MODIFICATION OF THE CERES GRAIN SORGHUM MODEL TO SIMULATE OPTIMUM SWEET SORGHUM ROOTING DEPTH FOR RAINFED PRODUCTION ON COARSE TEXTURED SOILS IN A SUB-TROPICAL ENVIRONMENT

Jose R. Lopez¹, John Erickson^{1*}, Senthod Asseng², Edmundo Lopez Bobeda³

¹Agronomy Dept., Univ. of Florida, PO Box 110500, Gainesville, FL, 32611, USA

²Dept. of Agricultural and Biological Engineering, Univ. of Florida, PO Box 110500, Gainesville, FL, 32611, USA

³Centre Universitaire d'Informatique, Univ. of Geneva, 7 rue de Dize, 1227 Carouge, Switzerland

*Corresponding author. John E. Erickson, Email: jerickson@ufl.edu; PH:1-352-392-6189; FAX: 1-352-392-6110.

E-mail addresses: joserobertolopezbobeda@lopezbeda.net (J.R. Lopez), jerickson@ufl.edu (J.E. Erickson), sasseng@ufl.edu (S. Asseng), edmundo@lopezbobeda.net

Abstract

There is potential to reduce irrigation water requirements in bioenergy feedstock cropping systems by breeding for deep rooted sweet sorghum cultivars that intercept more rainfall water. Such cultivars would require little or no irrigation in some environments. Consequently, the objective of this study was to quantify the potential benefit of deeper rooted sweet sorghum cultivars by simulating a range of root depth and planting date scenarios in the subtropical climate of the southeastern USA by modifying the CERES grain sorghum cropping system model for sweet sorghum. A two year field study was conducted to collect data for model development. The new sweet sorghum model was validated against independent studies from six different locations around the world. The root mean squared error of prediction of the model was 4.7 % for days to maturity (6 days), 21 % for total biomass weight, and 22.6 % for stem dry weight. We then simulated sweet sorghum growth and yield for nineteen hypothetical rooting depths between 30 and 210 cm. Based on model simulations, including uncertainty analysis associated with model parameters, the optimal root depth for our environment in the southeastern USA under rainfed conditions, was between 110 and 140 cm to maximize final biomass yield. The simulated hypothetical 120 cm root depth sweet sorghum had final biomass yields up to 48.2 % higher than the simulated widely grown cultivar 'M81 E' in rainfed systems and would require up to 32 % less irrigation to meet actual evapotranspiration demand. These results highlight the importance of breeding for deeper rooted sweet sorghum cultivars along with optimized sowing dates for higher biomass yields. However, model simulations also indicated that, even with optimal rooting depth and density, irrigation would be needed to maximize final biomass yields.

Keywords: water, CERES, modeling, RLD, irrigation, rainfed

Nomenclature

CSM	Crop System model.
DAP	Days after planting
DD	Growing degree day or thermal time ($^{\circ}\text{C d}$).
DSSAT	Decision Support System for Agrotechnology Transfe (software).
ET	Evapotranspiration (mm)
GS1	Growth stage one: Emergence – end juvenile
GS2	Growth stage two: End juvenile – floral or panicle initiation
KCAN	Canopy extinction coefficient
KGROSTM	Stem growth rate ($\text{g plant}^{-1} \text{DD}^{-1}$).
LA	Leaf area (cm^2)
LAI	Leaf area index
LDW	leaf dry weight (g)
MSE	Mean squared Error
MSEP	Mean squared error of prediction
ORD	Optimal root depth (cm)
R^2	Coefficient of determination
RLD	Root length density (cm cm^{-3}).
RMSE	Root mean squared error
RRMSE	Relative root mean squared error
RUE	Radiation use efficiency (g MJ^{-1})
RWUMX	Maximum water uptake per unit root length ($\text{cm}^3 \text{water cm}^{-1} \text{root}$)
SDW	Stem dry weight (kg ha^{-1})
SDW	Stem dry weight (g plant^{-1}).
SGRF	Root growth factor
SLW	Specific leaf weight (g cm^{-2})
Ta	Simulated mean seasonal transpiration (mm)
TDW	Total aboveground dry weight (kg ha^{-1})
TT1	Cumulative DD between emergence and the end of leaf expansion.
TT2	Cumulative growing degree days (DD) from the onset of stem growth to the beginning of grain filling.
μ^*	Mean of the elementary effects

1. Introduction

Sweet sorghum has been identified as a promising biofuel crop for the southeastern United States (Erickson et al., 2012, 2011). Although sweet sorghum as a C_4 crop uses water relatively efficiently to produce biomass (Stanhill, 1986) and is relatively drought tolerant (Ali et al., 2009), concerns over the impacts of bioenergy crop production on water resources remain. For example, it has been reported that bioenergy crop production in the southeastern U.S.A. could lead to an increase of 25% or more in additional irrigation (Evans and Cohen, 2009). Reducing irrigation could potentially be

7 achieved by breeding sweet sorghum genotypes with deeper root systems and access
8 to deeper soil water. Crops with deeper root systems can access water stored in deep
9 soil layers, and thus could have higher yields in dry years (Acuña et al., 2010).

