.7°C	27.7°C	31.5°C	33.9°C	35.4°C	35.8°C	37.7°C	30.3°C
Precipitation	152 mm	306 mm	177 mm	131 mm	201 mm	118 mm	130 mm	140 mm
Irrigation water applied	457 mm	25 mm	279 mm	432 mm	381 mm	406 mm	381 mm	254 mm
Reference ET	740 mm	435 mm	520 mm	595 mm	612 mm	611 mm	533 mm	402 mm
Estimated sorghum ET	638 mm	332 mm	493 mm	585 mm	595 mm	549 mm	473 mm	365 mm
Total solar radiation	2327 MJ m^{-2}	1394 MJ m^{-2}	2452 MJ m^{-2}	2742 MJ m^{-2}	2824 MJ m^{-2}	2782 MJ m^{-2}	2473 MJ m^{-2}	1832 MJ m^{-2}
Cumulative GDD at harvest	2155 °D	1555 °D	1959 °D	2177 °D	2336 °D	2342 °D	2224 °D	1761 °D
Days with daylight > 12:20 h	120 days	13 days	94 days	120 days	120 days	91 days	62 days	20 days

2.3.3. Computation and statistical analysis of the data

Sorghum phenological progress was obtained for every sowing season across the two-year growing season of study. They were recorded in calendar days and converted to growing degree days (GDD, °D). The cardinal temperatures for phenological development were: base temperature (t_{base}) = 8°C, lower optimal temperature (t_{opt1}) = 30°C, upper optimal temperature (t_{opt2}) = 37°C, and ceiling temperature (t_{ceil}) = 45°C (Soltani and Sinclair, 2012). A 3-segment linear function, as described by Soltani and Sinclair (2012), was used to calculate GDD for each treatment from the sowing date until 120 days after sowing. GDD was calculated as follows:

$$GDD = \left(t_{opt1} - t_{base}\right) \times t_{fun} \quad (2)$$

where:

$$t_{fun} = 0 \quad if \quad t_{mean} \leq t_{base}$$

$$t_{fun} = \frac{t_{mean} - t_{base}}{t_{opt1} - t_{base}} \quad if \quad t_{base} < t_{mean} < t_{opt1}$$

$$t_{fun} = 1 \quad if \quad t_{opt1} \leq t_{mean} \leq t_{opt2}$$

$$t_{fun} = \frac{t_{ceil} - t_{mean}}{t_{ceil} - t_{opt2}} \quad if \quad t_{opt2} < t_{mean} < t_{ceil}$$

$$t_{fun} = 0 \quad if \quad t_{mean} \geq t_{ceil}$$

where t_{fun} is a scalar factor between 0 and 1, and t_{mean} is the average of daily maximum and minimum temperatures. The GDD values were summed for the growth period of each growing season.

Changes in the dry biomass to the time of three sorghum hybrids over the sowing seasons were fitted to a sigmoidal model using the logistic growth function (Richards, 1959), as given in the following equation:

$$DB = \frac{DB_{max}}{1 + a \cdot exp^{(-c \cdot t)}} \quad (3)$$

where DB_{max} is the maximal end value of growth, a is a constant parameter ($a > 0$), c is the crop growth rate ($c > 0$), and t is the duration from sowing to harvest. Parameter estimates were derived for each experimental unit following the procedures described by Gregorczyk (1991). After deriving the relationship between DB with time from the logistic growth function, the slope of the curve or the crop growth rate (CGR, Mg ha^{-1} d^{-1}) was calculated. CGR was defined as the rate of change of DB with time ($\Delta DB/\Delta t$). CGR was calculated as the increase in biomass (ΔDB) between two dates divided by the increase in time (Δt). For more accurate values, the first derivative (dDB/dt) of Eq. (3) was taken. The CGR for each sorghum hybrid at each sowing season was obtained. The first derivative was equated to zero ($dDB/dt = 0$) (which is the time when the tangent to the curve is horizontal) to obtain the day when maximum growth occurred during the sowing season. Finally, the second derivative of the growth function (d^2DB/dt^2), which is the crop growth acceleration, was calculated and then equaled 0 to determine its inflection points (also known as maximum and minimum points of a function). The inflection points of the growth acceleration function of the crop were used to determine the duration of the crop growth phases of crop development.

The seasonal crop water use (CWU, mm) was calculated according to the simplified water balance equation:

$$CWU = R + I \pm SW \tag{4}$$

where R is the in-season effective rainfall (mm), I is the in-season irrigation (mm), and SW is the soil water depletion from the root zone during the sowing season. Eq. (4) is a surrogate estimate of the water used to produce the crop, depending on the neglect of percolation, groundwater use, and surface runoff. The daily CWU values were summed to determine the cumulative CWU (mm). The WUE for each sorghum hybrid at each sowing season was estimated as the slope of the fitted regression of the first-order equation between DB and the cumulative CWU. The WUE was also calculated for each hybrid as follows:

$$WUE = \frac{DB}{\sum_{d\,=\,sowing\ date}^{d\,=s\ ampling\ date} CWU} \tag{5}$$

where WUE (g m^{-2} mm^{-1}) is the ratio between total DB and the cumulative CWU that is also expressed as kg m^{-3}.

The x-axis intercept of the DB versus the cumulative CWU determined the amount of water that did not contribute to biomass production during the sowing season, i.e., the amount of water that did not produce dry biomass ($DB = 0$). This intercept indicates the loss of water from the soil by evaporation, percolation, or runoff (Passioura, 2006). The amount of water lost during the growing season was determined as follows:

$$WL = \frac{-b}{WUE} \tag{6}$$

where WL is a rough estimate of the water loss (mm), b (g m^{-2}) is the intercept coefficient taken from a linear equation, and WUE (kg m^{-3}) is the water-use efficiency (or slope) of the hybrid.

Analyses of variance (ANOVA) were conducted for the two years of sorghum experiments. Sorghum data were analyzed separately over seasons (sowing seasons). Data from all sowing seasons were examined in a combined analysis of variance to explore both how sorghum hybrids responded to different environmental conditions that could occur during a year and to provide information on the nature of the interaction between treatments (sorghum hybrids) and seasons. These analyses were conducted on sorghum hybrids using the SAS PROC GLM (SAS Institute, 2014) for DB, LAI, and WUE variables at harvest time. For analysis, the treatment was set as a fixed effect and the season as a random effect. Mean comparisons among treatments were conducted using the least significant difference (LSD) at the alpha level of 0.05. The canopy extinction coefficient was estimated for each hybrid using the REG procedure in SAS. Also, the REG procedure in SAS was used to conduct regression analyses to describe the relationship between DB on cumulative IPAR and DB on cumulative CWU.

2.4. Results

2.4.1. Environmental conditions

The weather data recorded during the study period, January to December 2013 and 2016, compared with the long-term averages (30 years), is shown in Table 2.2. The patterns of daily mean temperature recorded during the study are shown in Figure 2.2. In general, the monthly minimum and maximum air temperatures were higher in 2016 than both 2013 and the 30-year period. Warm conditions were observed with a remarkable heatwave at the end of July and beginning of August in 2016, with maximum daily temperatures over 40°C. Differences in daily air temperatures through the sowing seasons caused variation in total GDD across the sowing seasons (Table 2.1). The sorghum sown on June 15 and harvested on October 13 in 2016 attained the highest cumulative GDDs (2342°D), followed by the one planted on May 11 and harvested on September 08 (2336°D) as a result of higher temperatures recorded during that summer. The lowest cumulative GDDs were observed in the sorghum sown in September in 2013 (1555°D) and August 25 and March 01 in 2016 (1959 and 1761°D, respectively), probably it was due to the lower daily temperature recorded during those months and the shorter days. In general, the total GDD data and plant maturity corresponded well with the accepted GDDs and sorghum development.

Table 2.2 Monthly average minimum (T min, °C) and maximum (T max, °C) air temperature, monthly total precipitation (mm), monthly total solar radiation (MJ m-2), and monthly average relative humidity at the Texas A&M AgriLife Research Center, Weslaco, TX. in 2013, 2016, and 30-year average.

Parameter	Jan.	Feb.	Mar.	Apr.	May	June	July	Aug.	Sep.	Oct.	Nov.	Dec.	Average / Total
						---------- 2013 ----------							
T min	11.5	14.8	15.2	17.4	21.8	24.5	24.6	24.8	23.6	20.5	13.8	10.0	18.6
T max	21.7	26.5	27.2	29.1	31.3	35.4	35.4	35.6	32.1	31.3	24.0	19.8	29.1
Precipitation	35.1	0	0	71.6	29.2	33.5	18.3	59.7	193.4	17.5	93.0	91.4	642.4
Solar radiation	318.2	404.7	560.4	539.3	643.6	708.2	672.0	661.5	457.1	492.9	324.0	256.4	6038.4
Relative humidity	0.74	0.66	0.62	0.72	0.73	0.70	0.69	0.70	0.80	0.71	0.75	0.78	0.72
						---------- 2016 ----------							
T min	9.6	13.3	18.0	20.4	23.0	24.0	26.2	25.8	24.4	20.7	16.8	13.3	21.26
T max	21.4	27.1	28.3	31.1	33.0	34.4	36.6	36.6	35.3	33.1	27.3	23.4	31.91
Precipitation	37.3	0	62.5	29.5	56.6	167.6	4.1	32.8	56.6	3.0	47.5	12.2	472.4
Solar radiation	350.0	527.0	537.3	601.9	611.1	727.5	810.3	733.2	581.8	580.6	363.1	218.0	6641.7
Relative humidity	0.73	0.63	0.75	0.75	0.75	0.75	0.68	0.68	0.71	0.69	0.75	0.78	0.73
						---------- 30-year ----------							
T min	9.4	11.3	14.7	18.2	21.6	23.7	24.2	24.1	22.4	18.6	14.4	10.9	19.28
T max	21.5	23.6	26.8	29.9	32.4	34.7	35.6	36.0	33.6	30.9	26.2	22.7	30.88
Precipitation	21.2	21.8	26.1	31.3	47.3	57.4	46.2	51.3	106.2	50.1	33.9	26.4	476.2
Solar radiation	465.0	522.0	533.2	588.0	716.1	732.0	740.9	716.1	576.0	530.1	378.0	344.1	6841.5
Relative humidity	0.70	0.68	0.65	0.65	0.68	0.68	0.68	0.65	0.69	0.68	0.70	0.70	0.68

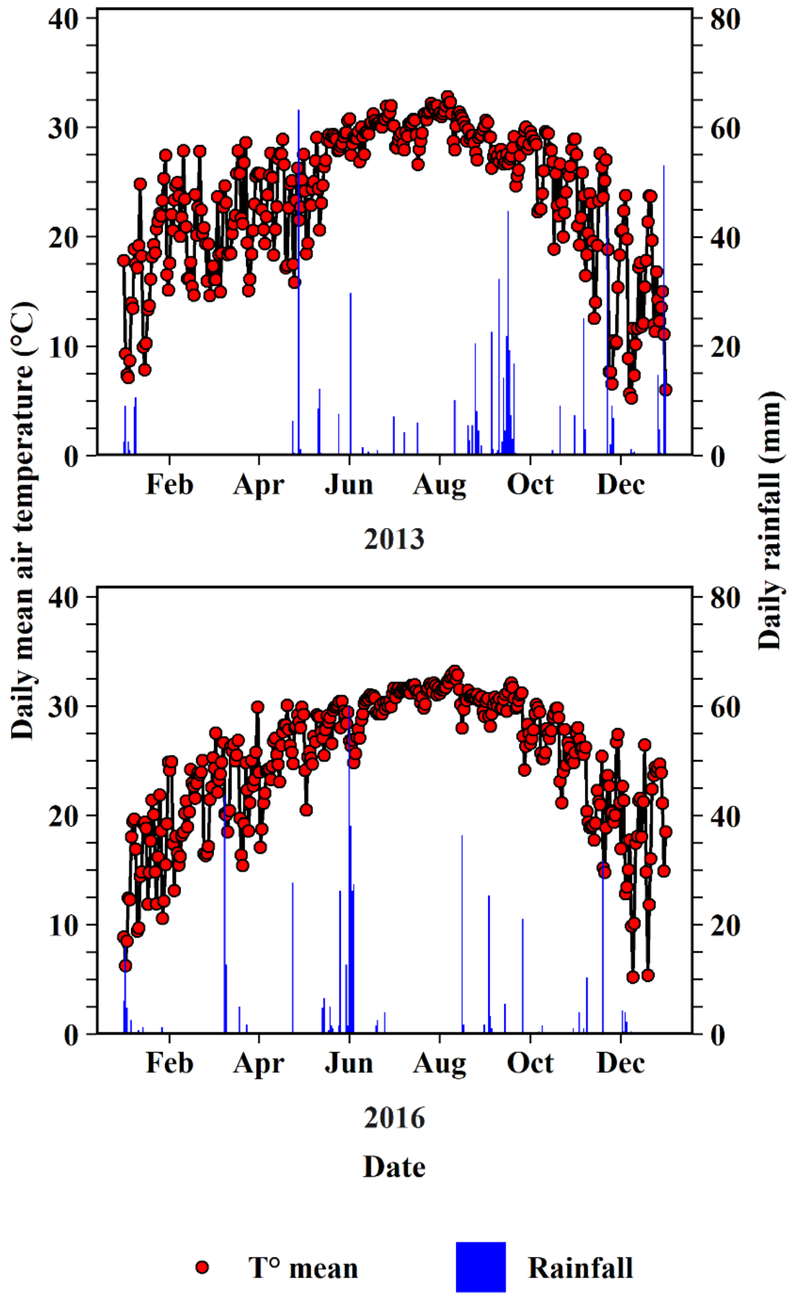

Figure 2.2 Mean daily air temperature and daily total rainfall in years 2013 and 2016 in Weslaco, TX.

Total precipitation (Table 2.2 and Figure 2.2) was excessive in 2013 with 642 mm compared to 472 mm in 2016 and 476 mm in the 30-yr average. Precipitation patterns were highly variable during each month during the study periods, resulting in different irrigation needs for each of the sowing seasons (Table 2.1). In 2013, the sorghums sown on April 23 needed more irrigation water (457 mm) due to the dry conditions observed in the previous months and during the beginning of the sowing season. While in 2016, the sorghums sowed on April 04, May 11, June 15, and July 14 (432, 381, 406, and 381 mm, respectively, required more irrigation water due to the interaction of high ET and low precipitation observed during that particular study period.

During the study, monthly solar radiation values were like those recorded on the last 30-year average (Table 2.2). However, in 2013 less R_s was observed through the growing season because of the variations in cloud cover and the number of days with precipitation. September and December of 2013 observed (21 and 25%, respectively) less R_s than the 30-year average. While in 2016, July was the month with the most solar radiation received with a monthly value of 810 MJ m^{-2}, followed by August and June with 733.2 and 727.5 MJ m^{-2}, respectively. As a result of the differences in R_s, the cumulative IPAR varied significantly for each sorghum hybrid throughout each sowing season and gradually declined through the end of each year. In general, mean daily PAR and cumulative IPAR were lower for those sorghums sown on early and late sowings.

Photoperiod-sensitive sorghums continue in vegetative growth if the day's length is more than the photoperiod trigger of 12:20 h, less than that will induce flowering. The number of days with the daylight of more than 12:20 h varied significantly throughout the sowing seasons (Table 2.1). Sorghum hybrids sown between early April and the late May were those that received equal or more than 12:20 h of daylight during their time of growing.

2.4.2. Dry biomass accumulation

Total DB differed significantly among hybrids and sowing seasons during the two-year study period (Table 2.3). There were significant differences in DB among the three hybrids ($p < 0.05$) at harvest for every sowing season in the two-year experiment, except for the experiments on the sowing dates of September 01, 2013 ($p = 0.714$) and August 25, 2016 ($p = 0.905$). The calculated p-value for both Hybrid treatment and Season × Hybrid (S × H) interaction were significant. This significance implies that DB is responsive to the hybrids, but there is a difference in yield responses with respect to sowing seasons. A higher DB was observed in treatments that were sown between March and June during the study period. This higher productivity was due to the better weather conditions compared to the treatments sown from July to September. For the two-year study period, the DB ranged from 12.1 to 32.8 Mg ha^{-1} for all hybrids in all experiments (Figure 2.3). The lowest average DB observed was on the sowing date of September 01, 2013 (12.1, 13.0, and 12.9 Mg ha^{-1} for Pioneer 877F, Blade ES 5140, and Blade ES 5200, respectively), and August 25, 2016 (12.6, 13.5, and 13.4 Mg ha^{-1} for Pioneer 877F, Blade ES 5140, and Blade ES 5200, respectively). While the highest average DB was observed on the sowing date of April 04, 2016 (22.7, 28.3, and 32.8 Mg ha^{-1} for Pioneer 877F, Blade ES 5140, and Blade ES 5200, respectively), and May 11, 2016 (24.7, 26.8, and 32.0 Mg ha^{-1} for Pioneer 877F, Blade ES 5140, and Blade ES 5200, respectively) (Table 2.4).

Table 2.3 Analysis of variance (p-values) of dry biomass productivity (DB), leaf area index (LAI), and water use efficiency (WUE) during the two-year study period.

Year	Effect / sowing date	DB	LAI	WUE
2013	Hybrid / 23 April	< 0.001	< 0.001	0.001
	Hybrid / 01 Sep.	0.714	0.330	0.281
	Season (S)	a	a	a
	Hybrid (H)	0.002	< 0.001	0.003
	S × H	< 0.001	< 0.001	0.544
2016	Hybrid / 01 March	0.001	< 0.001	0.042
	Hybrid / 04 April	0.003	< 0.001	0.012
	Hybrid / 11 May	0.015	< 0.001	0.039
	Hybrid / 15 June	0.006	< 0.001	0.036
	Hybrid / 14 July	< 0.001	< 0.001	<0.001
	Hybrid / 25 Aug.	0.905	0.236	0.910
	Season (S)	< 0.001	< 0.001	<0.001
	Hybrid (H)	< 0.001	< 0.001	<0.001
	S × H	< 0.001	< 0.001	0.008

a = As the degree freedom is not adequate, a valid test of significance cannot be performed.

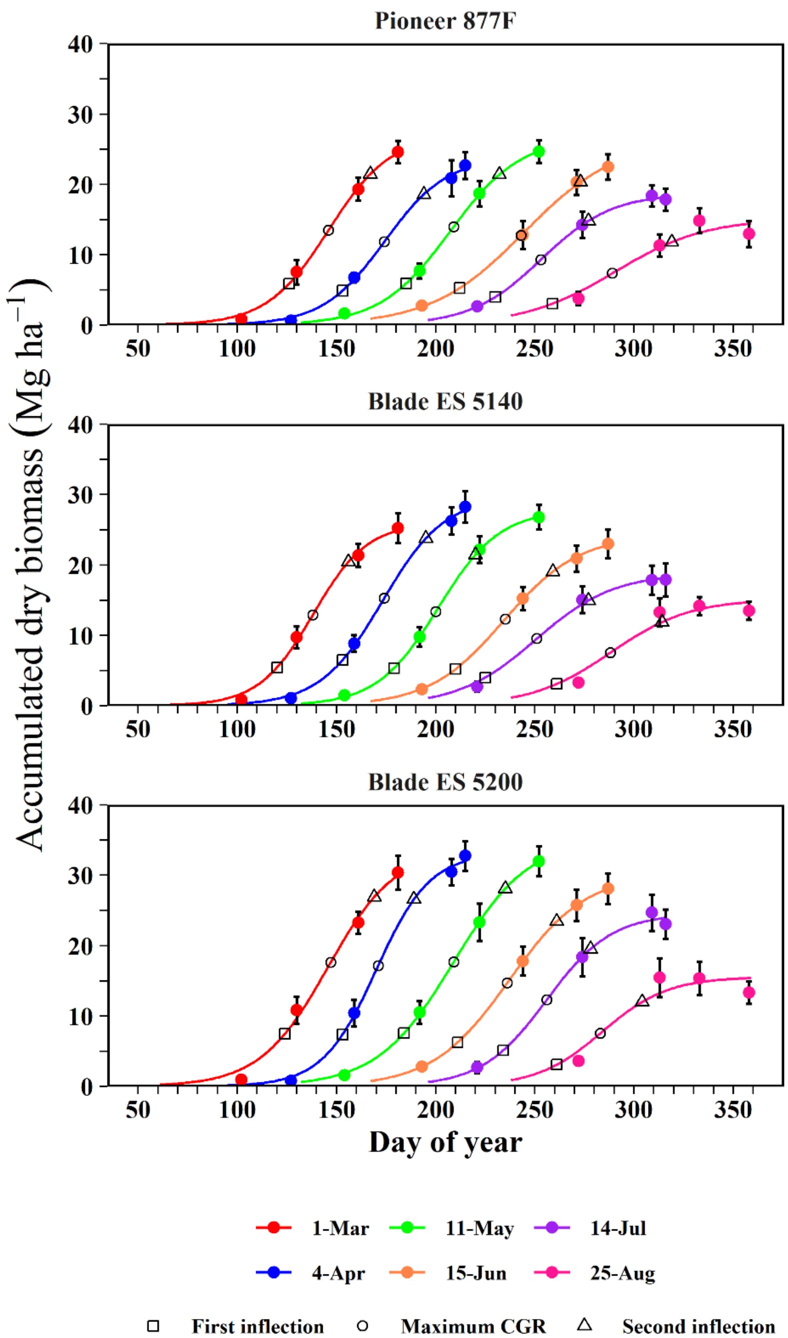

Figure 2.3 Modeled and averaged accumulation of total dry biomass productivity on all sowing seasons of 2016 for the three sorghum hybrids over time. The first inflection point is the end of the exponential phase and the beginning of the vegetative phase. The second inflection point is the end of the vegetative phase and the beginning of maturity. See Table 2.5.

Table 2.4 Mean dry biomass productivity (DB), green leaf area index (LAI), and cumulative intercepted photosynthetically active radiation (CIPAR) for the three sorghum hybrids in the two-year study period.[a]

Sowing date	Sorghum hybrid	DB (Mg ha^{-1})	LAI ($m^2\ m^{-2}$)
23 April, 2013	Pioneer 877F	19.500 b	3.39 c
	Blade ES 5140	21.114 b	4.75 b
	Blade ES 5200	28.350 a	5.55 a
	LSD	1.938	0.316
01 Sep., 2013	Pioneer 877F	12.057 n.s.	2.68 n.s.
	Blade ES 5140	13.003 n.s.	2.57 n.s.
	Blade ES 5200	12.886 n.s.	2.74 n.s.
	LSD	---	---
01 March, 2016	Pioneer 877F	24.606 b	3.27 c
	Blade ES 5140	25.263 b	4.07 b
	Blade ES 5200	30.370 a	4.43 a
	LSD	1.745	0.137
04 April, 2016	Pioneer 877F	22.711 c	3.23 c
	Blade ES 5140	28.285 b	4.36 b
	Blade ES 5200	32.774 a	5.04 a
	LSD	3.358	0.213
11 May, 2016	Pioneer 877F	24.667 b	3.25 c
	Blade ES 5140	26.806 b	4.14 b
	Blade ES 5200	31.998 a	5.41 a
	LSD	3.881	0.344
15 June, 2016	Pioneer 877F	22.464 b	3.23 c
	Blade ES 5140	23.009 b	3.82 b
	Blade ES 5200	28.101 a	4.67 a
	LSD	2.462	0.153
14 July, 2016	Pioneer 877F	17.839 b	2.91 b
	Blade ES 5140	17.908 b	3.66 a
	Blade ES 5200	23.047 a	3.67 a
	LSD	1.146	0.144
25 Aug.2016	Pioneer 877F	12.595 n.s.	2.92 n.s.
	Blade ES 5140	13.504 n.s.	2.79 n.s.
	Blade ES 5200	13.345 n.s.	3.09 n.s.
	LSD	---	---

[a] Means followed by different letters are significantly different according to LSD test at $\alpha < 0.05$; n.s = not significant.

2.4.3. Leaf area index

Leaf area index (LAI) differed significantly among hybrids and sowing seasons during the two-year experiment (Table 2.3). There were significant differences in LAI among the three hybrids ($p < 0.05$) at harvest for every sowing season in the two-year experiment, except for the experiments on the sowing dates of September 01, 2013 ($p = 0.330$) and August 25, 2016 ($p = 0.236$). The calculated p-values for the Hybrid treatment and the Season × Hybrid (S × H) interaction were significant ($p < 0.001$). This result implies that LAI responses were different among hybrids, and in responses among sowing seasons. Higher LAI values were observed in sorghums that were sown between April and May, then decreased to half of the maximum LAI values through the rest of the sowing seasons (Table 2.4). The hybrids' ranking over the sowing seasons was consistent among cultivars (Blade ES 5200 > Blade ES 5140 > Pioneer 877F), except for those sown on September 01, 2013, and August 25, 2016. The LAI of the hybrid Blade ES 5200 showed averaged values higher than 5 $m^2 m^{-2}$ when sown in April (in the two-year study) (Table 2.4). While the Pioneer 877F hybrid showed the lowest LAI values during most of the experimental period except when sown on September 01, 2013, and August 25, 2016, since it was observed on those sowing dates no statistical differences among the three hybrids and the averaged LAI values were the lowest of the experiment.

2.4.4. Crop growth rate

Crop growth rate (CGR) of sorghum hybrids was analyzed under optimal water and nutrient condition for all the sowing seasons in the two-year study to define the dates of growth development phases (Figure 2.3). Table 2.5 presents the average CGR ranged from

0.108 to 0.309 Mg ha^{-1} d^{-1}, and the maximum CGR values ranged from 0.167 to 0.636 Mg ha^{-1} d^{-1}. For the Pioneer 877F, the average CGR varied from 0.108 to 0.203 Mg ha^{-1} d^{-1} across the sowing seasons. The highest CGR of the hybrid Pioneer 877F was observed when sown on the dates of March 01, 2016, and May 11, 2016, with 0.203 and 0.202 Mg ha^{-1} d^{-1}, respectively; while the lowest values were observed on September 01, 2013, and August 25, 2016, with 0.115 and 0.108 Mg ha^{-1} d^{-1}, respectively. For the Blade ES 5140, the average CGR varied from 0.113 to 0.230 Mg ha^{-1} d^{-1} across the sowing seasons. The highest CGR values of Blade ES 5140 were observed when sown on the dates of April 04, 2016, and May 11, 2016, with 0.203 and 0.202 Mg ha^{-1} d^{-1}, respectively; while the lowest values were observed on September 01, 2013, and August 25, 2016, with 0.125 and 0.113 Mg ha^{-1} d^{-1}, respectively. For the Blade ES 5200, the average CGR varied from 0.120 to 0.309 Mg ha^{-1} d^{-1} across the sowing seasons. The highest CGR values of Blade ES 5200 were observed when sown on the dates of March 01, 2016, and April 04, 2016, with 0.309 and 0.265 Mg ha^{-1} d^{-1}, respectively; while the lowest values were observed on September 01, 2013, and August 25, 2016, with 0.126 and 0.120 Mg ha^{-1} d^{-1}, respectively.

Table 2.5 Results of the growth curve fitting and crop growth rate (CGR, Mg ha^{-1} d^{-1}) of the three sorghum hybrids at each sowing season.

Sowing date	Sorghum hybrid	P_1 (doy)	P_2 (doy)	CGR at P_1 and P_2	P_{max} (doy)	Maximum CGR	Average CGR
Apr. 23, 2013	Pioneer 877F	160	192	0.267	176	0.401	0.173
	Blade ES 5140	174	197	0.424	185	0.636	0.201
	Blade ES 5200	173	208	0.389	190	0.583	0.259
Sep. 01, 2013	Pioneer 877F	279	319	0.139	299	0.209	0.115
	Blade ES 5140	277	317	0.153	297	0.230	0.125
	Blade ES 5200	277	315	0.161	296	0.241	0.126
Mar. 01, 2016	Pioneer 877F	126	167	0.289	146	0.433	0.203
	Blade ES 5140	120	156	0.316	138	0.474	0.207
	Blade ES 5200	124	169	0.326	147	0.489	0.309
Apr. 04, 2016	Pioneer 877F	153	194	0.255	174	0.382	0.185
	Blade ES 5140	153	195	0.314	174	0.470	0.230
	Blade ES 5200	153	189	0.404	171	0.606	0.265
May 11, 2016	Pioneer 877F	185	232	0.249	209	0.374	0.202
	Blade ES 5140	179	220	0.302	200	0.453	0.222
	Blade ES 5200	184	235	0.306	209	0.460	0.261
June 15, 2016	Pioneer 877F	212	273	0.189	243	0.283	0.183
	Blade ES 5140	210	259	0.214	235	0.321	0.185
	Blade ES 5200	211	261	0.262	236	0.393	0.228
July 14, 2016	Pioneer 877F	230	277	0.175	253	0.263	0.146
	Blade ES 5140	225	277	0.160	251	0.240	0.142
	Blade ES 5200	234	278	0.250	256	0.375	0.195
Aug. 25, 2016	Pioneer 877F	259	319	0.111	289	0.167	0.108
	Blade ES 5140	261	314	0.126	288	0.190	0.113
	Blade ES 5200	261	304	0.158	283	0.237	0.120

P_1 = the first inflection of the growth curve rate. It indicates: (1) the end of the exponential phase, (2) the beginning of the linear (vegetative) phase of the crop, and (3) is where the maximum acceleration of growth occurs.

P_2 = the second inflection point of the growth rate curve. It indicates: (1) the end of the linear phase, (2) the beginning of the mature or senescent phase, and (3) the maximal negative acceleration of growth.

P_{max} = inflection of the sigmoid curve. It indicates: (1) the point where the growth rate attains its maximum, and (2) where zero acceleration of growth occurs.

2.4.5. Water use efficiency

Water use efficiency (WUE) was determined as the slope of a first-order linear regression between DB observed on all sampling dates versus the corresponding cumulative crop water use (Table 2.6 and Figure 2.4). Analysis of variance (Table 2.3) of the WUE values showed significant differences among the three sorghum hybrids ($p < 0.05$) at harvest in the two-year experiment, except for those experiments sown on September 01, 2013 ($p = 0.281$), and August 25, 2016 ($p = 0.910$). In the "over the season" analysis of variance, the calculated p-values for the Hybrid treatment and the Season × Hybrid interaction were significant. This significance implied that WUE varied among sorghum hybrids, but there was a difference in response among the sowing seasons. Table 2.7 shows the statistics for the linear regression between DB and cumulative CWU for each sorghum hybrid at every sowing season. The highest values of WUE were observed in the energy hybrids (Blade ES 5200 > Blade ES 5140 > Pioneer 877F). The response in WUE varied significantly among the sowing seasons (Figure 2.4a). The average WUE varied from 3.634 to 7.042 kg m^{-3} among all experimental units. For the Pioneer 877F, the highest WUE value was observed on those sorghums sown on March 01, 2016, and May 11, 2016, with 6.395 and 5.055 kg m^{-3}, respectively; and the lowest when sown on July 14 and August 25, 2016, with 3.634 and 3.854 kg m^{-3}, respectively. For the hybrid Blade ES 5140, the highest WUE values were observed on those sorghums sown on March 01, 2016, and April 04, 2016, with 6.587 and 5.897 kg m^{-3}, respectively, and the lowest on August 25, 2016, and April 23, 2013, with 4.003 and 4.229 kg m^{-3}. For the hybrid Blade ES 5200, the highest WUE values were observed on the sowing dates of March 01, 2016, and April

04, 2016, with 7.042 and 6.654 kg m^{-3}, respectively; and the lowest values were observed on August 25, 216, and July 14, 2016, with 4.002 and 4.973 kg m^{-3}, respectively.

Table 2.6 Precipitation (P, mm), irrigation water applied (I, mm), change in soil water content (ΔSW, mm), seasonal crop water use (CWU, mm), slope (WUE, kg m^{-3}), coefficient of determination (R^2), standard error of the slope (SE), significance probability (*p*-value), intercept coefficient (b) for the linear regression, and water loss (WL, mm) between dry biomass productivity (DB, g m^{-2}) and accumulated crop water use (mm).

Sowing date	Sorghum hybrid	P	I	ΔSW	CWU	WUE[a]	R^2	SE[b]	*p*-value[c]	b	WL
April 23, 2013	Pioneer 877F	152	457	18	627	3.872 a	0.97	0.4795	0.0150	-362.86	94
	Blade ES 5140	152	457	30	639	4.229 b	0.96	0.5863	0.0187	-434.83	103
	Blade ES 5200	152	457	37	646	5.296 b	0.98	0.5251	0.0097	-626.86	118
	LSD	---	---	---	---	0.485	---	---	---	---	---
Sep. 01, 2013	Pioneer 877F	306	25	27	358	4.92 ns	0.73	2.1152	0.1455	-447.24	91
	Blade ES 5140	306	25	32	363	5.286 ns	0.76	2.1126	0.1294	-496.81	94
	Blade ES 5200	306	25	30	361	5.808 ns	0.76	2.2774	0.1255	-660.05	114
	LSD	---	---	---	---	1.228	---	---	---	---	---
Mar. 01, 2016	Pioneer 877F	177	279	23	479	6.395 b	0.99	0.215	0.0011	-670.68	105
	Blade ES 5140	177	279	30	486	6.587 ab	0.99	0.487	0.0054	-622.68	95
	Blade ES 5200	177	279	44	500	7.042 a	0.97	0.912	0.0164	-574.63	82
	LSD	---	---	---	---	0.468	---	---	---	---	---
April 04, 2016	Pioneer 877F	131	432	5	568	4.688 b	0.99	0.283	0.0036	-478.98	102
	Blade ES 5140	131	432	12	575	5.897 a	0.99	0.512	0.0075	-651.40	110
	Blade ES 5200	131	432	23	586	6.654 a	0.99	0.227	0.0012	-664.87	100
	LSD	---	---	---	---	0.960	---	---	---	---	---

Table 2.6 Continued.

Sowing date	Sorghum hybrid	P	I	ΔSW	CWU	WUE[a]	R^2	SE[b]	*p*-value[c]	b	WL
May 11, 2016	Pioneer 877F	201	381	10	592	5.055 b	0.99	0.1123	0.0005	-502.74	99
	Blade ES 5140	201	381	19	601	5.384 b	0.99	0.15	0.0009	-512.72	95
	Blade ES 5200	201	381	31	613	6.288 a	0.99	0.1643	0.0007	-613.91	98
	LSD	---	---	---	---	0.870	---	---	---	---	---
June 15, 2016	Pioneer 877F	118	406	15	539	4.500 b	0.97	0.5414	0.0142	-260.65	58
	Blade ES 5140	118	406	26	550	4.653 b	0.99	0.1011	0.0005	-226.48	49
	Blade ES 5200	118	406	29	553	5.572 a	0.97	0.7372	0.0171	-406.30	73
	LSD	---	---	---	---	0.779	---	---	---	---	---
July 14, 2016	Pioneer 877F	130	381	8	519	3.634 b	0.95	0.5970	0.0260	-20.00	6
	Blade ES 5140	130	381	22	533	3.626 b	0.96	0.5086	0.0191	-22.39	6
	Blade ES 5200	130	381	31	542	4.973 a	0.96	0.6874	0.0187	-158.55	32
	LSD	---	---	---	---	0.170	---	---	---	---	---
Aug. 25, 2016	Pioneer 877F	140	254	25	419	3.854 ns	0.83	1.2308	0.0886	-97.81	25
	Blade ES 5140	140	254	24	418	4.003 ns	0.82	1.3423	0.0964	-125.62	31
	Blade ES 5200	140	254	31	425	4.002 ns	0.68	1.9514	0.1768	-26.97	7
	LSD	---	---	---	---	1.078	---	---	---	---	---

[a] Means followed by different letters are significantly different according to LSD test at $\alpha < 0.05$; ns = not significant.
[b] SE measures the precision of the regression analysis. The smaller the number, the more confidence about the regression equation.
[c] For regression analysis, a *p*-value less than 0.05 means the model is acceptable; if a *p*-value greater than 0.05 means the independent (explanatory) variable does not influence the dependent variable.

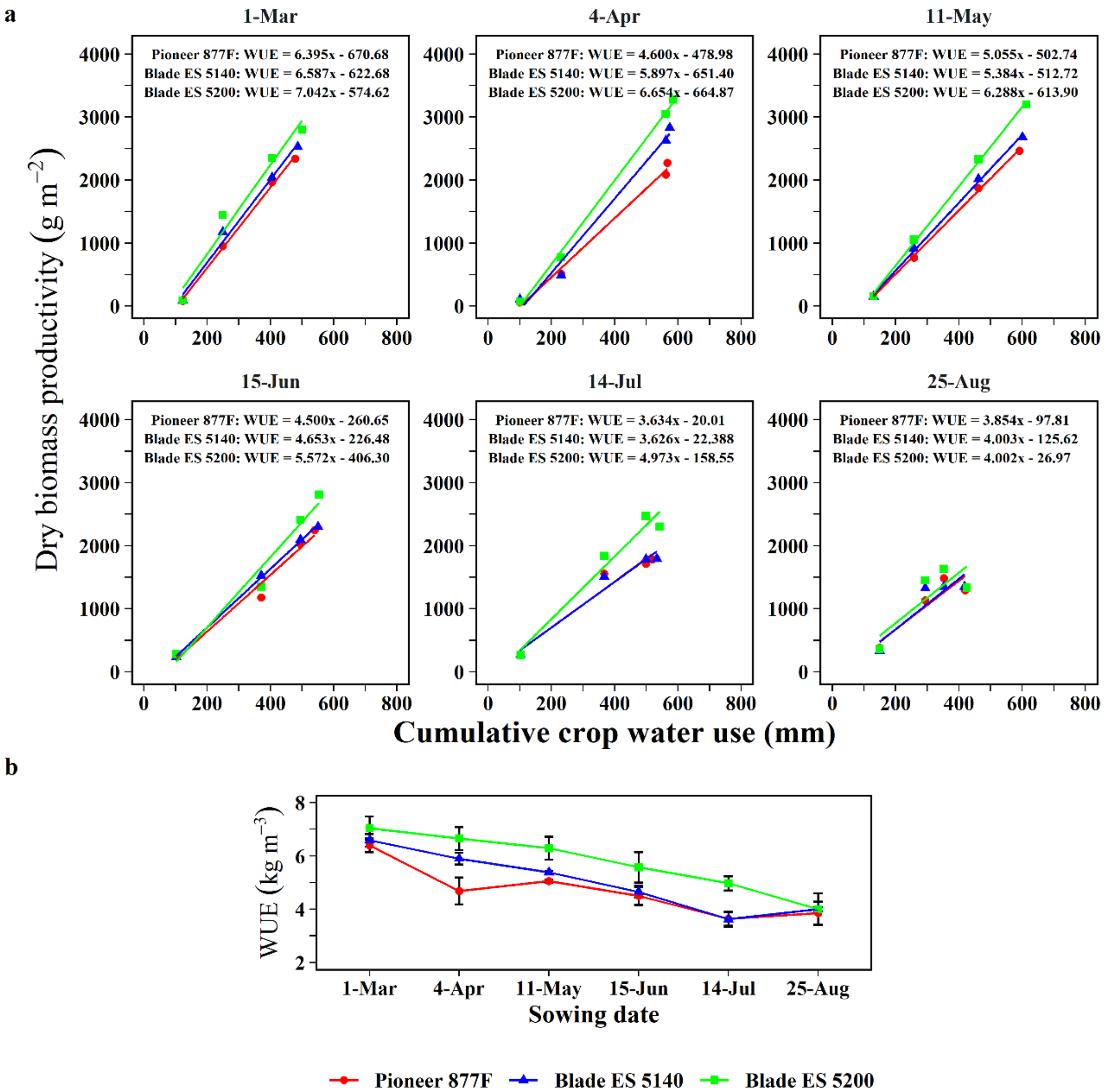

Figure 2.4 a) Linear regressions between dry biomass productivity and accumulated crop water use for the three sorghum hybrids at each sowing season, and b) averaged WUE on each sowing season of the growing season of 2016.

2.5. Discussion

This chapter evaluated the potential productivity and growth response of three biomass sorghums under variable timed sowing dates regarding the accumulation of DB and LAI with time, growth rate, and dry biomass per unit of water. The experiments conducted in this chapter were designed to provide optimal growth conditions for the three sorghum hybrids.

The accumulated DB was different among the three hybrids across different sowing seasons. Sorghums sown from March to June showed similar yields, while the yield was lower for those sown from July to September (Table 2.3). The DB yield was lower by more than 50% when the sorghum hybrids were sown in August or later despite being well irrigated and fertilized. The observed low DB in all hybrids sown on September 01, 2013, July 14, 2016, and August 25, 2016, was possibly due to the following causes: late sowings, variation in the weather conditions, lower ET demands (332, 473 and 365 mm, respectively), a small amount of solar radiation captured by the plants (1394, 2473 and 1832 MJ m^{-2}, respectively) causing low accumulated IPAR, the low GDD, and for the limited number of days with more than 12:20 h of daylength (13, 62 and 20 days, respectively) (Table 2.1) during the time that the crop was standing. These causes indicate that biomass accumulation in sorghum hybrids is affected combinedly by weather conditions, crop management, and the plant's efficiency to intercept solar energy and convert it in dry biomass (this last point is studied in Chapter 4). The maximum averaged yields observed on the hybrid Blade ES 5200 (32.8 Mg ha^{-1} from the sowing date of April 04, 2016, and 32.0 Mg ha^{-1} from the sowing date of May 11, 2016) were comparable to those reported in Temple, TX, by Meki et al. (2017) who obtained a maximum yield of 37.4 Mg ha^{-1}. Similarly, Rinaldi and Garofalo (2011) obtained 34.07 Mg ha^{-1} under full irrigation in Southern Italy; and Dercas and Liakatas (2007) reported 31 Mg ha^{-1} in Greece with 680 mm of cumulative ET.

The term LAI describes the sum of areas of all leaves in the foliage per unit area of ground. Leaf area development is critical for crop light interception and dry matter production, and hence it has a substantial influence on crop yield (Sinclair, 1984). With a decrease in LAI, also the interception of solar radiation and photosynthesis are both reduced. Therefore, LAI is a determinant parameter that affects the amount of IPAR and respiration, both of which are essential functions to achieve maximum crop production. The LAI values obtained in our study are similar to those reported by Rinaldi and Garofalo (2011), who reported the LAI values between 5.52 and 6.39 m^2 m^{-2} of biomass sorghum in a full irrigation experiment. However, Ceotto et al. (2013) and Olson et al. (2012), in a similar experiment, reported higher LAI values that ranged from 7.0 to 8.4 m^2 m^{-2}, respectively. According to Bégué (1993), the crops with LAI greater than 4.0 can intercept more than 90% of the incident PAR. The hybrids Blade ES 5140 and Blade ES 5200 showed a high capacity to intercept PAR when they were sown from March to June.

Crop growth rate (CGR) is the principal determinant analyzing biomass sorghum growth and its relation to light interception. Based on the sorghum DB obtained in the field experiments across all sowing seasons, the DB accumulation was modeled for each sorghum hybrid at each sowing season. The constant parameters that describe the shape of the growth curve were obtained by nonlinear regression analysis. After deriving a relationship between productivity and sowing date from a sigmoidal equation, it was fundamental to know the rate at which sorghum grew at each sowing season (Table 2.5). The curve slope is known as the CGR, defined as the rate of DB change with time. The results obtained from those analyses were similar to those reported by Meki et al. (2017), who observed an average CGR in biomass sorghum of 0.225 Mg ha^{-1} d^{-1} in 2013 in Temple, Texas. The potential DB of a crop can be obtained from the product of the growth rate times the duration of growth (Ritchie, 1998).

The rate of biomass accumulation is primarily influenced by the amount of light intercepted by plants over an optimum temperature range (Ritchie et al., 1998). Therefore, sorghum hybrids are entirely regulated by the accumulation of growing degree days and daylength photoperiod triggers; because, according to Childs et al. (1997), daylength is the most critical climatic factor that regulates flowering in sorghum hybrids. This relation between growing degree days, day length, and biomass yield was observed in this study. According to Rooney et al. (2007), photo-sensitive sorghums will not flower or produce high biomass through continued vegetative growth if sown when the day length is more than the photoperiod trigger of 12:20 h. Sorghum entered a linear (vegetative) period when it reached a full canopy cover, and light interception and photosynthesis were maximal. So, the sorghum growth rate varied mainly with changes in solar radiation and sowing seasons. Then, the sorghum declining phase of crop growth was due to maturation and senescence. The sorghum growth rate also declined as solar radiation and temperature decreased towards the end of summer or late sowings. Seasonal sorghum production was highest when the full cover was achieved early in the sowing seasons and maintained through the growing season with favorable weather conditions. Water and nutrient uptake occurred meanly during the vegetative growth phase when large amounts of water and nutrients were needed to create a photosynthesis mechanism in leaves. Thus, a more significant portion of biomass accumulation was obtained during the linear growth period.

Differences in WUE occurred among hybrids across sowing seasons or years due to differences in weather conditions, crop management, and crop capacity to extract water from the soil and produce biomass. In this study, irrigation demands varied across sowing seasons (Table 2.6). During the sowing season of April 23, 2013, April 04, 2016, and June 15, 2016, more irrigation was applied (457, 432, and 406 mm) to meet the needs of the crop (Table 2.6) due to the higher water demand caused by high temperatures (which were higher than the 30-year average) and the scarce rainfall observed. In general, rainfall pattern across sowing seasons was not uniform, resulting in fewer events with more rainfall, which produced less effective rainfall for crop growth. Thus, it was necessary to increase the number of irrigation events to keep the soil close to field capacity by providing the water needed for the crop during most sowing seasons.

This study's WUE results are within the range of 2.8 to 12.6 kg m^{-3} for 49 sorghum lines reported by Hammer et al. (1997). Other authors observed WUE values similar to those presented in this chapter. For instance, this chapter results agree with those reported by Narayanan et al. (2013), who reported WUE values ranging from 3.39 to 7.63 kg m^{-3}. In another study in the High Plains of Texas, the WUE values between 3.0 and 4.7 kg m^{-3} were observed (Rooney et al., 2007). Higher WUE values were observed because of the higher biomass productivity observed, notably, in those sowing seasons under better weather conditions for biomass sorghum growth.

The water lost during the study period ranged from 6 to 118 mm (Table 2.6). In most cases, weather conditions were the principal factor related to water loss. The higher water loss observed during the study period resulted from the atypical weather conditions.

The crop used only a minimal proportion of that excessive, intensive, and nonuniform rainfall between late May, early June, and early September; therefore, the rest was lost.

2.6. Conclusion

The results obtained in this study show that the effect of crop variety and sowing date has a crucial impact on the sorghum development. Sorghum development among hybrids was sensitive to temperature, solar irradiance, and photoperiod. Differences in response among sorghum hybrids were observed on DB, LAI, CGR, and WUE under different sowing seasons.

Energy sorghums exhibited the highest potential in DB productivity and LAI. They were most cost-effective when sown during March, April, and May, producing more than 30 Mg per ha in South Texas if supplied with adequate water and nutrients.

The biomass sorghum growth rate is influenced mainly by the hybrid, solar radiation, and temperature. Maximum growth rates are obtained with energy sorghums when they are sown in early sowings. Higher growth rates are observed when sorghum is sown from March to early June.

Higher WUE values can be obtained in early sowings, despite the higher amount of irrigation water applied, because of the high biomass productivity of biomass sorghum when the sowing took place from March to early June. The WUE results suggest that the energy sorghum hybrids have a high potential for producing up to 33 Mg of dry biomass ha^{-1} with 530 mm of water using drip irrigation. In comparison, the forage hybrid produced approximately 20 Mg of dry biomass ha^{-1} with 476 mm of water.

Yearlong production of biomass sorghum is required for the optimum operation of a biorefinery. Therefore, staggered sowing of biomass sorghum hybrids is an excellent alternative for providing a continuous supply of feedstock for a biorefinery to ensure its optimum function. It should be considered that the land area may need to be staggered sown with different sorghum hybrids and adapted according to the sowing date.

3. CALIBRATION AND EVALUATION OF THE EPIC MODEL FOR FULL AND LIMITED IRRIGATED BIOMASS SORGHUM PRODUCTION [2]

3.1. Synopsis

Crop simulation models are suitable decision support tools for assessing biomass production and crop water use under different spatial and climatic conditions. Calibration of simulation models to local conditions is a necessary procedure to improve model's reliability. This chapter's objective was to calibrate and evaluate the Environmental Policy Integrated Climate (EPIC) model to produce biomass sorghum under different irrigation levels. The calibrated model was then used to simulate crop biomass productivity and crop water use to identify appropriate irrigation strategies. This study was conducted at the Texas A&M AgriLife Research Center in Weslaco, Texas, during the growing seasons of 2013 and 2015. Simulations were performed to determine the total dry biomass, leaf area index (LAI), crop water use (CWU), the relationship between crop productivity and crop evapotranspiration (ET_c), and water use efficiency (WUE). Simulated ET_c agreed well with estimates from a weather station, except for a few simulation events. The statistical parameters derived from measured versus simulated dry biomass indicated that the model performed well (R^2 = 0.99 and PBIAS = -5.35%). The calibrated model showed great potential for simulating the total dry biomass. At full irrigation, the difference between

[2] Part of this section is reprinted with permission "Simulation of Energy Sorghum under Limited Irrigation Levels using the EPIC Model" by Chavez J.C., Enciso J., Meki M.N., Jeong J., Singh V.P. Transactions of the ASABE Vol.61(1): 121-131. https://doi.org/10.13031/trans.12470. Copyright 2018 American Society of Agricultural and Biological Engineers.

measured and simulated total dry biomass was 4.3% in 2013 and 3.0% in 2015. This study showed that biomass sorghum requires approximately 600 mm of water for up to 24 Mg ha^{-1} of total dry biomass production. It also demonstrated that the EPIC model could assess crop water use and total biomass under limited irrigation levels, especially in semi-arid regions.

3.2. Introduction

Simulation models are increasingly gaining favor as decision support tools for managing and assessing crop production and crop water use (Ko et al., 2009). Food and fiber production face many challenges, particularly in regions where water resources are limited. Several studies have demonstrated the utility of crop simulation models as useful technological tools to determine crop productivity and irrigation requirements at the farm, county, and state levels (Rinaldi, 2001; Guerra et al., 2003, 2005, 2007; Heinemann et al., 2002; Liu et al., 2007). These crop modeling studies were focused on finding management strategies to maximize food production without compromising land and water resources. However, crop simulation models must be calibrated and validated before being used as decision tools.

One of the most robust crop models is the Environmental Policy Integrated Climate (EPIC) model, which was originally developed to evaluate the relationship between soil erosion and soil productivity in the U.S. (Williams et al., 1985). EPIC has been continuously improved to allow simulations of many environmental processes (Sharpley and Williams, 1990; Williams et al., 1985). Ko et al. (2009) used the EPIC crop model to evaluate its application as a decision support tool for irrigation and management of cotton and maize to determine crop yield, crop water use, and the relationship between yield and crop water parameters in southern Texas regions. Balkovič et al. (2013) evaluated the ability of a Pan-European EPIC implementation to predict long-term average crop yields at a regional level and reproduced interannual variability of winter wheat, spring barley, rainfed and irrigated maize, and winter rye. In a study carried out in southern Italy, the EPIC model was used to assess climate change effects on sorghum hay production under different future climate scenarios (Rinaldi and De Luca, 2012).

Wang et al. (2012) described procedures for field-scale calibration and validation of EPIC, emphasizing relevant calibration parameters and guidance regarding logical sequences of calibration steps. Some studies have calibrated EPIC for crop-growing regions. For instance, Wang et al. (2014) presented a study conducted at an experimental station in China in which they calibrated and validated a model based on CHAIN_2D (Šimůnek et al., 2008) coupled with the EPIC growth model to simulate dynamic root growth, root water uptake, and crop yield under furrow irrigation. Xiong et al. (2014) examined the effects of calibration, step by step, of EPIC for a global implementation of rice cropping systems, identifying four important parameters controlling plant growth (potential heat units, planting density, harvest index, and biomass energy ratio). Because of the growing interest in applying simulation models to evaluate crop production better, calibration is necessary to improve model reliability.

A significant portion of marginal croplands remains idle every year because of low-profit margins, high water pumping costs, and limited water supplies. In recent years, water availability has been one of the critical factors for crop production. To offset the reduced availability of water in agriculture, cropping patterns may need to adapt to irrigation water availability and climate variability to sustain agricultural production in these areas. Although field experimentation is necessary to provide data for model evaluation, crop models may be useful tools for obtaining information on possible outcomes without extensive and expensive field experiments.

This chapter's objective was to calibrate and evaluate the EPIC model for the production of biomass sorghum under different irrigation levels using data derived from field experiments conducted at the Texas A&M AgriLife Research Center in Weslaco, Texas, over two years. The model was used to simulate crop biomass productivity and crop water use to identify appropriate irrigation strategies. The results of this study will allow farmers and other stakeholders to identify opportunities for saving water while improving biofuel crop production.

3.3. Material and methods

3.3.1. Model description

The EPIC model was chosen due to its proven high performance in simulating different cropping systems under diverse climatic conditions (Williams et al., 1989; Sharpley and Williams, 1990; Rinaldi and De Luca, 2012). EPIC consists of components that include crop growth, hydrology, weather simulation, nutrient cycling, pesticide fate, erosion and sedimentation, soil temperature, tillage, economics, and plant environment control (Williams et al., 1989). EPIC performs long-term simulations continuously using a daily time step. EPIC provides five options for estimating potential evapotranspiration (PET) that allow the user to simulate ETc for different regions. The PET equations are as follows: Penman (Penman, 1948), Penman-Monteith (Monteith, 1965), Priestley-Taylor (Priestley and Taylor, 1972), Hargreaves-Samani (Hargreaves and Samani, 1985), and Baier-Robertson (Baier and Robertson, 1965). Daily precipitation, maximum and minimum air temperature, and solar radiation are weather input variables that are considered essential. Wind speed and relative humidity are also needed if the Penman methods are selected to estimate reference evapotranspiration. These weather variables can all be entered by the user or generated by the model at runtime. Crop development is simulated, based on daily heat unit accumulation (Williams et al., 1989). Potential biomass weight is calculated daily based on photosynthetically active radiation and radiation-use efficiency. It is then adjusted to the actual biomass through daily stresses due to extreme temperatures, inadequate aeration, and water or nutrient deficiencies. EPIC calculates crop yield using the ratio of economic yield to aboveground biomass at harvest, defined as the harvest index.

The plant growth sub-model in EPIC simulates crop rotations and other cropping/vegetation systems, such as agronomic crops, pasture, and trees (Wang et al., 2012). Each crop has unique values of model parameters. The values of several yield-related parameters used for crop simulation in this study are listed in Table 3.1. The biomass to energy ratio (WA) is the crop parameter for converting solar energy into biomass, also called radiation-use efficiency. The Soil Conservation Service (SCS) curve number index coefficient (PARM 42) regulates PET's effect in driving the SCS curve number retention parameter. The retention parameter impacts the runoff volume and the changes in soil water content. The root soil strength (PARM 2) is set to minimize the soil strength constraint on root growth. Potential heat units (PHU) are the total heat units required by the crop to reach maturity. The harvest index (HI) is the ratio of economic yield to aboveground biomass. The maximum leaf area index (DMLA) is the maximum leaf area index that the crop can attain. Optimum temperature (TOP) is when the crop will grow without being damaged by heat. Base temperature (TBS) is the minimum temperature at which the crop will grow without being damaged by cold. Available soil water capacity, which is the amount of water stored in the soil and available for growing crops, is also a critical parameter in EPIC.

Table 3.1 Default and adjusted of the most important parameters for simulation of biomass sorghum.

Parameter	Description	Default value	Range	Adjusted value
WA	Biomass-energy ratio, which is the potential growth rate per unit of IPAR (also called radiation-use efficiency) (kg ha^{-1} MJ^{-1} m^2)	33.9	10 - 100	36.9
PARM 42	SCS curve number index coefficient	1.5	0.5 – 1.5	0.5
PARM 2	Root growth soil strength	1.5	1.15 – 2.0	1.15
PHU	Potential heat units required by the plant from germination to reach maturity (degree days)	0	1 - 5000	2200
PARM 13	Hargreaves-Samani PET equation exponent	0.6	0.5 - 0.6	0.5
PARM 38	Hargreaves-Samani PET equation coefficient	0.0032	0.0023 – 0.0032	0.0027
ORHI	Ratio of economic yield to the total aboveground biomass (g g^{-1})	0.95	0 – 1.0	0.95
DMLA	Maximum potential of leaf area index (m^2 m^{-2})	6.34	1 - 15	6.34
TOP	Optimal temperature for plant growth (°C)	25	0.5 – 100	25
TBS	Minimum temperature at which the crop will grow without being physiologically damaged by cold (°C)	8	0 - 130	8
HMX	The greatest potential height the crop will reach (m)	3.99	0.1 – 30	3.99

3.3.2. Field experiment and measured data

Measured data for evaluating the EPIC crop model's performance in simulating biomass sorghum growth and productivity were obtained from field experiments conducted during the spring growing seasons of 2013 and 2015 at the Texas A&M AgriLife Research Center located in Weslaco, Texas (26° 10' 1.76'' N, 97° 56' 25.85'' W, 24 m above sea level). The study area (Figure 2.1) has a semi-arid climate, and the average annual rainfall is 558 mm. The soil is a Hidalgo silt clay loam (fine-loamy, mixed, hyperthermic Typic Calciustolls). Table 3.2 lists the data for each layer in the top 2 m of the soil profile. Preliminary soil data were measured at the 0.2 m depth. The 0.2 m soil depth presented the following characteristics: organic matter = 0.67%, nitrate-N = 0.009 g kg^{-1}, phosphorus = 0.057 g kg^{-1}, soil pH = 8.2, upper limit of available water = 0.24 m^3 m^{-3}, lower limit of available water = 0.16 m^3 m^{-3}, clay = 27%, sand = 40.1%, and electrical conductivity = 0.274 dS m^{-1}. The remaining soil layers' properties were determined, based on the Hidalgo sandy loam data in the Soil Survey Geographic (SSURGO) database (USDA, 2013).

Table 3.2 Soil conditions of the study area. The soil properties obtained from the NRCS SSURGO database (USDA, 2013) for the soil type: Hidalgo silt clay loam (0-1%).

	Soil Layers				
Soil Property	**1**	**2**	**3**	**4**	**5**
Depth (m)	0.2	0.43	0.71	0.97	2.00
Bulk density (Mg m^{-3})	1.45	1.45	1.4	1.4	1.5
Available water:					
Lower limit (m^3 m^{-3})	0.16	0.08	0.14	0.14	0.14
Upper limit (m^3 m^{-3})	0.24	0.2	0.23	0.23	0.23
Sand content (g kg^{-1})	401	630	480	350	300
Silt content (g kg^{-1})	329	190	250	350	400
Soil pH	8.2	8.2	8.2	8.2	8.2
Organic matter content (%)	0.67	1	0.65	0.3	0.2
Calcium carbonate content (g kg^{-1})	30	30	90	230	230
Cation exchange capacity (cmol kg^{-1})	9.5	9.5	13	14	16
Electrical conductivity (dS m^{-1})	0.27	1.0	1.5	2.0	2.0

Weather inputs were obtained using an automatic weather station (model ET106, Campbell Scientific, Logan, Utah) located 100 m away from the experimental plots. This weather station uses a TE525 tipping-bucket rain gauge (Texas Electronics, Dallas, Tex) for measuring rainfall, a CS500 sensor (Vaisala, Helsinki, Finland) placed 2 m above ground level for measuring of maximum and minimum air temperature and relative humidity, a LI200X pyranometer (LI-COR Biosciences, Lincoln, Neb.) for measuring total irradiance, and a 034A wind set (Campbell Scientific, Logan, Utah) placed 3 m above ground level for measuring wind speed. All weather data were averaged at hourly intervals using a CR10X data logger. The weather data were used for irrigation scheduling with the South Texas Weather Program (STWP, http://southtexasweather.tamu.edu) (Enciso et al., 2015), which is an internet program posted online. The STWP used for field experiments used a water balance approach and estimated ET_o with the FAO-56 Penman-Monteith equation, which was multiplied by specific crop coefficients (K_c) recommended by FAO-56 for Sudan grass to get crop evapotranspiration (ET_c) (Allen et al., 1998). The irrigation scheduling program estimated the irrigation timing and amount needed to achieve a predetermined allowed depletion level, which is 60% for the soil at the experimental site. Table 3.3 provides a monthly summary of the observed weather data for the two-year growing seasons.

Table 3.3 Summary of monthly weather data for 2013 and 2015 growing seasons at the Texas A&M AgriLife Research Center, Weslaco, Texas.[a]

Year	Parameter	March	April	May	June	July	August	Total	Mean
2013	T max (°C)	-	29.1	31.3	35.4	35.4	35.6	-	33.4
	T min (°C)	-	17.5	21.8	24.5	24.6	24.8	-	22.6
	Srad (MJ m^{-2})	-	539.3	643.5	708.2	672.0	661.5	3224.5	-
	Prec (mm)	-	72	29	34	18	60	213	-
	RH (%)	-	72	73	70	69	70	-	71
	Wv (m s^{-2})	-	3.00	3.05	2.80	2.69	2.36	-	2.78
2015	T max (°C)	23.5	29.1	31.3	34.0	37.3	-	-	31.0
	T min (°C)	14.5	20.7	22.9	24.0	24.8	-	-	21.4
	Srad (MJ m^{-2})	337.7	421.5	528.2	597.3	693.2	-	2577.8	-
	Prec (mm)	108	106	100	48	25	-	387	-
	RH (%)	83	81	79	75	71	-	-	78
	Wv (m s^{-2})	1.99	2.52	3.11	2.46	3.23	-	-	2.66

[a] T max = maximum daily air temperature, T min = minimum daily air temperature, Srad = solar radiation, Prec = precipitation, RH = relative humidity, Wv = wind velocity.

A biomass sorghum hybrid, Blade ES 5200, was sown on 1.02 m (40 in.) wide rows on 23 April 2013 and 24 March 2015. The plots used for the experiments were 4.06 m wide and 91.44 m long. Sorghum seeds were sown at a plant density of 115,000 plants ha^{-1} on raised beds to accommodate furrow irrigation. The plant density after emergence was about 100,000 plants ha^{-1} in both years. Fertilization and irrigation management are shown in Table 3.4. All plots received nitrogen fertilizer at a rate of 100 kg ha^{-1} as urea ammonium nitrate (UAN; 32% mass fraction of N) applied in two equal split applications. The same total fertilizer amount was used on all plots in the experiment.

Table 3.4 Agronomic and irrigation data of energy sorghum at the Texas A&M AgriLife Research Center, Weslaco, Texas, in 2013 and 2015.

Activity	2013	2015
Sowing date	4/23	3/24
Harvesting date	8/13	7/08
Length of growing season (days)	112	106
Growing season precipitation (mm)	163	284
Limited irrigation treatment; planting irrigation (mm)	125	0
Full irrigation treatment; four irrigations (mm)	304	54
Reference ET (mm)	613	442
Sorghum ET (mm)[a]	598	424
Fertilizer: N32 (kg ha^{-1})	100	100

[a] ET was estimated by the STWP using the FAO-56 Penman-Monteith equation and crop coefficients suggested by FAO-56 for Sudan grass (Allen et al., 1998).

Two water application levels were used in this study: limited irrigation and full irrigation. There were three replications for the limited and full irrigation levels in both years. Full irrigation was achieved by irrigation to replace crop water use as determined by the irrigation scheduling program previously described. In 2013, full irrigation was conducted with four irrigation events, and limited irrigation was conducted with one irrigation at sowing. However, 2015 was a wet year, and only one irrigation was applied for the full irrigation treatment and none for the limited treatment. The sorghum was irrigated using furrow irrigation. In 2013, irrigation at sowing (125 mm) was applied to the limited irrigation treatment to facilitate seed germination. However, irrigation at sowing was not necessary for 2015, because it was wet enough to ensure germination. The amount of water applied was recorded with totalizing water meters connected to the irrigation system. One flowmeter was used for all the furrow-irrigated plots. The furrows were blocked at the end. Irrigation was stopped when the water reached the lower end of the furrow to avoid runoff.

Crop development was monitored four times in 2013 between May and August and seven times in 2015 between April and July through destructive and non-destructive measurements. Measured plant variables included fresh and dry weight, open and closed leaves, plant height, stalk diameter, and leaf area index. Before harvesting, a subsample of five to six plants was randomly selected from the center two rows and oven-dried at 60°C until the plants reached constant weight to determine the dry matter and tissue moisture content. Field plots were harvested at the end of each season using a forage harvester (Jaguar 940, Claas, Herzebrock, Germany) (Figure 3.1). A separate weighing wagon, pulled alongside the harvester, was used to collect and measure harvested plots' fresh weight.

Figure 3.1 Biomass sorghum (Blade ES 5200) after 113 days of growth in 2013 at the Texas A&M AgriLife Research Center in Weslaco, TX.

3.3.3. Evaluation of model performance

The model was calibrated and evaluated to simulate biomass sorghum dry biomass productivity by comparing measured and simulated data from the limited and fully irrigated treatments in 2013 and 2015. The EPIC model for biomass sorghum was calibrated using measured data from the full irrigation treatment in 2013, which was expected to represent the minimum or no stress conditions. Data from the remaining treatments, including the limited irrigation treatment in 2013 and the limited irrigation and full irrigation treatments in 2015, were used for validation.

EPIC does not calculate ET_o as defined in FAO-56, in which the reference surface is described as "a hypothetical reference crop with an assumed crop height of 0.12 m, a fixed surface resistance of 70 s m^{-1} and albedo of 0.23" (Allen et al., 1998). Instead, the model estimates PET using the five previously listed methods and then uses PET as a reference in calculating actual evapotranspiration. Actual evapotranspiration is estimated as the sum of soil evaporation and canopy transpiration. FAO-56 indicates that the Hargreaves-Samani method can be used as an alternative to the Penman-Monteith method to estimate PET. After preliminary test runs of the ET methods in EPIC, the Hargreaves-Samani (Hargreaves and Samani, 1985) ET method was selected to simulate ETc in this study because it was the most robust among the available methods, including the Penman-Monteith method, and because it could be calibrated easily by varying its linear coefficient and an exponent (BREC, 2015).

A calibration was carried out by adjusting sensitive influential model parameters and inputs within their reasonable ranges so that the model results were consistent with the available measured data. The modeled process' effects were analyzed by comparing the simulated versus measured crop growth and productivity data and simultaneously assessing the model performance statistics. After calibration and validation, the model was used to conduct long-term (30-year) simulations using actual 30-year weather data (1986 to 2015). Irrigation regimes and agronomic activities used for the long-term simulations were applied based on the field experiment conducted in 2013 (Table 3.4). In addition to irrigation, rainfall measurements were incorporated from each of the 30 weather years in the long-term simulations in order to explore crop responses to water. Model simulation results were evaluated for dry biomass productivity responses and the relationships between WUE and dry biomass productivity.

3.3.4. Test statistics

Linear regression, coefficient of correlation (*r*), and coefficient of determination (R^2) were used to compare the simulated and measured productivity data during both calibration and validation. The linear model is $y = \propto + \beta x + \varepsilon$, where α and β are the regression intercept and slope, respectively, and ε is the random error. The *t*-test was used to test the null hypothesis H_0: α = 0 and H_0: β = 1. H_0 is maintained when α and β are not significantly different from 0 and 1, respectively. The goodness of fit estimators used the *p*-value from the *t*-test. R^2 measures the proportion of the variation in *y*, which is accounted for by the linear model. Therefore, R^2 tests the "goodness of fit" of the linear model. The R^2 value ranges from 0 to 1 and describes the degree of collinearity between measured and simulated data (Moriasi et al., 2007), where higher values indicating a minimum variance. However, R^2 only estimates the linear relationship between two variables and is not sensitive to the regression intercept (α). Other statistics used to assess this study's model performance included the root mean square error (RMSE):

$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{n}(s_i - M_i)^2} \tag{7}$$

where S_i is the ith simulated value, M_i is the ith measured value, and n is the number of data pairs. RMSE represents the discrepancy between observations and predictions. A value of 0 indicates a perfect fit. The Nash and Sutcliffe model efficiency (NSE) was also used to quantify the model performance. It was used to show how well the measured mean versus the simulated data fit the measured data. The NSE was calculated as:

$$NSE = 1 - \frac{\sum_{i=1}^{n}(S_i - M_1)^2}{\sum_{i=1}^{n}(M_i - M_a)^2} \tag{8}$$

where Ma is the mean of the measured values. The NSE ranges from -∞ (poor model) to 1 (perfect model). A value from 0 to 1 indicates that the model is better than using the measured mean as a predictor, while values less than zero indicates an unacceptable model performance. Percent of bias (PBIAS) was also used:

$$PBIAS = \left[\frac{\sum_{i=1}^{n}(M_i - S_i)}{\sum_{i=1}^{n} M_i}\right] \times 100 \tag{9}$$

PBIAS measures the average tendency of the simulated data to be higher or less than the measured data. The optimal PBIAS is zero. A value of low magnitude indicates accurate model simulation. Positive values indicate model underestimation bias, and negatives indicate model overestimation bias. According to Wang et al. (2012), model performance is considered satisfactory when $R^2 \geq 0.60$, NSE ≥ 0.55, and PBIAS within ±25% for water yield; and $R^2 \geq 0.60$ and PBIAS $\leq$ ±25% for crop yield.

The following procedure was carried out to adjust the simulated crop productivity. First, the cultivar-specific parameters affecting crop phenology stages from sowing to harvest were adjusted until the simulated results matched as close as possible to the measured data. Second, the parameters affecting crop growth were adjusted until there was a reasonable match between measured and simulated LAI and crop canopy. Finally, parameters that affect crop biomass productivity were adjusted until there was a good match between the measured and simulated data.

In this study, the cumulative crop water use was estimated as the sum of daily crop water use during the growing season (112 days for 2013 and 106 days for 2015). The WUE, which is critically essential in semi-arid agriculture (Howell, 2001), is defined in agronomy (Viets, 1962) with Eq. (4). The WUE was calculated as follows:

$$WUE = \frac{DB}{CWU} \tag{10}$$

where DB is the dry biomass productivity (g m^{-2}), CWU is the crop water use (mm) or seasonal water input (irrigation + rainfall ± SW), and WUE is the water use efficiency in terms of seasonal crop water use (g m^{-2} mm^{-1}), which can also be expressed in alternative units (kg m^{-3}).

3.4. Results

3.4.1. Model calibration

The calibration procedure used in this study can be observed in Figure 3.2. The first calibration process was conducted using the energy sorghum crop parameters developed by Meki et al. (2017) with productivity data from field trials conducted in Hawaii and Texas. The model showed less than a 25% error in dry biomass productivity and LAI across the growing season with these cultivar parameters. EPIC does not provide predictions of crop stages during the growing season, but it gives plant emergence predictions. The simulated emergence was six days after sowing compared to the five to seven days measured, indicating high predictive capability. Because appropriate parameter calibration is crucial for accurate simulation of crop growth and development under field conditions, a local parameterization was performed, as described by Wang et al. (2012). Six parameters were identified in EPIC that needed to be adjusted to achieve appropriate crop biomass productivity for biomass sorghum (Table 3.1). They were the biomass to energy ratio (WA), the NRCS curve number coefficient (PARM 42), root growth-soil strength (PARM 2), potential heat units (PHU), the Hargreaves-Samani PET equation exponent (PARM 13), and the Hargreaves-Samani PET equation coefficient (PARM 38). The model simulated biomass sorghum growth without any water and nitrogen stress during calibration.

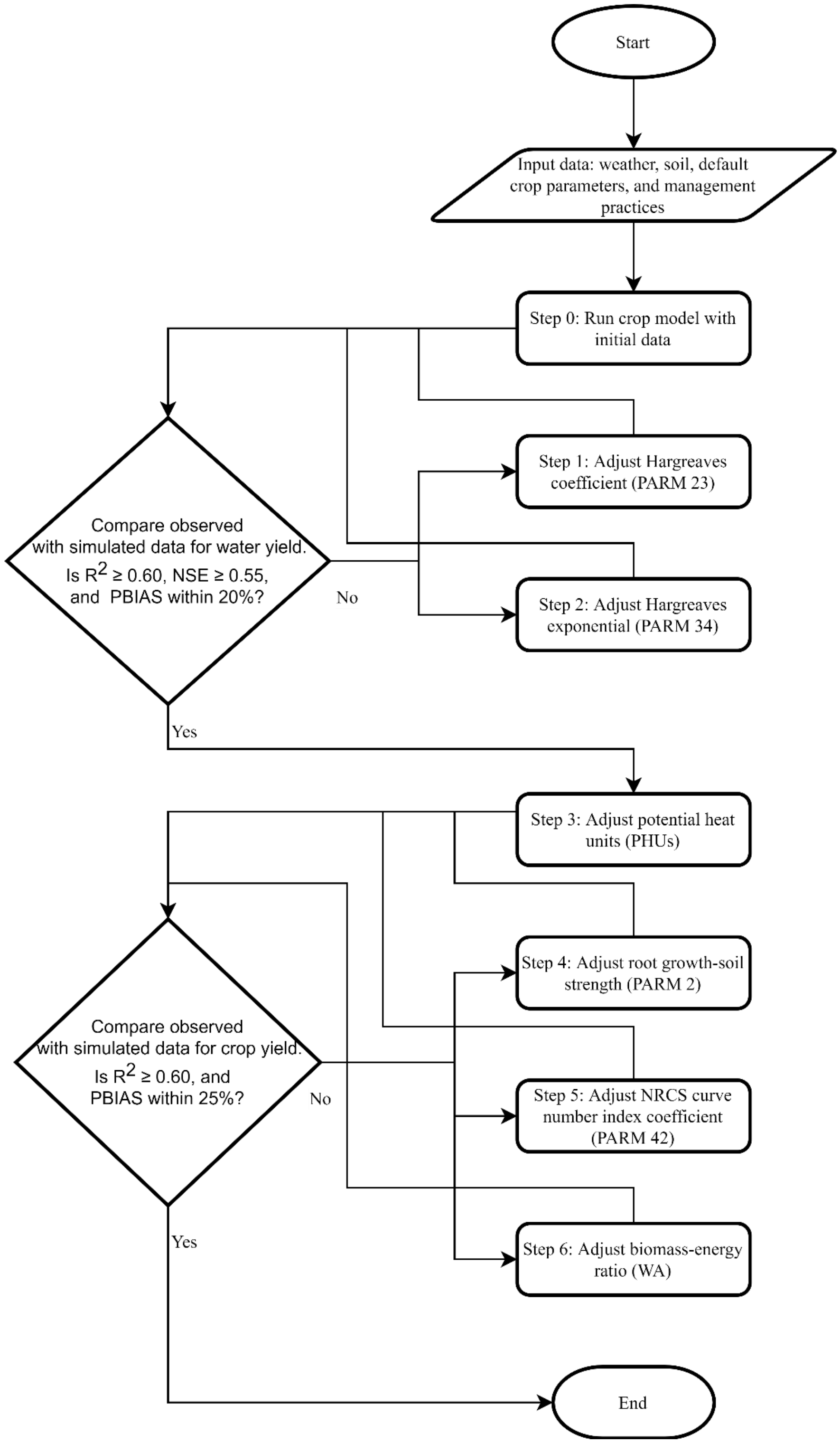

Figure 3.2. Steps followed in the calibration procedure of biomass sorghum.

The exponent of the Hargreaves-Samani PET equation in the EPIC model, with a default value of 0.6, was returned to its original value of 0.5 and the linear coefficient of was modified from 0.0032 to 0.0027 because the default equation's values underestimated ET_c as compared to the ET_c from the automatic FAO-56 Penman-Monteith estimation with the online weather program. By trial and error, the PHUs were adjusted until HUSC (fraction of total base-zero heat units at which operation takes place) at harvest ranged between 0.9 and 1.1. The PHUs were finally set to 2200 growing degree days. PARM 2 was adjusted from 2.0 to 1.15. PARM 42 was changed from 1.5 to 0.5. WA was the last parameter to be modified due to its high sensitivity. It was adjusted to 36.9 kg ha^{-1} MJ^{-1} m^2, while the default value was 33.9 kg ha^{-1} MJ^{-1} m^2.

The simulated EPIC ET_c agreed with the estimated ET_c from FAO-56 Penman-Monteith, with R^2 of 0.63. However, some variations of ET_c were observed, possibly due to the Hargreaves-Samani method, which did not account for wind speed, which directly caused the underestimation of simulated ET_c (Figure 3.3a). For satisfactory calibration of crop yield, Wang et al. (2012) suggested that $R^2 \geq 0.60$ and PBIAS within 25% should be achieved. After calibration, the statistical parameters indicated that the predictive capability of the EPIC model for dry biomass was satisfactory, with $R^2 = 0.99$, NSE = 0.97, PBIAS = -5.35%, and RMSE = 1.60 Mg ha^{-1} (Table 5). As well, calibration parameters for LAI showed satisfactory results, with $R^2 = 0.88$, NSE = 0.85, PBIAS = -7.64%, and RMSE = 0.70 m^2 m^{-2} (Table 3.5).

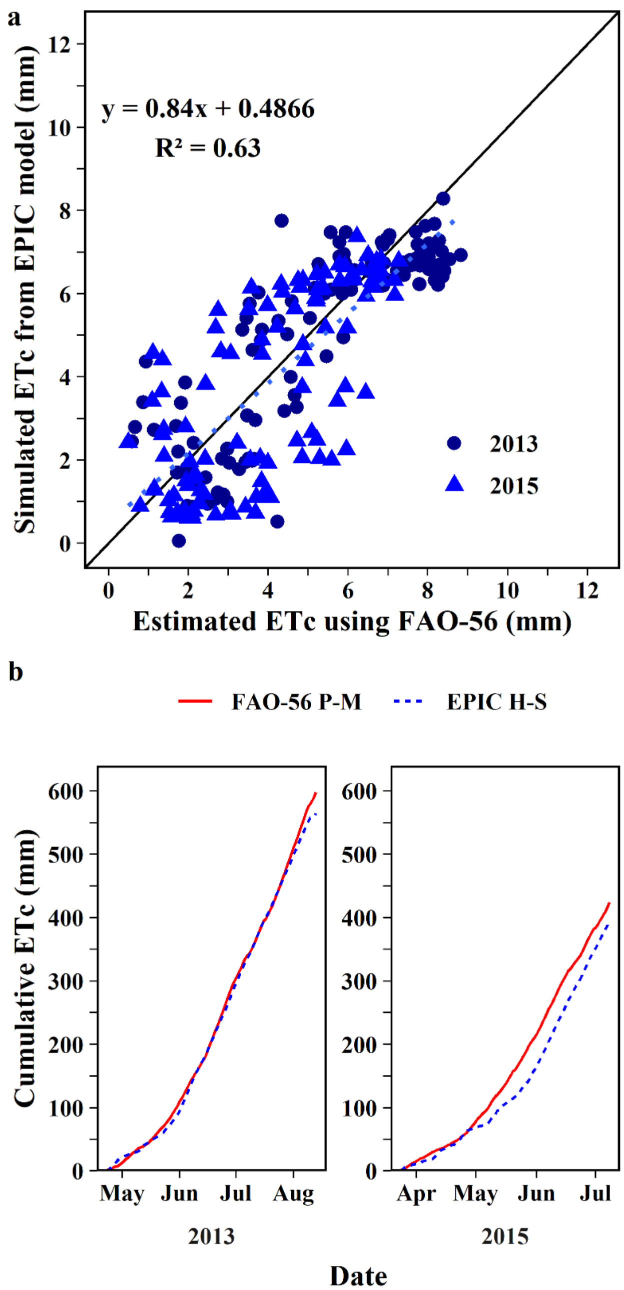

Figure 3.3 a) Comparison between estimated daily crop evapotranspiration (ET_c) calculated using FAO-56 Penman-Monteith versus simulated ET_c from EPIC using Hargreaves-Samani, and b) cumulative crop evapotranspiration (ET_c) using FAO-56 Penman-Monteith versus EPIC-simulated crop evapotranspiration using Hargreaves-Samani for biomass sorghum. Estimated ET_c data were obtained from the STWP (K_c varies between 0.5 and 1.1 for sorghum) for the growing seasons of 2013 and 2015 at the Texas A&M AgriLife Research Center in Weslaco, Texas.

Table 3.5 Statistical indices to assess simulation efficiency during calibration and validation of the EPIC model for biomass sorghum.[a]

	Variable	Dry Biomass	LAI
Calibration	R^2	0.99	0.88
	NSE	0.97	0.85
	PBIAS	-5.35%	-7.64%
	RMSE	1.60 Mg ha^{-1}	0.70 m^2 m^{-2}
Validation	R^2	0.96	0.90
	NSE	0.95	0.83
	PBIAS	-7.53%	-7.62%
	RMSE	1.98 Mg ha^{-1}	0.69 m^2 m^{-2}

[a] R^2 = determination coefficient, NSE = Nash-Sutcliffe efficiency, PBIAS = percent bias, RMSE = root mean square error.

3.4.2. Model validation

The calibrated EPIC model for biomass sorghum was validated using the other three irrigation scheduling treatments: limited irrigation in 2013, and limited and full irrigation in 2015. These three treatments had the same experimental setup as the treatment used for calibration. The total irrigation amounts applied during the growing seasons for validation were 288 mm for limited irrigation in 2013, 284 mm for limited irrigation in 2015, and 338 mm for full irrigation in 2015. The agreement between measured and simulated dry biomass productivity (Table 3.5) resulted in R^2 = 0.96, NSE = 0.95, PBIAS = -7.53%, and RMSE = 1.98 Mg ha^{-1}, while the simulated LAI had error statistics of R^2 = 0.90, NSE = 0.83, PBIAS = -7.62%, and RMSE = 0.69 Mg ha^{-1}. Although the EPIC model simulated dry biomass at validation reasonably well compared to calibration, it slightly overestimated dry biomass and LAI among all treatments (Figure 3.4). Overall, the simulated crop biomass productivity for the three treatments matched well, as shown in Table 3.5.

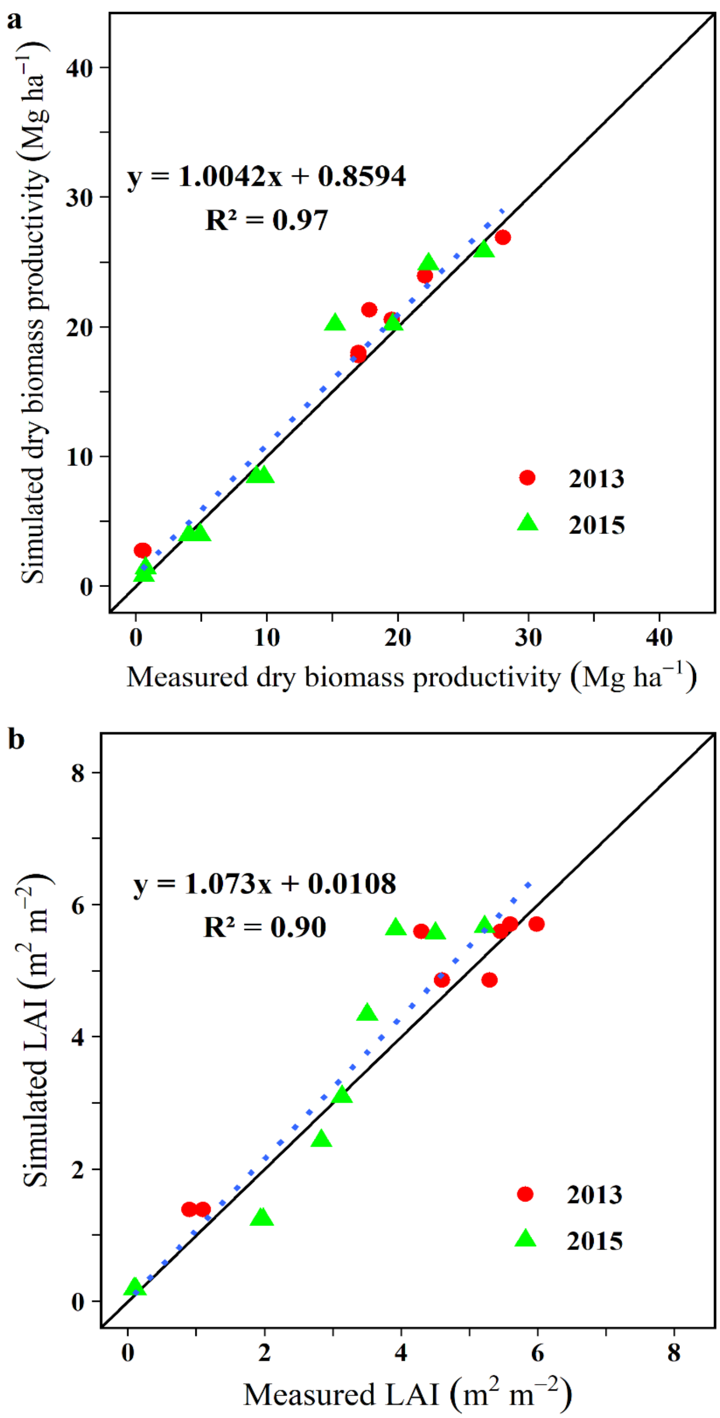

Figure 3.4 a) Measured versus simulated biomass sorghum dry biomass and b) biomass sorghum leaf area index (LAI) in 2013 and 2015 at the Texas A&M AgriLife Research Center, Weslaco, Texas. Dotted lines represent linear regression trendlines.

3.4.3. Crop simulations

The EPIC model for biomass sorghum was further evaluated using data from the two-year field study of biomass sorghum development and furrow irrigation management. During both growing seasons, both daily and cumulative EPIC-simulated ET_c values diverged in an error of 6.41% from the ET_c values estimated with the online STWP due to EPIC's method (Hargraves-Samani) to calculate actual ET (Figure 3.3).

A high correlation was observed between simulated and measured dry biomass of biomass sorghum at full and limited irrigation levels in 2013 and 2015. The EPIC model was able to simulate dry biomass productivity and LAI with acceptable accuracy. The slopes and intercepts of the linear regressions, shown in Figure 4.4, were not significantly different from 1 and 0, respectively.

The measured total dry biomass productivity of biomass sorghum with limited irrigation was 19.6 Mg ha^{-1} in 2013 and 22.3 Mg ha^{-1} in 2015, while the simulated productivity was 20.6 Mg ha^{-1} in 2013 and 24.9 Mg ha^{-1} in 2015. For full irrigation, the measured total dry biomass productivity was 28.1 Mg ha^{-1} in 2013 and 26.6 Mg ha^{-1} in 2015, while the simulated productivity was 26.9 Mg ha^{-1} in 2013 and 25.8 Mg ha^{-1} in 2015 (Table 6). An error of 5.88% was calculated between measured and simulated productivities. Also, student *t*-tests were conducted to demonstrate that simulated productivity was not significantly different from measured productivity ($p > 0.05$) with 16 degrees of freedom. Regression statistics also showed that the slope was close to the 1:1 line ($p < 0.05$). These results agree with those obtained by Meki et al. (2013). They used the ALMANAC crop model to evaluate energy sorghum dry biomass productivity under different biomass removal rates and tillage cropping systems in Alabama. The irrigation water use efficiency (WUE) was estimated using the simulated results and then compared to the measured efficiencies. The WUE results are shown in Table 3.6. A student *t*-test showed no statistical differences between measured and simulated WUE (p = 0.48) at a significance level of 0.05. Higher efficiencies were calculated under limited irrigation for both measured and simulated data.

Table 3.6 Comparison of measured and simulated total dry biomass productivity and water use efficiencies at the Texas A&M AgriLife Research Center, Weslaco, Texas.

Year	Irrigation level	Total dry biomass (Mg ha^{-1})		WUE (kg m^{-3})	
		Measured	Simulated	Measured	Simulated
2013	Limited	19.55	20.57	6.79	7.04
	Full	28.05	26.90	6.01	4.90
2015	Limited	22.33	24.87	7.86	8.02
	Full	26.57	25.83	7.86	7.67

3.4.4. Long-term simulations

Average simulated dry biomass productivity and WUE from the 30-year simulations for full and limited irrigation are shown in Table 3.7. Based on the long-term simulation results, the simulated dry biomass of biomass sorghum showed a sigmoid curve response to total water applied (irrigation + rainfall ± soil water content) during the growing season (Figure 3.5). The constant parameters that describe the shape of the growth curve were obtained by numerical analysis. After deriving the relationship between productivity and irrigation water applied from the logistic equation, it was essential to know the crop growth rate. Therefore, the first derivative was obtained from the logistic function and then plotted (Figure 3.6a) to observe the biomass sorghum's growth rate. The second derivative was obtained and plotted to observe the growth acceleration of the biomass sorghum (Figure 3.6b) and then equated to zero to show the amount of water applied at which the maximum and minimum acceleration occurred. This maximum and minimum points are also the inflection point of the sigmoid response curve. It can be observed in Figure 3.6a that the maximum rate of absolute growth was attained at 310 mm with a rate of increase of 0.072 Mg ha^{-1} mm^{-1}. The first critical point was found at coordinates 201, 5.062, indicating the end of the exponential phase and the beginning of the linear phase (Figure 3.5). Biomass productivity, as a function of accumulated applied water, increased with exponential growth up to 201 mm with productivity of 5.062 Mg ha^{-1}. The second critical point was found at coordinates 419, 18.893, indicating the end of the linear (vegetative) phase and the beginning of the stationary phase (Figure 3.5).

Table 3.7 Means ± 95% confidence intervals of dry biomass and water use efficiency concerning water input (irrigation + rainfall ± soil water content), regarding simulated dry biomass productivity. Data are mean annual values based on a 30-year simulation (1986 to 2015). The calibrated model was used to run the 30-year simulations.

Irrigation level	Dry biomass (Mg ha^{-1})	WUE (kg m^{-3})
Limited	20.89 ± 1.34	7.31 ± 0.51
Full	24.46 ± 0.59	4.60 ± 0.27

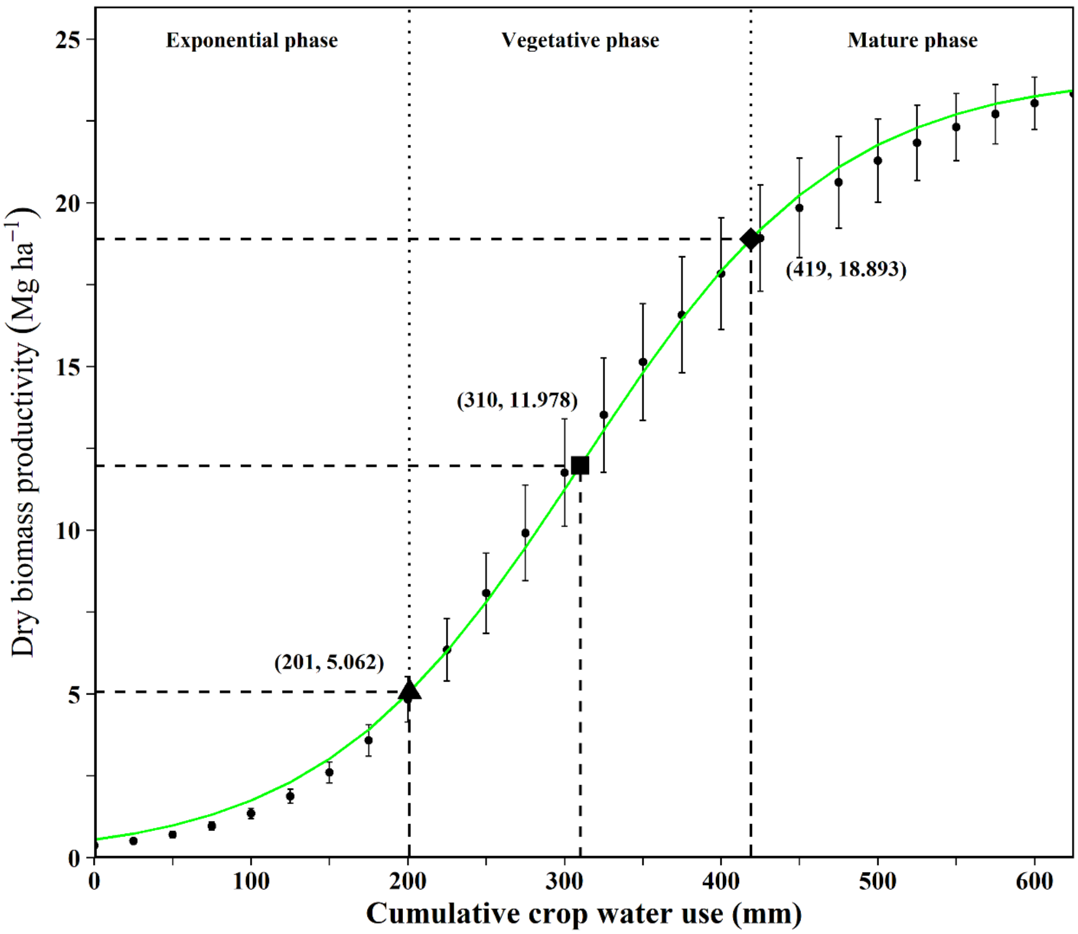

Figure 3.5 Sorghum dry biomass response as a function of cumulative water applied (irrigation + rainfall ± soil water content) as simulated with full irrigation. Data are averages for 30 years (1986 to 2015) at the Texas A&M AgriLife Research Center, Weslaco, Texas. Vertical bars indicate errors at 95% confidence intervals for means of data points. The first infection point (indicated by a triangle) is the end of the exponential phase and the beginning of the vegetative phase. The second inflection point (indicated by a rhombus) is the end of the vegetative phase and the beginning of the mature phase. The square indicates the point of maximum crop growth rate.

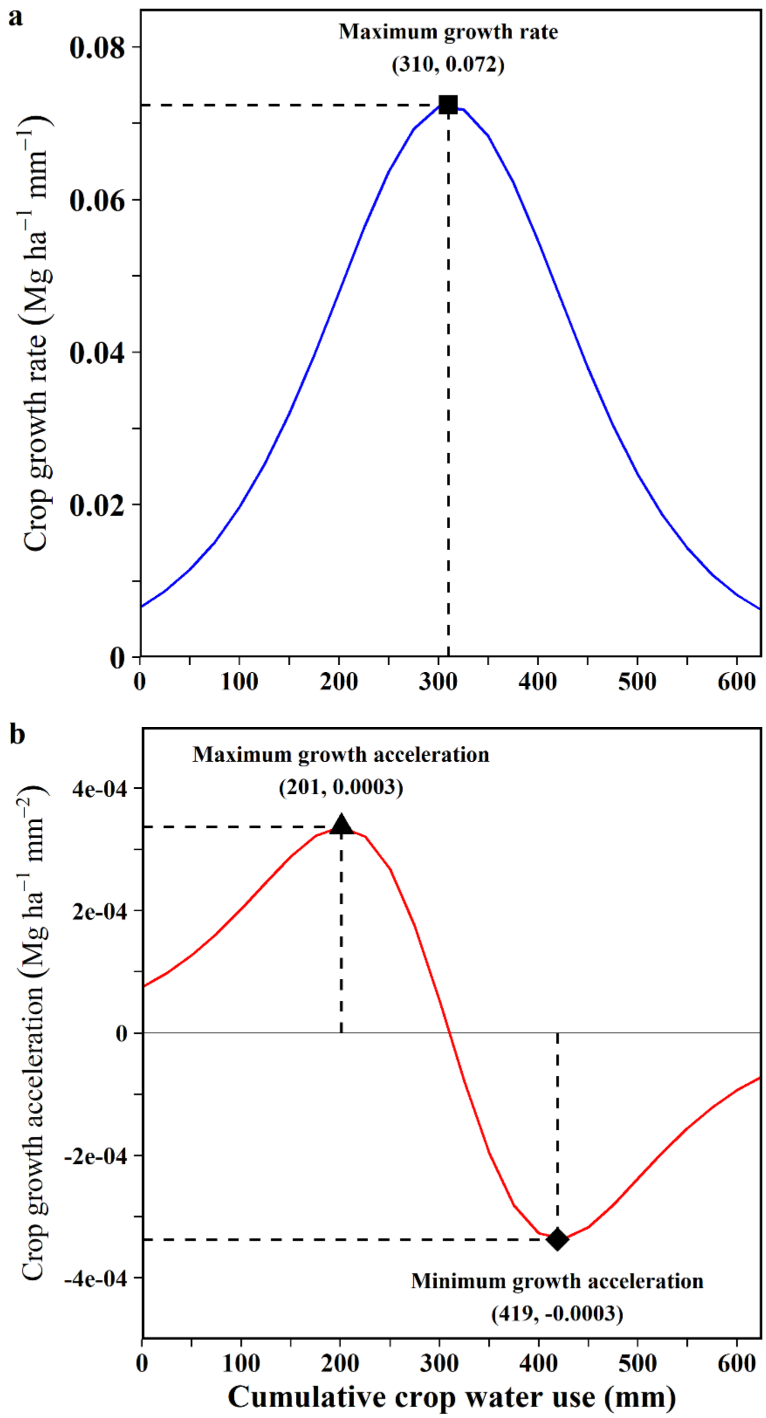

Figure 3.6 a) Sorghum dry biomass growth rate and b) sorghum dry biomass growth acceleration as a function of cumulative water applied (irrigation + rainfall ± soil water content) as simulated with full irrigation. Data are averages for 30 years (1986 to 2015) at the Texas A&M AgriLife Research Center, Weslaco, Texas.

3.5. Discussion

In general, the calibration results showed a reasonable agreement between measured and simulated crop productivity and crop water use during the growing season. However, the model tended to overestimate dry biomass productivity at the beginning of the season. These results agree with observations by Cabelguenne et al. (1990), Ceotto et al., (1993), Martin et al. (1993), and Warner et al. (1997), who reported that EPIC tended to overestimate low yields.

EPIC computes plant transpiration (EP) as a fraction of PET using the LAI linear relationship developed by Ritchie (1972). So, EPIC assumes that EP increases linearly as a function of LAI until LAI reaches 3.0, and then EP is assumed to be the same as PET, and no soil evaporation occurs. For most crops, LAI is initially zero. It increases exponentially during early vegetative growth when the leaf primordia development rate, the leaf appearance, and blade expansion are linear functions of heat unit accumulation (Tollenaar et al., 1979; Watts, 1972). In vegetative crops such as biomass sorghum, LAI reaches a plateau where leaf senescence and growth are approximately equal. LAI then decreases after the maximum LAI is reached and approximates to zero at physiological maturity (Williams et al., 1989). Therefore, EPIC uses LAI to split between ET_c and PET, while the values estimated with the STWP used the growth stages for sorghum and specific crop coefficients recommended by FAO-56 for Sudan grass.

When 30 years of weather data were used in the simulation, the average productivity for limited and full irrigation ranged between 21.9 and 26.3 Mg dry biomass ha^{-1} (Table 3.7). The dry biomass value simulated in this study coincided with results reported in other studies, such as Hao et al. (2014), who reported 23.5 Mg ha^{-1} at full irrigation, Rooney et al. (2007), who reported 20 Mg ha^{-1}, and Rocateli et al. (2012), who reported 26.0 to 31.6 Mg ha^{-1}, and Palumbo et al. (2014) that reported 20.9 to 26.4 Mg ha^{-1} for a Mediterranean environment.

The EPIC model simulates LAI using a temperature-based method in which temperature was the most limiting factor for leaf expansion (Amir and Sinclair, 1991; Chapman et al., 1993). However, the carbon-based methods used to estimate LAI indicate that plant leaf expansion depends on the amount of dry matter available for leaf growth (Soltani and Sinclair, 2012). Carbon-based methods first calculate dry matter production, and then leaf area development is estimated as a function of dry matter. For this reason, the specific leaf area, which is the ratio of leaf area to leaf weight, was affected by the low solar radiation recorded in 2015 (Table 3.3), causing a decrease in the dry matter (m^2 g^{-1}). In other words, solar radiation determines the daily amount of photosynthate available for leaf expansion, while temperature affects the rate of cell division and cell extension (Kropff and Van Laar, 1993; Van Delden et al., 2001; Xinyou and Van Laar, 2005). Hence, EPIC overestimated LAI in 2015.

Linear growth, which is the most crucial phase of crop development, was obtained from 201 to 419 mm of applied water (Figure 3.5). At the end of this phase, dry biomass productivity of ~19.0 Mg ha^{-1} was obtained. These results demonstrated that 600 mm of water was necessary to reach up to 24 Mg ha^{-1} of sorghum's dry biomass (Figure 3.5). Experiences in Mediterranean environments showed that 350 to 480 mm of water applied could produce 19.8 to 34.6 Mg ha^{-1} (Garofalo et al., 2011). The difference between irrigation input and cumulative ET_c was due to irrigation inefficiencies that promote water losses by deep percolation. Irmak et al. (2000), who evaluated the yield response of corn in a Mediterranean semi-arid climate, reported that the relationship between yield and irrigation tended to be linear.

3.6. Conclusion

The EPIC model satisfactorily simulated plant emergence, ET_c, LAI, and dry biomass for the full irrigation treatment in 2013. The model also accurately simulated the productivity response for the limited irrigation experiments, in which the mean percent error of simulation was less than 6% in 2013 and 12% in 2015.

There was also a close match between measured and simulated ET_c and LAI for the three other irrigation treatments (limited irrigation in 2013, limited irrigation in 2015, and full irrigation in 2015).

LAI is an essential crop parameter used for the EPIC model to split between ETc and PET. It has to be constantly monitored during crop development for satisfactory model calibration.

The EPIC model was used to assess crop productivity and water responses over 30 years under local conditions. From the long-term simulations, we conclude that it is possible for biomass sorghums to produce up to 24 Mg ha^{-1} of dry mass with 600 mm of water.

The EPIC model is found to be suitable for use as a decision tool to evaluate biomass sorghum experiments conducted under deficit irrigation because it can integrate different stress factors that affect crop development.

WUE results from long-term simulations indicated that switching from full to limited irrigation is an appropriate strategy for biomass sorghum production in areas with limited water resources.

4. ANALYSIS OF RADIATION USE EFFICIENCY AND SIMULATION OF BIOMASS SORGHUM PRODUCTION UNDER STAGGERED SOWING DATES

4.1. Synopsis

Biomass sorghum [*Sorghum bicolor* (L.) Moench] has been identified as a high yield potential crop alternative for producing energy; however, there is a lack of information on its performance and yield response under the influence of different sowing dates with adequate water and fertilized conditions. This study's objective was to determine the radiation use efficiency (RUE) of biomass sorghum and evaluate the EPIC model for the production of biomass sorghum under the effects of variable timed sowing dates of three sorghum hybrids. Three sorghum hybrids (one forage sorghum and two energy sorghums) were grown and evaluated at staggered sowing seasons under optimal growth conditions over two years (2013 and 2016) at the Texas A&M AgriLife Research Center in Weslaco, Texas. The dry biomass (DB) ranged from 12.57 to 32.77 Mg ha^{-1}. The highest DB values were observed when the sowing took place between March and May, while the lowest DB values were observed in the sowings of August and September. Higher leaf area index (LAI) values were observed on the energy hybrids (LAI > 4.0), which means that they can intercept over 90% of incident photosynthetically active radiation (PAR). RUE is mainly a sensitive parameter useful to enhance the effectiveness of crop simulation models. It is a crucial parameter used to predict the potential dry matter accumulation of a crop. RUE ranged from 2.71 to 4.42 g MJ^{-1}. Higher RUE values were observed for the energy hybrids for the sowing dates from March to May. The statistical

parameters derived from measured versus simulated DB indicated that the EPIC model performed well at estimating DB with an average $R^2 = 0.91$, and an average RMSE = 2.36 Mg ha^{-1}. This chapter's results show that RUE values' adjustments for different sowing seasons and varieties will enhance crop simulation effectiveness in predicting sorghum growth and yield response for staggered biomass production.

4.2. Introduction

Production of bioenergy in a bio-refinery requires a continuous supply of feedstocks during the year, and consequently, a plan to staggered sowing dates. Most bioenergy experiments involving high-biomass crops are conducted to determine an optimum sowing date, seeking maximum biomass yields with minimum use of inputs such as water and fertilizers. However, there is a need to continuously supply feedstock to biorefineries, which require strategically sowing high-biomass crops to maximize dry biomass production during a yearlong duration.

High-biomass crops, such as sorghum [*Sorghum bicolor*], sugarcane [*Saccaharum officinarum L.*], corn, maize [*Zea mays L. subsp mays*], and Miscanthus [*Miscanthus spp.*], are warm-season C4 crops that have often been identified as a feedstock for bioenergy production. However, sorghum, especially, is an excellent candidate for bioenergy production because of its high biomass potential, water stress tolerance, short growing cycle, increased water use efficiency, and highly efficient in converting solar energy into biomass (Enciso et al., 2019; Monge et al., 2014). Biomass sorghums have been genetically improved to increase its biomass accumulation and maximize its cellulosic content. They can produce high biomass yields in just 90-100 days and can remain their vegetative growth phase for more than 200 days at most latitudes (Rooney et al., 2007).

Information about staggered sowing for sorghum is limited in scope, and very few studies exist in the literature, probably because farmers looked at optimal production in a single crop cycle. Rao et al. (2013) reported that late of sweet sorghum typically had lower yields of stalks and sugar than earlier sowings. Another study conducted in the Rio Grande Valley by Hipp et al. (1970) evaluated the influence of sowing dates and solar radiation on sweet sorghum. They observed that the highest sugar yield was found in crops sown in May. The plants' solar radiation received during the period between boot and early seed formation accounted for about 75% of the variation in yield.

Connor et al. (2011) stated that photosynthetic rates of crops depended on the quantity of radiation intercepted and utilization efficiency. For this reason, the RUE measured at several sowing seasons may provide a better understanding of sorghum's physiological ability to produce dry biomass under different weather conditions, such as temperature and photoperiod. The amount of PAR received from the sun, and the efficiency of crop canopy for the absorption of PAR principally influences the rate of biomass accumulation. Hence, total dry plant matter, under optimal crop growth conditions, depends on the quantity of radiation absorbed by the crop canopy (Kiniry et al., 1989). Consequently, the estimations of dry biomass are based on the concept of RUE (g MJ^{-1}), which is defined as the ratio of dry matter produced (g m^{-2}) and the absorbed PAR (MJ m^{-2}) (Soltani and Sinclair, 2012). Thus, simulation of DB production is the central part of many crop growth models, such as EPIC, CERES and CropSyst, which adopted the concept of RUE as a significant parameter used to predict the accumulation of potential DB production.

According to the literature, RUE has been widely used to evaluate diverse crop management conditions and weather environments. Wang et al. (2015) conducted a 3-year field experiment to assess the influence of row spacings and plant densities on canola seed yield and canopy RUE in Central China. They found that higher LAI and RUE under wide-narrow row arrangements can lead to more biomass accumulation than uniform ones. Du et al. (2015) conducted field experiments in China to study the effects of four cropping systems on RUE in wheat-cotton double cropping. They found that the wheat-cotton double-cropping improved radiation use by increasing the intercepted PAR and RUE compared with monoculture cotton. A handful of studies have explored RUE responses among sorghum cultivars specifically. For instance, Houx III and Fritschi (2015) observed decreases in RUE and biomass production of four sweet sorghum cultivars in response to two late sowing dates in a 2-year study. They observed that even when sown late, sweet sorghum converts efficiently intercepted PAR to biomass. Rinaldi and Garofalo (2011) conducted a three-year field experiment of sorghum under four different irrigation levels in southern Italy. They obtained RUE values that confirmed a high efficiency in biomass production with adequate irrigation water supply for a Mediterranean environment.

Because many crop models use RUE as a parameter to estimate crop growth, it is necessary to determine accurate values to account for the agronomic effect on simulating DB production at staggered sowing seasons. In the present study, a 2-year experiment with diverse weather conditions (solar irradiance, temperature, and photoperiod) was observed to estimate RUE values for three sorghum hybrids sown on different dates. RUE values obtained from field experimentation were incorporated into the EPIC model (Williams et al. 1989). EPIC is a crop simulation model recognized as one of the most robust crop models used as a decision support tool that simulates the physicochemical process that occurs in soil and water under agricultural management. EPIC has been widely used in many studies under different climatic and management conditions. For instance, EPIC was calibrated and evaluated for its potential to simulate maize yield for South Africa conditions (Choruma et al., 2019). It was used to assess and manage crop water use and crop production of cotton in the USA (Ko et al., 2009), and the assessment of climate change impacts on crop yield in southern Italy (Rinaldi and De Luca, 2012). Hence, it was imperative to experiment to quantify the effect of weather on biomass sorghum growth and yield under staggered sowing seasons. This chapter's objectives were to determine the RUE and evaluate the EPIC model biomass sorghum production under the effects of variable timed sowing dates of three sorghum hybrids. The results obtained in this study will allow crop modelers to increase the ability to determine the optimal crop parameter values for a more precise prediction of dry biomass productivity of high-biomass crops under staggered production systems.

4.3. Material and methods

4.3.1. Field experiment and measure data

Measured data were obtained from experiments conducted during the 2013 and 2016 growing seasons in fields located at the Texas A&M AgriLife Research Center in Weslaco, Texas (latitude 26° 09’ 26’’ N, longitude 97° 57’ 32’’ W; elevation 24 m above sea level). The study area (Figure 2.1) has a semi-arid climate with an average annual precipitation of 558 mm, and the soil type is a Hidalgo sandy loam. The biomass sorghum hybrids used in this study were two energy sorghum hybrids from Blade® Energy Crops, Blade ES 5140 and Blade ES 5200, and one forage sorghum hybrid from Pioneer®, Pioneer 877F. They were sown in 1.02 m wide spacing. The plots used for experiments were 4.1 m wide and 91.4 m long. The plant density in all plots was approximately 140,000 seeds per ha, with a sowing depth of 30 to 45 mm. The plant density after emergence showed no differences among the sowing seasons. A subsurface drip irrigation system was installed to assure uniform germination of seeds and better control of water inputs (Henggeler et al., 2002). Drip tape with 15 mm thickness was placed in each bed's center, resulting in an irrigation water application rate of 2.5 mm h^{-1}. The fertilizer urea ammonium nitrate (UAN; 32% mass fraction of N) was applied through the drip irrigation system in two equal split applications. The same total fertilizer was applied to all experimental units.

Full irrigation was applied to all experimental plots. It was achieved by replacing the water used by the crop ET_c. ET_c was calculated using the Sudan grass crop coefficients suggested by FAO 56 and using the Penman-Monteith reference evapotranspiration (ET_o) equation (Allen et al., 1998). ET_c requirements for sorghum was based on the relation to a well-watered reference grass using the equation: $ET_c = K_c \times ET_o$, where ET_c is crop evapotranspiration, and K_c is the crop coefficient (Enciso and Wiedenfeld, 2005). The standard $K_{c\ ini}$, $K_{c\ mid}$, and $K_{c\ end}$ values of 0.15, 1.15, and 1.1, respectively, were applied to ET_o to calculate ET_c using the Penman-Monteith approach (Rajan et al., 2015). Soil water depletion was calculated at harvest measuring the soil water content at the beginning and end of each sowing season using gravimetric methods. The South Texas Weather Program (STWP), an internet-based program developed by Texas A&M AgriLife Research Center, http://southtexasweather.tamu.edu/ (Enciso et al., 2015), was used to create an irrigation schedule for each sowing season. STWP calculated the number of irrigation events during each sowing season and the timing and amount of irrigation water required using a predetermined allowable depletion level of 90%. The irrigation system was assumed to have a 100% efficiency. Weather data used for ET calculations were collected through a weather station (model ET106, Campbell Scientific, Logan, Utah) as described by Chavez et al. (2019), installed 100 m away from the field experiments.

Table 2.1 shows agronomic data and dates in which crop development was monitored. Plant sampling was conducted in each of the experimental units four to five times throughout the sowing season (as described in Chapter 2) if weather conditions were favorable. LAI and biomass were determined using destructive sampling. The destructive samples were randomly collected from 1 m^2 area at the center of each plot to avoid the border effects. DB and plant water content were determined after drying all plant materials at 60°C until the material stabilized. Measurements of PAR above and below the canopy cover were taken at three locations within each experimental plot using a ceptometer (model AccuPAR LP-80, Decagon, Pullman, WA, USA) at noon to eliminate the influence of solar zenith angle and within a short period to reduce variations in readings of solar irradiance.

4.3.2. Computation of field data

Sorghum phenological development was monitored for every sowing season across the 2-year study. This development was recorded daily and then converted into growing degree days (GDD, °D) following the 3-segment linear function procedure described by Soltani and Sinclair (2012) for each of the sowing seasons from sowing to harvest. The cardinal temperatures used for estimation of the phenological development for sorghum were: base temperature of 8°C, lower optimal temperature of 30°C, upper optimal temperature of 37°C, and ceiling temperature of 45°C (Soltani and Sinclair, 2012). Daily GDD values were accumulated for every sowing season.

According to Salisbury and Ross (1985), the total irradiance that hits at the upper boundary of the Earth's atmosphere is 1360 J m^{-2} s^{-1} (called solar constant), which includes ultraviolet and infrared wavelengths. While this irradiance passes through the atmosphere to the Earth's surface, energy is lost by absorption and scattering caused by water vapor, dust, CO_2, and ozone, so that only about 900 J m^{-2} s^{-1} reach plants, which depends on latitude, elevation, time of day and other factors. About 50% of this energy is in the infrared, and about 5% is ultraviolet. The rest (approximately 400 J m^{-2} s^{-1}) has wavelengths between 400 – 700 nm capable of causing photosynthesis. It is called photosynthetically active radiation (PAR). The actual amount of energy in the PAR range can vary with atmospheric conditions, depending on cloud cover, location, and date. Monteith and Unsworth (2007) reported that PAR represents about 48% of total solar radiation. Therefore, solar radiation (R_s) was converted into PAR using the following equation:

$$PAR = 0.48 \times R_s \tag{11}$$

Biomass accumulation deals with the absorption of PAR for the assimilation of plant biomass. Therefore, biomass growth is dependent on the amount of PAR received from the sun and the amount of leaf surface available for the absorption of PAR for photosynthesis (Ritchie et al., 1998). The canopy extinction coefficient (*K*) is a parameter that describes the efficiency of the light interception for the canopy (Zhang et al, 2014). *K* is determined by the leaf inclined angle and the solar zenith angle, and is usually calculated with the Beer Lambert Law (Monsi and Saeki, 1953), which in many cases is simply expressed as:

$$K = \frac{-ln\left({}^{I_i}/_{I_0}\right)}{LAI} \tag{12}$$

where I_i is the solar radiation under the canopy, I_0 is the solar radiation above the canopy, and LAI is the leaf area index. The ratio of I_i to I_0 is known as transmittance (τ), which is the fraction of irradiance transmitted by the canopy. The τ values and LAI were measured on all the plots at locations with adequate crop stand in order to estimate *K* for every sorghum hybrid on all sowing seasons. Additionally, the *K* values were also estimated for each sorghum hybrid as the slope of the fitted regression of the first-order equation between the negative natural logarithm of transmittance (-ln τ) and the LAI of the plant canopy on the date of sampling of the appropriate treatment. Therefore, the intercepted photosynthetically active radiation (IPAR) by the crop canopy was calculated as follows:

$$IPAR = PAR \times \left[1 - exp^{(-k \times LAI)}\right] \quad (13)$$

The RUE is the dry matter produced per unit of IPAR, and its units are expressed as g MJ^{-1} of IPAR or kg ha^{-1} MJ^{-1} m^2. RUE was experimentally estimated as the slope of the fitted regression of the first-order equation between dry biomass productivity and accumulated IPAR for each hybrid at each sampling date. The regression equation for RUE was fitted to four sampling dates. The RUE values were determined for each sorghum hybrid at each sowing season of the experiment. Also, the RUE was calculated for each sampling date by determining the dry biomass productivity (DB, g m^{-2}) and the accumulated IPAR using the following equation:

$$RUE = \frac{DB}{\sum_{d\,=\,sowing\ date}^{d\,=\,sampling\ date} IPAR} \quad (14)$$

4.3.3. Model description

The EPIC model was chosen due to its proven performance on simulating cropping systems under diverse climatic conditions (Rinaldi and De Luca, 2012; Sharpley and Williams, 1990; Williams et al., 1989). EPIC consists of various model components that include crop growth, hydrology, weather simulation, nutrient cycling, pesticide fate, erosion-sedimentation, soil temperature, tillage, economics, and plant environment control (Williams et al., 1989). It has the capability of performing long-term continuous simulations using a daily time step. Penman (Penman, 1948), Penman-Monteith (Monteith, 1965), Baier-Robertson (Baier and Robertson, 1965), Priestley-Taylor (Priestly and Taylor, 1972), and Hargreaves-Samani (Hargreaves and Samani, 1985) are the five options for estimating potential evapotranspiration (PET) that allows users to simulate ET_c under different climatic conditions. Maximum and minimum air temperature, solar radiation, and daily precipitation are required weather input variables for PET estimation; wind speed and relative humidity are also needed if the Penman or Penman-Monteith methods are selected. These weather variables are entered by the user or generated by the runtime model from long-term averages. Crop development is simulated based on daily heat unit accumulation (Williams et al., 1989). Daily potential DB is calculated using PAR and RUE and then adjusted to the actual biomass through daily stresses such as extreme temperatures, inadequate aeration, water deficit, and nutrient deficiencies. Finally, EPIC calculates crop yield by the ratio of economic yield to the aboveground biomass at maturity, defined by the harvest index (HI).

4.3.4. Sorghum simulations

Chavez et al. (2018) calibrated and validated an EPIC model developed for energy sorghum for the south Texas conditions (Table 3.1). Sensitive model parameters and inputs were adjusted to obtain an acceptable performance of the model. Those calibrated crop parameters were used for the simulation of biomass sorghum in the present study. However, the crop parameter that refers to RUE (biomass to energy ratio, WA) was readjusted for each sowing season simulation based on the measured RUE values obtained from field experiments. All of the management details regarding cropping practices listed in Table 2.1 were incorporated into the model for simulation. Predominant soil properties of the field experiment site are described in Table 3.2. Additionally, Table 4.1 lists the EPIC parameters adjusted to set auto irrigation ensuring the full irrigation.

Table 4.1 Adjusted EPIC parameters to set auto irrigation for simulation of biomass sorghum.

Parameter	Description	Default value	Range	Adjusted value
BIR	Irrigation trigger. Irrigation will be triggered at specified plant stress	0	0 - 1	0.95
EFI	Runoff volume / volume irrigation water applied	0	0 - 1	0.1
VIMX	Maximum annual irrigation water allowed (mm)	2000	0 – 2000	600
ARMN	Minimum single application volume allowed (mm)	199.9	---	10
ARMX	Maximum single application volume allowed (mm)	1000	---	100

EPIC outputs used for model evaluation were ET_c, DB and LAI. Daily measured ET_c was determined using the STWP, assuming unstressed crop growth conditions. The Hargreaves-Samani PET equation was selected to simulate ET_c in this study, because it performs better for the South Texas climatic conditions (Chavez et al., 2018). After the preliminary run test, the measured ET_c from the South Texas Weather program was compared to EPIC simulated using the Hargreaves-Samani. As a result, no statistical difference was found between the seasonal ET_c from STWP using FAO-56 Penman-Monteith formula and those simulated with EPIC.

4.3.5. Test statistics

Linear regression, correlation coefficient (r), and coefficient of determination (R^2) were used for model evaluation. The linear model is $y = \propto + \beta x + \varepsilon$, where α and β are the regression intercept and slope, respectively, and ε is the random error. The student *t*-test was used to test the null hypothesis H_0: α = 0, β = 1. H_0 is maintained when α and β are not significantly different from 0 and 1, respectively. The goodness of fit estimators used the *p*-value from the *t*-test. R^2 measures the proportion of the variation in *y*, which is accounted for by the linear model. Therefore, R^2 tests the "goodness of fit" of the linear model. The R^2 value ranges from 0 to 1 and describes the degree of collinearity between measured and simulated data (Moriasi et al., 2007), where higher values indicating a minimum variance. However, R^2 only estimates the linear relationship between two variables and is not sensitive to the regression intercept (α). Additional useful statistics were used to assess the model performance: Root Mean Square Error (RMSE), eq. (7); Nash-Sutcliffe Efficiency (NSE), eq. (8); and Percent Bias (PBIAS), eq. (9). RMSE represents the discrepancy between observations and predictions. For RMSE, the values closer to zero imply an excellent fit between measured and simulated data, and RMSE equal to 0 indicates a perfect fit. NSE is used to quantify the model performance and shows how well the average of the measured data versus the simulated data fit the measured data. NSE ranges from -∞ (poor model) to 1 (perfect model). NSE < 0 indicates an unacceptable model performance, while NSE values from 0 to 1 indicates the model is better than merely using measured data as a predictor. PBIAS measures the average tendency of the simulated data to be greater or less than measured data. The optimal PBIAS is zero, while positive values indicate underestimation bias, and negative values indicate overestimation bias. According to Wang et al. (2012), model performance is considered satisfactory when $R^2 \geq 0.60$, NSE ≥ 0.55, and PBIAS within ±25% for water yield; and $R^2 \geq 0.60$ and PBIAS $\leq$ ±25% for crop yield.

4.4. Results

4.4.1. Environmental conditions

The weather data recorded for the study period, January to December 2013 and 2016, compared with the long-term averages (30 years), is shown in Table 2.2. The daily mean air temperature was recorded during the study period, as shown in Figure 2.2. The monthly minimum and maximum air temperatures were higher in 2016 than in 2013 and the 30 year-period. Warm conditions were observed with a remarkable heatwave at the end of July and beginning of August in 2016, with maximum daily temperatures over 40°C. Differences in daily air temperatures through the growing seasons caused variation in total GDD across the sowing seasons (Table 2.1). The sorghum sown on June 15 and harvested on October 13 in 2016 attained the highest cumulative GDDs (2342°D), followed by the one planted on May 11 and harvested on September 08 (2336°D); this occurred as a result of high temperatures recorded during that summer. The lowest cumulative GDDs were observed in the sorghum sown in September in 2013 (1555°D) and August 25 and March 01 in 2016 (1959°D and 1761°D, respectively). The variation was due to the lower daily temperature recorded during those months and shorter days. In general, the total GDD data and plant maturity corresponded well with the accepted GDDs and sorghum development.

Total precipitation (Table 2.2 and Figure 2.2) was excessive in 2013 with 642 mm compared to 472 mm in 2016 and 476 mm in the 30-yr average. Precipitation patterns were highly variable during each month during the study periods, resulting in different irrigation needs for each of the sowing seasons (Table 2.1). In 2013, the sorghum sown on April 23 needed more irrigation water (457 mm) due to the dry conditions observed in the months previous and during the beginning of the sowing season. While in 2016, sorghum sowed on April 04 and June 15 (432 and 406 mm, respectively) required more irrigation water due to the interaction of high ET and low precipitation observed during that particular study period.

During the study period, monthly R_s values were like those recorded on the last 30-year average (Table 2.2). However, the less R_s that was observed in 2013 was due to the variations in cloud cover and in the number of days with precipitation. September and December of 2013 observed (21 and 25%, respectively) less R_s than the 30-year average. While in 2016, July was the month with the most solar radiation received with a monthly value of 810 MJ m^{-2}, followed by August and June with 733.2 and 727.5 MJ m^{-2}, respectively (Table 3). Because of R_s differences, the cumulative IPAR varied significantly throughout each sowing season and for each hybrid and gradually declined through the end of each year. In general, mean daily PAR and cumulative IPAR were lower for those sorghum sown on early and late sowings.

Photoperiod-sensitive sorghums continue in vegetative growth as long as the daylength be more than the photoperiod trigger of 12:20 h, less than that will induce flowering. The number of days with the daylight of more than 12:20 h varied significantly throughout the sowing seasons (Table 2.1). Sorghum hybrids sown between the beginning of April and the end of May were those that received equal to or more than 12:20 h of daylight during the growing season.

4.4.2. Biomass accumulation

For the 2-year study period, the DB ranged from 12.1 to 32.8 Mg ha^{-1} for all hybrids in all experiments (Table 4.2). The highest average DB was observed on the sowing date of April 04, 2016 (22.7, 28.3, and 32.8 Mg ha^{-1} for Pioneer 877F, Blade ES 5140, and Blade ES 5200, respectively), and May 11, 2016 (24.7, 26.8, and 32.0 Mg ha^{-1} for Pioneer 877F, Blade ES 5140, and Blade ES 5200, respectively; while the lowest average measured DB was on the sowing date of September 01, 2013 (12.1, 13.0, and 12.9 Mg ha^{-1} for Pioneer 877F, Blade ES 5140, and Blade ES 5200, respectively), and August 25, 2016 (12.6, 13.5, and 13.4 Mg ha^{-1} for Pioneer 877F, Blade ES 5140, and Blade ES 5200, respectively). Sorghums sown between April and May reached the highest DB values, then decreased through the rest of the sowing seasons (Figure 2.3). Overall, the sorghum hybrids' ranking at most of the sowing season were stable (Blade ES 5200 > Blade ES 5140 > Pioneer 877F). The DB of the hybrid Blade ES 5200 showed averaged values higher than 30 Mg ha^{-1} when sown between April and May (in the 2-year study) (Table 4.2), while the Pioneer 877F hybrid showed the lowest DB values during most of the experimental period, except for those sown on September 01, 2013, and August 25, 2016, where there were observed no statistical differences among the three hybrids, and the averaged DB values were the lowest of the experiment.

Table 4.2 Measured mean dry biomass (DB, Mg ha^{-1}), and simulated dry biomass (DB, Mg ha^{-1}), measured mean leaf area index (LAI, m^2 m^{-2}), and simulated leaf area index (LAI, m^2 m^{-2}) from the EPIC model at the final harvest date for the three sorghum hybrids for every crop cycle in the 2-year study period.

Sowing date	Sorghum hybrid	Measured DB	Simulated DB	Measured LAI	Simulated LAI
23 April, 2013	Pioneer 877F	19.500	21.631	3.39	4.03
	Blade ES 5140	21.114	23.351	4.75	4.80
	Blade ES 5200	28.350	28.054	5.55	5.58
01 Sep., 2013	Pioneer 877F	12.057	10.020	2.68	3.00
	Blade ES 5140	13.003	10.720	2.57	3.08
	Blade ES 5200	12.886	10.862	2.74	3.27
01 Mar, 2016	Pioneer 877F	24.606	22.070	3.27	3.30
	Blade ES 5140	25.263	25.528	4.07	4.08
	Blade ES 5200	30.370	28.317	4.43	4.45
04 April, 2016	Pioneer 877F	22.711	21.959	3.23	3.69
	Blade ES 5140	28.285	26.231	4.36	4.47
	Blade ES 5200	32.774	29.933	5.04	5.25
11 May, 2016	Pioneer 877F	24.667	22.343	3.25	3.12
	Blade ES 5140	26.806	24.401	4.14	3.97
	Blade ES 5200	31.998	27.981	5.41	5.52
15 June, 2016	Pioneer 877F	22.464	20.474	3.23	3.74
	Blade ES 5140	23.009	19.964	3.82	4.21
	Blade ES 5200	28.101	25.537	4.67	4.59
14 July, 2016	Pioneer 877F	17.839	17.830	2.91	3.52
	Blade ES 5140	17.908	19.901	3.66	3.61
	Blade ES 5200	23.047	19.401	3.67	3.84
25 Aug.2016	Pioneer 877F	12.595	9.371	2.92	3.34
	Blade ES 5140	13.504	11.157	2.79	2.99
	Blade ES 5200	13.345	10.093	3.09	3.64

4.4.3. Leaf area index

Generally, higher LAI values were observed in those hybrids that were sown between March and June during the study period (Figure 4.1). Those higher LAI values were due to the better weather conditions for sorghum growth than the hybrids sown from July to September. For the 2-year study period, the average measured LAI ranged from 2.57 to 5.55 $m^2\ m^{-2}$ for all hybrids in all experiments (Table 4.2). The highest average measured LAI was observed in the sowing dates of April 23, 2013 (3.39, 4.75, and 5.55 $m^2\ m^{-2}$ for Pioneer 877F, Blade ES 5140, and Blade ES 5200, respectively, and May 11, 2016 (3.25, 4.14, and 5.41 $m^2\ m^{-2}$ for Pioneer 877F, Blade ES 5140, and Blade ES 5200, respectively), while the lowest average LAI observed was on the sowing date of September 01, 2013 (2.68, 2.57, and 2.74 $m^2\ m^{-2}$ for Pioneer 877F, Blade ES 5140, and Blade ES 5200, respectively, and August 25, 2016 (2.92, 2.79, and 3.09 for Pioneer 877F, Blade ES 5140, and Blade ES 5200, respectively). It means that sorghums sown between April and May reached higher LAI values, then decreased to half through the rest of the crop seasons (Table 4.2). The sorghum hybrid's ranking at each sowing season was stable (Blade ES 5200 > Blade ES 5140 > Pioneer 877F), except for those sown on September 01, 2013, and August 25, 2016. The LAI of the hybrid Blade ES 5200 showed averaged values higher than 5 $m^2\ m^{-2}$ when sown in April (in the 2-year study) (Table 4.2), while the Pioneer 877F hybrid showed the lowest LAI values during most of the experimental period, except for those sown on September 01, 2013, and August 25, 2016, where there were observed no statistical differences among the three hybrids, and the averaged LAI values were the lowest for the experiment.

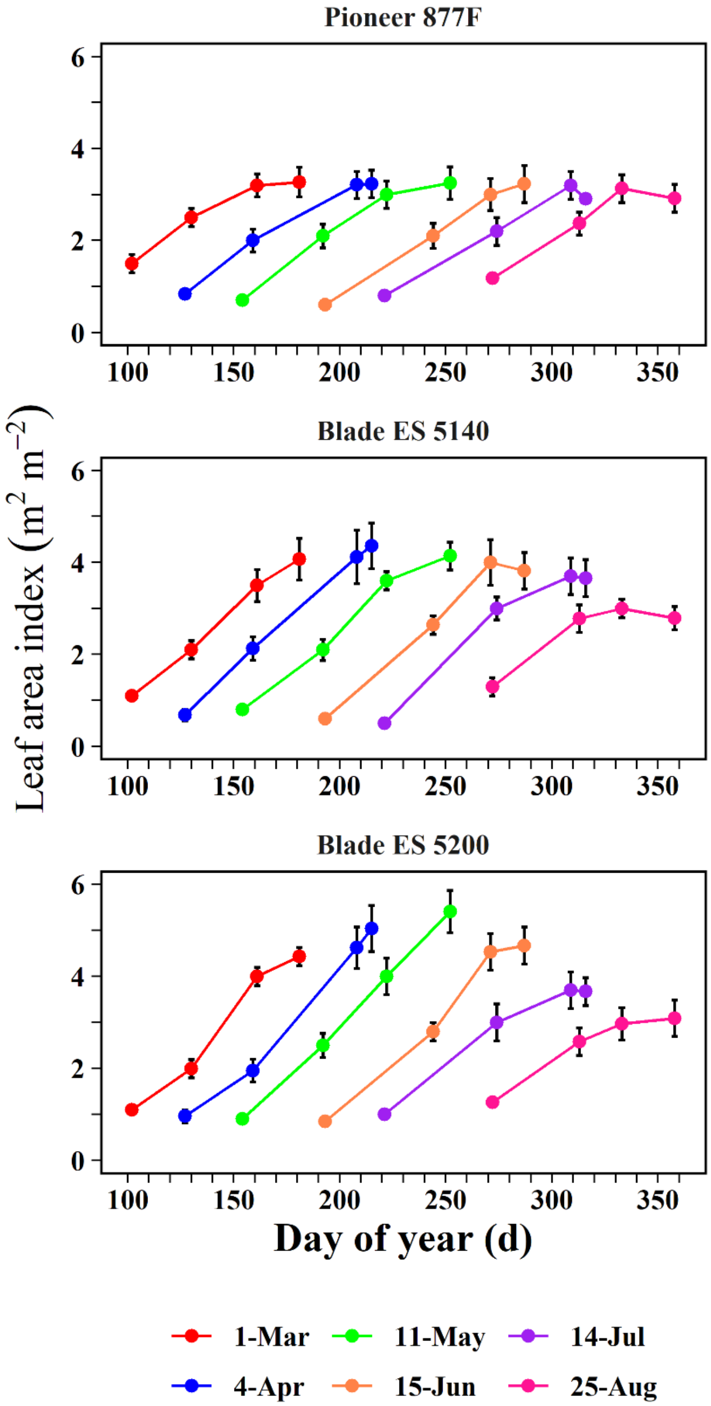

Figure 4.1 Accumulation of leaf area index over time of the three sorghum hybrids from experimental data of the growing season of 2016.

4.4.4. Canopy extinction coefficients

A canopy extinction coefficient (*K*) was obtained for each sorghum hybrid from measurements of PAR (transmitted and incident) and crop LAI from emergence to maturity. The *K* value is an important crop parameter that describes crop's leaf architecture, which is essential for determining the IPAR for each day. The *K* value is a constant that is used during the entire crop life cycle (Soltani and Sinclair, 2012). Figure 4.2 shows the *K* results for each sorghum hybrid in both growing seasons. Combining readings from all sowing seasons, a one-way analysis of variance (ANOVA) determined that there were differences among sorghum hybrids. It was observed that the F-statistic value was 21.148, and it was highly significant ($p < 0.001$). Thus, it is prudent to reject the null hypothesis of the equal mean value of *K* across the sorghum hybrids. The average (±sd) *K* values were greater for Pioneer 877F ($K = 0.75 \pm 0.05$), followed by Blade ES 5140 ($K = 0.67 \pm 0.08$) and Blade ES 5200 ($K = 0.66 \pm 0.08$). A Tukey's HSD (honest significance difference) test showed the pair-wise difference of average *K* of the three sorghum hybrids at 0.05 level of significance. Three possible pair-wise comparisons were obtained. The results showed that only for the pair between the hybrids Blade ES 5140 and Blade ES 5200 showed no statistical difference between them ($p = 0.666$). This result implies that the average *K* value from Pioneer 877F is statistically different from the other hybrids ($p < 0.05$).

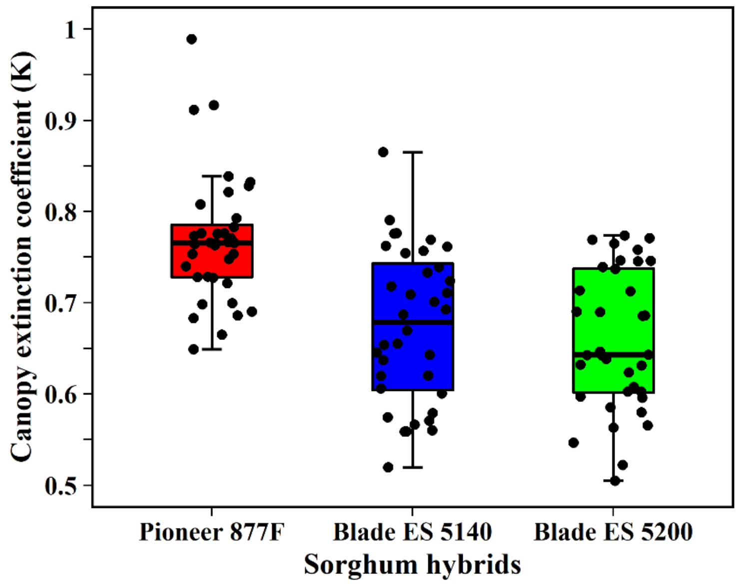

Figure 4.2 Canopy extinction coefficients obtained during the 2-year experiment for the three sorghum hybrids.

4.4.5. Radiation use efficiency

Table 4.3 shows statistics for the linear regression (intercept forced to 0) between DB and cumulative IPAR for each sorghum hybrid for each sowing season. In general, the highest values of RUE were observed in the energy hybrids (Blade ES 5200 > Blade ES 5140 > Pioneer 877F). The response in RUE varied significantly among the sowing seasons (Figure 4.3). RUE varied from 2.68 to 4.43 g MJ^{-1} among all experimental plots. For the Pioneer 877F, the highest RUE value was observed on those sorghums sown on April 04 and May 11, 2016, with 3.124 and 3.205 g MJ^{-1}, respectively; and the lowest when sown on September 01, 2013, and August 25, 2016, with 2.714 and 2.745 g MJ^{-1}, respectively. For the hybrid Blade ES 5140, the highest RUE values were observed on those sorghums sown on April 23, 2013, and April 04, 2016, with 3.708 and 3.62 g MJ^{-1}, respectively, and the lowest on August 25, 2016, with 2.683 g MJ^{-1}. For the hybrid Blade ES 5200, the highest RUE values were observed on the sowing dates of April 23, 2013, and April 04, 2016, with 4.426 and 4.079 g MJ^{-1}, respectively; and the lowest values were observed on September 01, 2013, and August 25, 2016, with 3.010 and 2.955 g MJ^{-1}, respectively.

Table 4.3 Cumulative IPAR (MJ m^{-2}), slope (RUE, g MJ^{-1}), coefficient of determination (R^2), standard error of the slope (SE), and model significance (*p*-value) for every linear regression between dry biomass productivity and cumulative IPAR.

Sowing date	Sorghum hybrid	CIPAR	RUE	R^2	SE[a]	*p*-value[b]
23 April, 2013	Pioneer 877F	669.91	3.036	0.97	0.331	0.003
	Blade ES 5140	687.84	3.708	0.97	0.407	0.003
	Blade ES 5200	724.14	4.426	0.99	0.229	< 0.001
01 Sep., 2013	Pioneer 877F	481.88	2.714	0.99	0.141	< 0.001
	Blade ES 5140	474.65	2.960	0.99	0.154	< 0.001
	Blade ES 5200	460.87	3.010	0.98	0.220	0.001
01 Mar., 2016	Pioneer 877F	770.41	2.928	0.96	0.194	< 0.001
	Blade ES 5140	777.76	3.443	0.96	0.226	< 0.001
	Blade ES 5200	823.28	3.903	0.93	0.317	0.001
04 April, 2016	Pioneer 877F	733.09	3.124	0.99	0.032	< 0.001
	Blade ES 5140	790.16	3.620	0.99	0.055	< 0.001
	Blade ES 5200	807.07	4.079	0.99	0.082	0.007
11 May, 2016	Pioneer 877F	804.62	3.205	0.99	0.123	< 0.001
	Blade ES 5140	828.81	3.400	0.98	0.139	< 0.001
	Blade ES 5200	869.91	3.798	0.99	0.086	< 0.001
15 June, 2016	Pioneer 877F	795.99	2.871	0.99	0.083	< 0.001
	Blade ES 5140	813.46	2.981	0.98	0.104	< 0.001
	Blade ES 5200	826.31	3.365	0.99	0.109	< 0.001
14 July, 2016	Pioneer 877F	684.05	2.813	0.84	0.274	0.002
	Blade ES 5140	690.97	2.824	0.86	0.263	0.002
	Blade ES 5200	783.53	3.210	0.96	0.174	< 0.001
25 Aug., 2016	Pioneer 877F	552.46	2.745	0.86	0.219	0.001
	Blade ES 5140	548.81	2.683	0.87	0.217	0.001
	Blade ES 5200	569.59	2.955	0.70	0.356	0.004

[a] SE measure the precision of the regression analysis. The smaller the number, the more certain one can be about the regression equation.
[b] For regression analysis, *p*-value less than 0.05 means the model is acceptable; if *p*-value greater than 0.05 means the independent (explanatory) variable has no influence on depended variable.

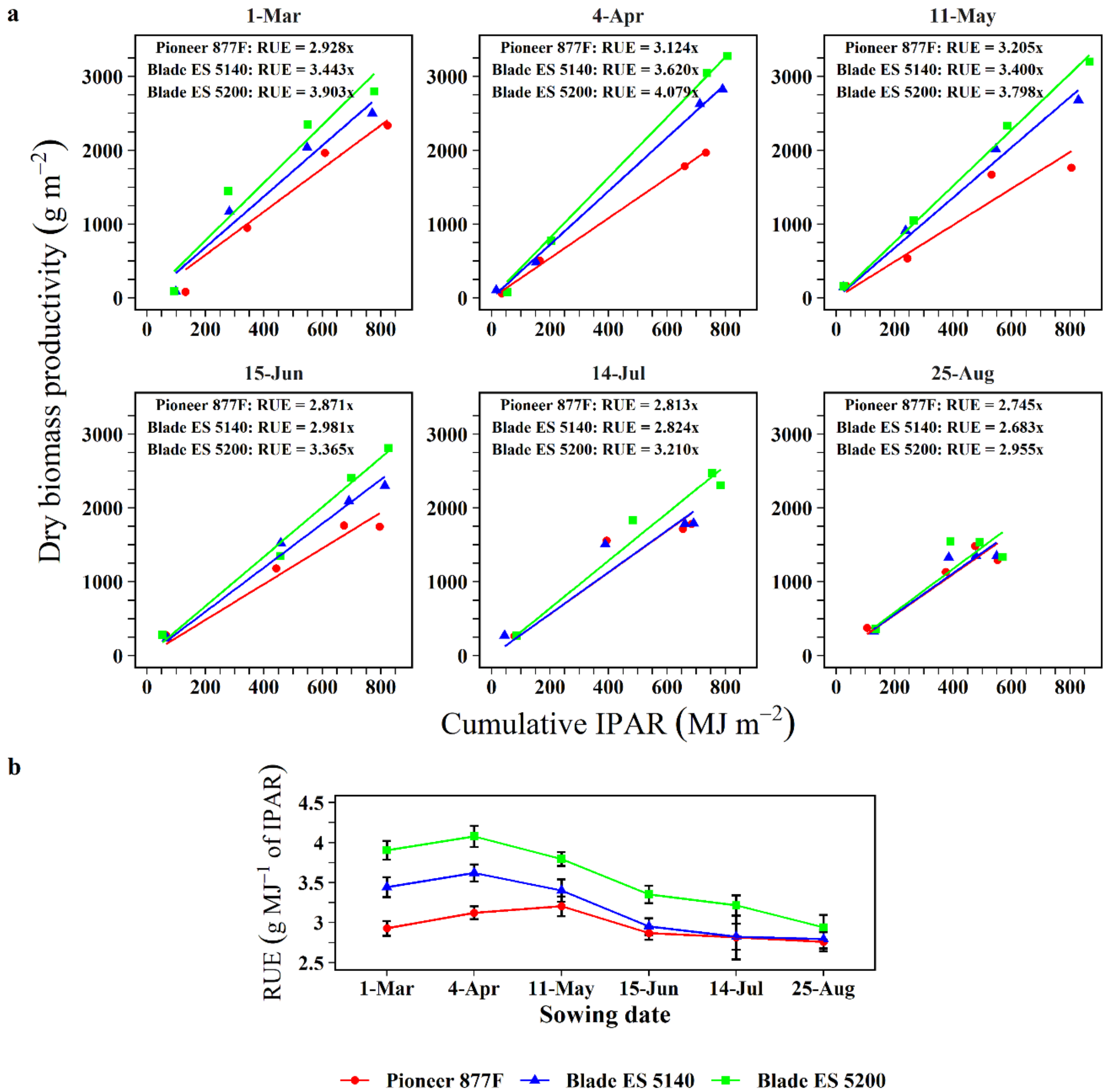

Figure 4.3 a) Linear regressions (intercept coefficient forced to 0) between dry biomass productivity and cumulative IPAR for the three sorghum hybrids at each sowing season, and b) averaged RUE on each sowing season of the growing season of 2016.

4.4.6. Model evaluation

For satisfactory parameterization criteria, Wang et al. (2012) suggested that $R^2 \geq 0.60$, NSE ≥ 0.55, and PBIAS within 20% for water yield; and $R^2 \geq 0.60$ and PBIAS within 25% for crop yield. Sorghum ET_c data under unstressed conditions from the STWP was compared with the EPIC-simulated data using the Hargreaves-Samani equation as part of this study. This calculation was performed as a preliminary evaluation of the EPIC model. *t*-Tests showed that simulated EPIC ET_c was not significantly different from the STWP FAO-56 with a $p = 0.44$ for the 2-year experiment ($p = 0.66$ for the 2013 experimental data and $p = 0.52$ for the 2016 experimental data). The simulated EPIC ET_c agreed with the estimated ET_c from FAO-56 Penman-Monteith, with R^2 of 0.70, RMSE of 1.22 mm, PBIAS of 2.02%, and NSE of 0.61 (Figure 4.4). However, some variations were observed, possibly due to the Hargreaves-Samani equation that does not account for wind speed, causing an underestimation of ET_c during the simulation.

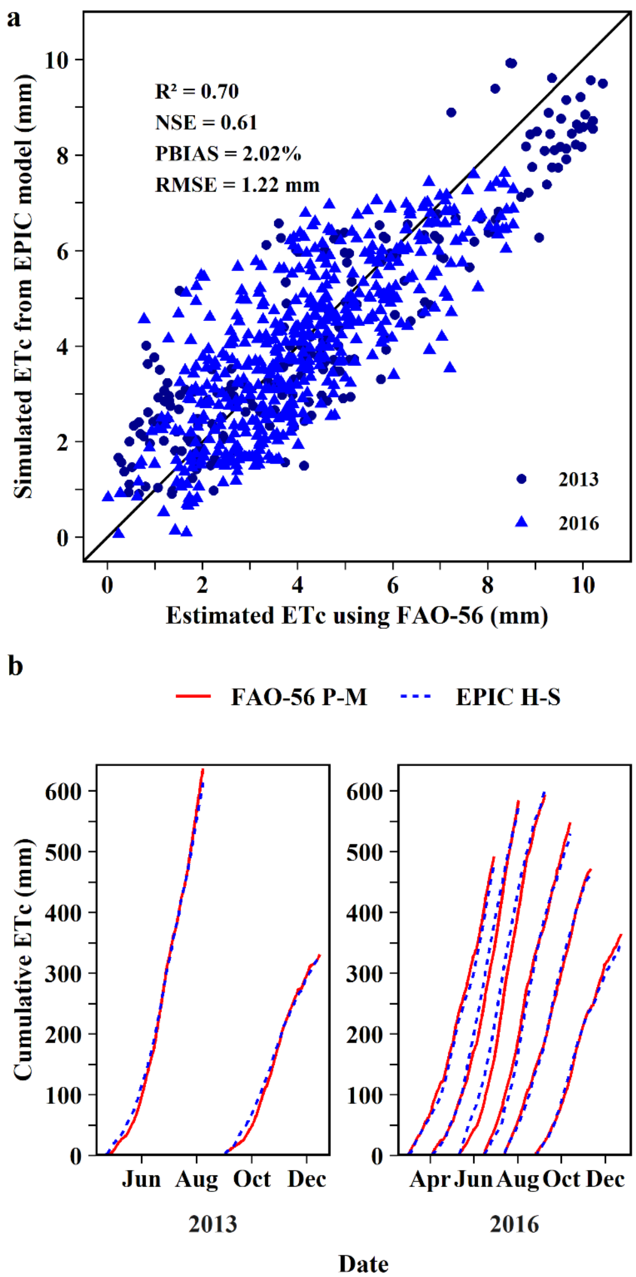

Figure 4.4 a) Comparison between estimated daily ET_c calculated using FAO-56 Penman-Monteith with the South Texas Weather program and crop coefficients versus simulated ET_c from EPIC using Hargreaves-Samani, and b) cumulative ET_c using FAO-56 Penman-Monteith (solid lines) estimated with the South Texas Weather program (K_c varies from 0.5 to 1.1 for Sudan grass) versus EPIC-simulated ET_c using Hargreaves-Samani (dashed lines) for biomass sorghum for the different sowing seasons in the growing seasons of 2013 and 2016 in the Texas A&M AgriLife Research Center, Weslaco, Texas.

The WA crop parameter was adjusted according to the RUE results obtained from experimental data (Table 4.3). After parameterizing the three sorghum hybrids for each sowing season, the statistical indices proved the EPIC model's potential to predict DB and LAI for staggered production in the 2-year experiment. Student *t* tests assuming equal variances were used to conduct hypothesis tests on the regression coefficients obtained from linear regressions. For the entire set of DB data from the 2-year experiment, the linear equation obtained for DB between the measured and the simulated values was $y = 0.8017 + 0.8904x$ with R^2 = 0.94. The agreement between measured and simulated accumulated DB productivity is considered satisfactory since the *t*-tests of the linear regression demonstrated that both α and β (p = 0.013 and p < 0.001, respectively, with 94 degrees of freedom) were not significantly different from 0 and 1, respectively. A statistical analysis of model performance was conducted between measured and simulated DB data per sorghum hybrid for the 2-year experiment. Results from this statistical analysis of model performance can be observed in Table 4.4. The values of R^2 ranged between 0.87 and 0.95, NSE between 0.88 and 0.92, PBIAS between -11.32% and 8.57%, and RMSE between 1.92 and 3.05 Mg ha^{-1}. All the performance indices obtained are within the range recommended by Wang et al. (2012) for crop yield assessment of model performance. Additionally, Figure 4.5 shows the results of analysis of model performance conducted between measured and simulated DB data every growing season for the 2-year experiment. So, EPIC showed a good performance in simulating DB under different sowing seasons. Table 4.2 summarizes measured and simulated total DB at harvest for the sorghum hybrids per sowing season during the 2-year experiment. The measured total DB of Pioneer 877F ranged from 12.057 to 24.667 Mg ha^{-1}, while the simulated productivity ranged from 9.371 to 22.343 Mg ha^{-1} in the 2-year study. The measured total DB of Blade ES 5140 ranged from 13.003 to 28.285 Mg ha^{-1}, while the simulated productivity ranged from 10.720 to 26.231 Mg ha^{-1} in the 2-year study. The measured total DB of Blade ES 5200 ranged from 12.886 to 32.774 Mg ha^{-1}, while the simulated productivity ranged from 10.093 to 29.933 Mg ha^{-1} in the 2-year study. The three sorghum hybrids had high productivities (measured and simulated) when sown between March and May, while the lowest productivities were on the sowings of August and September.

Table 4.4 Statistical indices for assessing simulation efficiency (hybrid × year) conducted for each sorghum hybrid during evaluation of the EPIC model for dry biomass productivity and leaf area index of biomass sorghum.

Variable	Year	Sorghum hybrid	R^2	NSE	PBIAS	RMSE
Dry biomass	2013	Pioneer 877F	0.89	0.90	-7.51%	2.04 Mg ha^{-1}
		Blade ES 5140	0.92	0.92	-8.17%	1.92 Mg ha^{-1}
		Blade ES 5200	0.87	0.88	-11.32%	3.05 Mg ha^{-1}
	2016	Pioneer 877F	0.93	0.92	4.86%	2.14 Mg ha^{-1}
		Blade ES 5140	0.94	0.92	3.57%	2.26 Mg ha^{-1}
		Blade ES 5200	0.95	0.92	8.57%	2.74 Mg ha^{-1}
LAI	2013	Pioneer 877F	0.98	0.88	-9.41%	0.34 m^2 m^{-2}
		Blade ES 5140	0.98	0.95	-1.64%	0.25 m^2 m^{-2}
		Blade ES 5200	0.99	0.99	-2.89%	0.17 m^2 m^{-2}
	2016	Pioneer 877F	0.89	0.80	-13.53%	0.49 m^2 m^{-2}
		Blade ES 5140	0.91	0.86	-9.11%	0.48 m^2 m^{-2}
		Blade ES 5200	0.95	0.93	-6.20%	0.38 m^2 m^{-2}

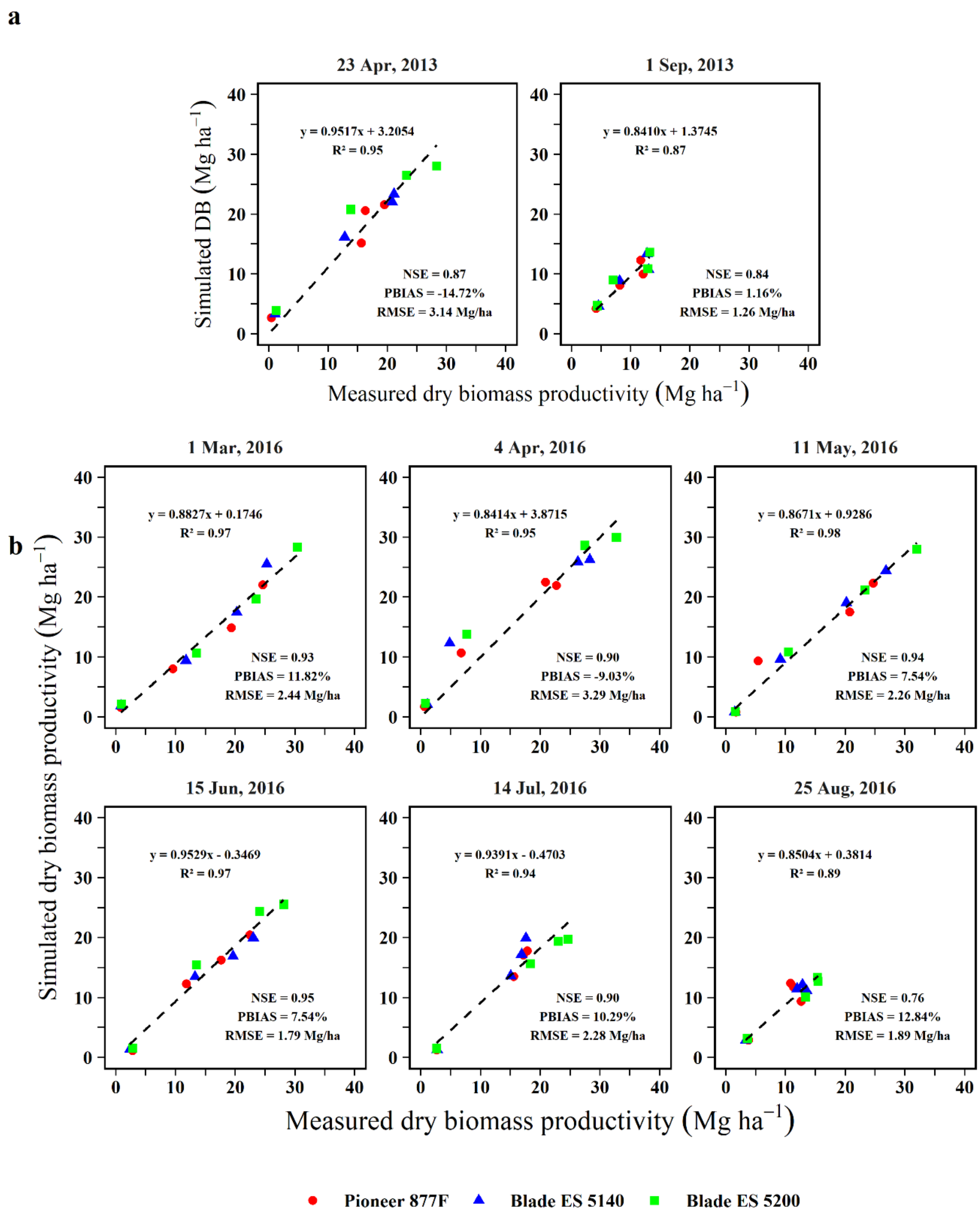

Figure 4.5 Measured dry biomass versus simulated dry biomass from EPIC model for the growing seasons of 2013 (a) and 2016 (b). Measured data was obtained at the experimental fields at Texas A&M AgriLife Research Center, Weslaco, Texas.

For the entire set of LAI data from the 2-year experiment, the linear equation obtained for LAI between the measured and the simulated values was $y = 0.2040 + 0.9840x$ with R^2 = 0.90. The agreement between measured and simulated LAI is considered satisfactory, since the *t*-tests demonstrated that both α and β (p = 0.039 and p < 0.001, respectively, with 94 degrees of freedom) were not significantly different from 0 and 1, respectively. The statistical analysis of model performance conducted between measured and simulated LAI data per sorghum hybrid for the 2-year experiment showed that R^2 ranged between 0.89 and 0.99, NSE between 0.80 and 0.99, PBIAS between -13.53% and -1.64%, and RMSE between 0.25 and 0.49 m^2 m^{-2} (Table 4.4). All the performance indices obtained were within the range recommended by Wang et al. (2012). Additionally, Figure 4.6 shows the results of analysis of the model performance conducted between measured and simulated LAI data for every crop cycle for the 2-year experiment. As well, EPIC demonstrated its good performance at simulating LAI for different sowing seasons. Table 4.2 summarizes measured and simulated LAI at harvest for the sorghum hybrids for every crop cycle during the 2-year study period. The measured LAI of Pioneer 877F ranged from 2.68 to 3.39 m^2 m^{-2}, while the simulated LAI ranged from 3.00 to 4.03 m^2 m^{-2}. The measured LAI of Blade ES 5140 ranged from 2.57 to 4.75 m^2 m^{-2}, while the simulated LAI ranged from 2.99 to 4.80 m^2 m^{-2}. The measured LAI of Blade ES 5200 ranged from 2.74 to 5.55 m^2 m^{-2}, while the simulated LAI ranged from 3.27 to 5.58 m^2 m^{-2}. The three sorghum hybrids had high LAI values (measured and simulated) when sown between March and May, while the lowest LAI were on the sowings of August and September.

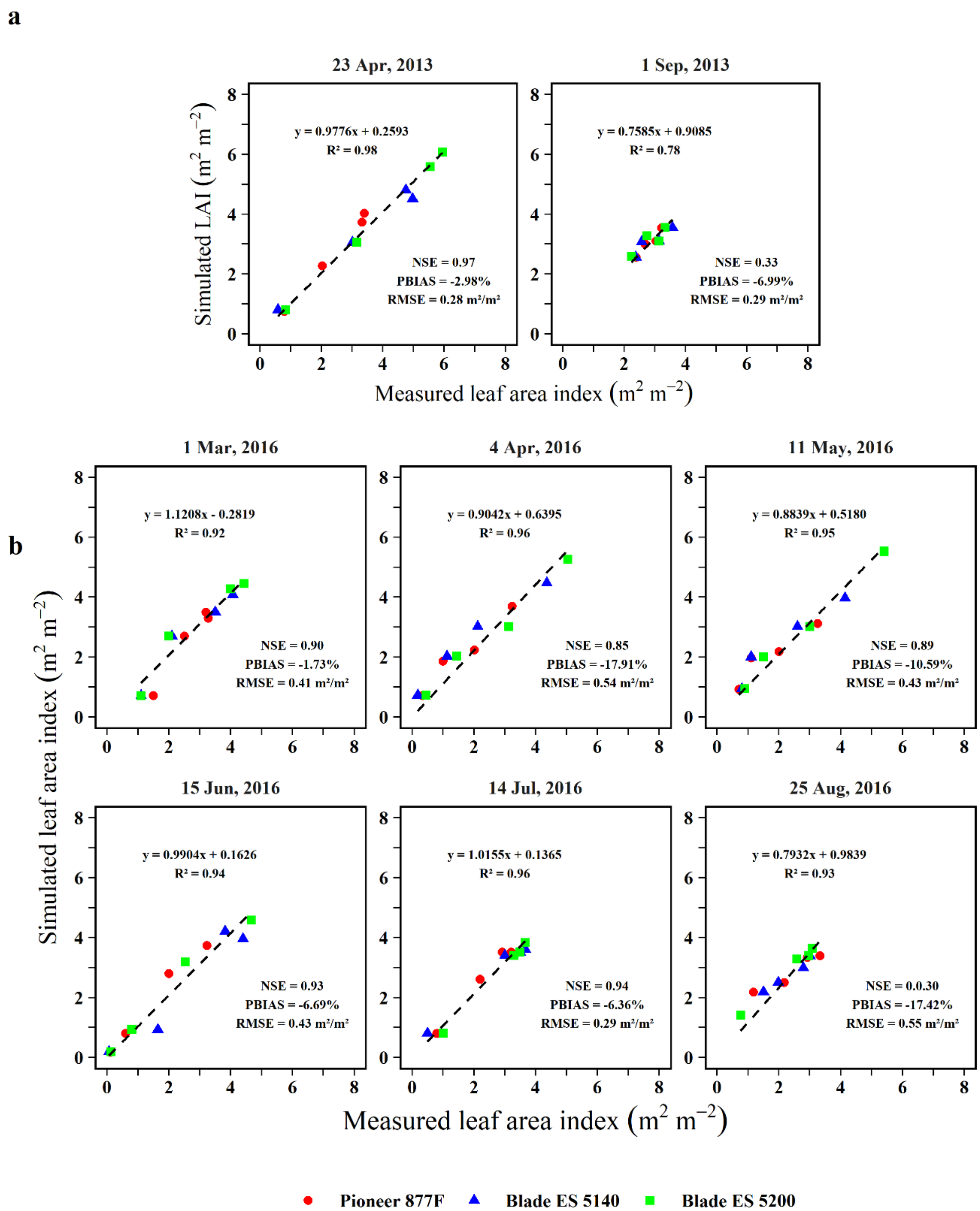

Figure 4.6 Measured leaf area index versus simulated leaf area index from EPIC model for the growing seasons of 2013 (a) and 2016 (b). Measured data was obtained at the experimental fields at Texas A&M AgriLife Research Center, Weslaco, Texas.

4.5. Discussion

The present chapter evaluated both the potential capacity of three biomass sorghums to convert solar irradiance into dry biomass under variable timed sowing dates and the capability of the EPIC model to simulate the potential sorghum dry biomass accurately and leaf area index at several sowing seasons by comparing the simulated data to those observed in the field experiments. The experiments conducted in this study were designed to provide optimal growth conditions for the three sorghums hybrids.

Sorghum hybrids were entirely regulated by the accumulation of growing degree days or daylength photoperiod triggers. According to Ritchie et al. (1998), the biomass accumulation rate was principally influenced by the amount of light intercepted by the crop canopy over an optimum temperature range. Results obtained for accumulated dry biomass and LAI in this study were used to estimate RUE and were widely discussed in Chapter 2.

The canopy extinction coefficient (*K*) is a dimensionless parameter that combines all factors affecting PAR in the canopy and is assumed constant through the crop cycle life. It is a crop species-specific parameter that involves plant canopy characteristics such as leaf angle, size, shape and thickness, and leaf area properties. However, the *K* values are affected by management factors, such as plant density, row spacing, and sun angle. The results of this chapter are comparable to those reported by Narayanan et al. (2013). They found $K = 0.668$ in a field experiment performed to evaluate eight sorghum genotypes for biomass production at Kansas State University. However, the *K* values obtained for the energy hybrids (0.66 and 0.67, for Blade ES 5140 and Blade ES 5200, respectively) obtained in this chapter were lower than that reported by Rinaldi and Garofalo (2011) (K = 0.75) in a three-year field experiment conducted to determine the RUE of biomass sorghum production over different irrigation regimes in Southern Italy. Smaller estimates of K were observed in the experimental units that showed higher LAI values, and larger estimates were obtained during maturity due to many dead leaves on the plants. This result agreed with Sinclair (2006), who concluded that K decreased with an increase of LAI. The sorghum hybrids differed in the cumulative IPAR, which was calculated from LAI and a given constant value of K. Therefore, the differences in IPAR were due to differences in LAI among the sorghum hybrids.

Radiation use efficiency (RUE) was determined as the slope of the first-order linear regression (the intercept coefficient forced to 0) of DB at different sampling dates and the corresponding cumulative IPAR (Figure 4.3). During the study period, the estimated RUE values ranged from 2.714 to 3.205 g MJ^{-1} for Pioneer 877F, from 2.683 to 3.708 g MJ^{-1} for Blade ES 5140; and from 2.955 to 4.426 g MJ^{-1} for Blade ES 5200 (Table 4.3). Most of the RUE values obtained in the present study were within the range of published seasonal RUE values for sorghum, which varied from 1.2 to 4.3 g MJ^{-1} IPAR (Hammer et al., 1989; Kiniry et al., 1989; Muchow, 1989). Similar RUE values for sorghum were reported: 3.4 g MJ^{-1} (Mastrorilli et al., 1995), 3.48 g MJ^{-1} (Ceotto et al., 2013), 3.55 g MJ^{-1} (Dercas and Liakatas, 2007). This chapter's results agreed with those reported by Houx III and Fritschi (2015), who found a decrease in RUE in late sowing of sweet sorghum in a study conducted to evaluate the influence of sowing dates on sweet sorghum in Columbia, MO, USA. Most of the higher RUE values were found in early sowing seasons for the three sorghum hybrids, mostly when sown from March to May. Then, the RUE values decreased for those sown in June, July, August, and September (Figure 4.3a). Our results confirmed that RUE was significantly dependent on temperature, IPAR, and the number of days with daylight > 12:20 h (for the photo-sensitive hybrid). Therefore, RUE is a crop parameter that cannot be used as a constant when estimated biomass sorghum production is obtained at different sowing seasons (Figure 4.3b). Rinaldi and Garofalo (2011) reported that RUE was significantly dependent on crop water consumption and that it cannot be considered a constant crop parameter for biomass sorghum.

Parameterization is crucial for accurate simulation of crop growth and development under various field conditions; then, a local reparameterization was conducted for every sowing season following the procedures described by Wang et al. (2012). The first calibration process of biomass sorghum for the south Texas conditions was conducted by Chavez et al. (2018). They reported several crop parameters for biomass sorghum simulation obtained from field experiments established for a single sowing season. With those crop parameters, our model showed an error greater than 25% on DB for across the sowing seasons. In this study, the WA parameter was identified as the source of inaccuracy. It was readjusted to achieve appropriate crop biomass productivity for biomass sorghum under a staggered production system. The EPIC model was then parameterized for different sowing seasons using the RUE estimates obtained from experimental field data and then evaluated for the simulation of staggering sowing seasons.

The EPIC model for biomass sorghum was evaluated using data from the 2-year study of biomass sorghum development under optimal growth conditions. Daily and cumulative EPIC-simulated ET_c values diverged from the values estimated by the STWP due to the PET equation used in EPIC for the estimation of ET_c (Figure 4.4). That variation happened because EPIC estimates ET_c by adjusting PET based on non-linear leaf area development during the growth stages, while the FAO-56 uses a linear K_c during leaf development stages. That difference between EPIC and the FAO-56 might cause a gap in cumulative PET values. High correlation was observed between measured and simulated DB (r = 0.97) and measured and simulated LAI (r = 0.95) of sorghum hybrids during the 2-year study period. The statistical tests demonstrated that the EPIC model was able to simulate DB and LAI of the three different sorghum hybrids under different sowing dates with acceptable accuracy. The slope and intercept of the linear regressions shown for measured versus simulated DB and LAI in Figures 4.5 and 4.6 were not significantly different from 1 and 0, respectively. The regression lines were close to the 1:1 line with a slope close to 1, and coefficient intercept close to 0. The simulated DB obtained in this study coincided with the results reported in other studies such as Rocateli et al. (2012) who reported productivities of 26.0 to 31.6 Mg ha^{-1}, and Palumbo et al. (2014) who reported those of 20.9 to 26.4 Mg ha^{-1} of biomass sorghum for the Mediterranean conditions.

4.6. Conclusion

The experiments conducted in this study were designed to provide non-stress water or nutrient conditions for sorghum biomass production. Sorghum development among hybrids and sowing seasons were sensitive to environmental conditions, such as temperature influence, solar irradiance, and photoperiod.

The results of this study show that the effect of sowing date has a crucial impact on the accumulation of dry biomass and how hybrids convert solar irradiance on dry biomass. Energy sorghum has the highest potential productivity (approximately 33 Mg dry biomass ha^{-1}). It is most cost-effective when sown during March, April, and May in South Texas if supplied with adequate water and nutrients.

RUE values varied among hybrids across sowing seasons. Energy sorghums (Blade ES 5200 and Blade ES 5140) resulted in higher RUE values if sown between March and July compared to forage sorghum (Pioneer 877F). These results suggest that energy sorghums are more efficient at converting solar radiation to biomass at non-stress water or nutrient conditions and also if weather conditions are favorable.

The evaluation results demonstrated that, using the RUE values obtained from experimental data, the EPIC model can reproduce field conditions of biomass sorghum under staggered sowing seasons for South Texas. Therefore, accurate estimation of RUE is crucial to replicate field conditions for staggered biomass sorghum production.

Yearlong production of biomass sorghum is required for the optimum operation of a biorefinery. So, staggering the sowing of biomass sorghum hybrids is an excellent alternative for providing a continuous supply of feedstock for a biorefinery to ensure its optimum operation. For this reason, it is considered that a land area might need to be staggered sown with different sorghum hybrids and adapted according to the sowing season.

5. CONCLUSIONS

Understanding of the influence of environmental conditions, such as temperature, solar radiation, photoperiod and crop management, such as crop variety, irrigation, and sowing date is crucial for efficient biomass sorghum production. This dissertation studied the growth response and the biomass productivity of biomass sorghum under south Texas's environmental conditions. In the first objective, analyses of dry biomass, leaf area index, crop growth rate, and water use efficiency of three sorghum hybrids under the effect of several sowing dates were conducted. The EPIC model was calibrated and validated for biomass sorghum simulation at different irrigation levels in the second objective. Furthermore, the third objective focused on the determination of radiation use efficiency values to parameterize the EPIC model for the simulation of biomass sorghum sown at different dates.

Experiments conducted in this study were designed to provide non-stress water or nutrient conditions for biomass sorghum development, except for the experiments conducted under deficit irrigation described in Chapter 3.

The methodology used in this study addresses an interesting practical and theoretical implications about energy crop production and crop modeling. It used sorghum field data to evaluate the response on biomass productivity under South Texas's climate conditions. The results obtained from field experiments were used to develop crop parameters to build a biomass sorghum crop model capable of precisely simulating and establishing better crop managements for sorghum biomass production for the South Texas conditions.

The crop growth rate analyses conducted for the biomass sorghum hybrids during the sowing seasons determined the sorghum's maximum and average growth rate and the phenological stages of sorghum from sowing to harvest. Results from those analyses showed the beginning and end of the vegetation phase, which are the most critical period when sorghum needs to be supplied the most amount of water and nutrients.

The water use efficiency analysis explored the crop response of biomass sorghum developed for several sowing seasons. The results obtained showed that energy crops had better water use efficiency because they produced more biomass per unit of water applied. Additionally, results obtained from experiments established for biomass sorghum under different water irrigation regimes showed that biomass sorghum could reach high production when irrigated under deficit irrigation. Therefore, this analysis provided valuable information about improving crop management practices for saving water without compromise productivity.

The radiation use efficiency analysis provided a better picture of how sorghum converts solar energy into biomass under several sowing dates for annual production. Regression analyses determined that energy sorghums, when sown from March to early May, had higher RUE values. Radiation use efficiency analysis for the study period demonstrated that RUE values could not be considered a constant crop parameter used for crop simulation when staggered sowing was considered for yearlong production.

This work's outcomes will provide a more accurate picture of how biomass sorghum production varies among hybrids and how biomass varies temporally under the influence of weather conditions. Also, this research determines the most sensible parameters that influence the production of biomass sorghum.

The EPIC crop model was fed with field data to calibrate and validate the crop model for conducting simulations on dry biomass over the study period and long-term simulations using 30-year weather data to simulate the average productivity using different irrigation regimes. The calibration process demonstrated that the most sensitive crop parameter in biomass sorghum for dry biomass production was the biomass to energy ratio (WA), followed by the coefficient and exponent of the Hargreaves-Samani PET equation.

The EPIC model demonstrated that it could simulate dry biomass and leaf area index of biomass sorghum under different sowing seasons and different irrigation regimes for south Texas's conditions.

The methodology developed and presented in this dissertation is not limited to biomass sorghum for the south Texas region. It should be extended and applied to other environmental regions or watersheds for assessing the production of other energy crops. Afterwards, it can also be used for formulating guidelines or establish crop management strategies for the production of energy crops for yearlong production. Future studies should include the influence of climate change, particularly the effect of global warming on the radiation use efficiency and water use efficiency of energy crops, and how they affect the dry biomass productivity at a regional scale.

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