10 The effect of root depth on yield must be considered in the context of the climatic
11 and edaphic conditions of a given region, as well as the specific features of the cropping
12 system. High root length density in deeper soil layers has been associated with higher
13 yields under drought by increasing the amount of water available to the crop (Kashiwagi
14 et al., 2006). However, in regions where the crop relies mainly on stored soil water,
15 vigorous root growth during the vegetative phase can deplete soil water reserves before
16 anthesis, thus reducing water available during grain filling and reducing grain yield
17 (Vadez, 2014). In situations where deeper root systems are advantageous, selecting for
18 deep-rooted genotypes remains a difficult task. Different strategies have been proposed
19 to achieve this goal in the field, such as burying herbicides at a certain depth in the soil
20 that will injure the plant if roots are present at that depth (Al-Shugeairy et al., 2014;
21 Robertson et al., 1985) or visually rating the plant for crown root angle, which has been
22 shown to be correlated with rooting depth (Trachsel et al., 2011).

23 In theory, deep-rooted sweet sorghum cultivars could be developed by plant
24 breeders to produce bioenergy mainly on rainfall water in some environments. Cropping
25 system models, which consider soil and environmental conditions, can be used to
26 simulate the performance of such cultivars and evaluate their potential. Having a crop
27 model calibrated across different seasons and environments, the effect of variation of
28 specific traits on model outputs can be evaluated (Brown et al., 2011; Brunel-Muguet et
29 al., 2011; Koehler and Challinor, 2011; Sarlikioti et al., 2011) to study new crop

ideotypes (Boote et al., 2001; Donald, 1968), i.e., particular value of a trait or suite of traits that optimize yield for a particular environment. For example, Manschadi *et al.* (2006) simulated the effect of root traits on wheat yield in various environments, Sinclair and Muchow (2001) simulated the effect of two contrasting root depths on maize yield, and Wong and Asseng (2007) evaluated the impact of incremental changes in potential root depth on wheat yield. However, the impact that a change in rooting depth will have on sweet sorghum crop performance across a broad spectrum of possible root depths and sowing dates in a subtropical production environment has not been studied yet.

There are different approaches to simulate root growth (Dupuy et al., 2010). The Cropping System Model (CSM) CERES model within the decision support system for agrotechnology transfer modeling platform (DSSAT; Hoogenboom et al., 2012; Jones et al., 2003) is a mechanistic model that can relate crop rooting depth with water uptake and biomass production using local weather, soil, and crop data as inputs. The model simulates root depth and root length density throughout the growing season and can be parameterized with field data using soil cores (Robertson et al., 1993).

However, the current implementation of CSM CERES for sorghum (White et al., 2015) does not simulate the rapid stem growth and carbohydrate partitioning of sweet sorghum (Li et al., 1991). This is not surprising as most of the previous studies on sorghum using this model were with grain sorghum (MacCarthy et al., 2010; Singh et al., 2014; Staggenborg and Vanderlip, 2005; White et al., 2015). Additionally, the optimal root ideotype for water uptake will be highly dependent on interactions with rainfall and soils. In the subtropical southeastern U.S.A., coarse textured soils are common and annual rainfall is relatively abundant. However, there is a distinct dry

season (approx. December through May), and often intermittent water stress during the wet season. Thus, planting date may also play a role on optimal rooting depth as crops sown early in the growing season (e.g., April) will grow in a drier environment, and thus may benefit more from deeper rooting than crops sown later (e.g., June). Therefore, the objectives of this study were to 1) modify the current version of CSM CERES to simulate sweet sorghum growth and partitioning; and 2) to evaluate a range of root depth by planting date scenarios for sweet sorghum grown on a sandy soil in a subtropical climate using the CSM CERES crop model, and estimate potential gains in yield of deeper rooted cultivars without irrigation.

2. Materials and Methods

2.1. Growth Study Field Trials for Model Development

Sweet sorghum cultivar 'M 81E' was planted at the University of Florida Plant Science Research and Education Unit (PSREU) located in Citra, Florida (29°24'38" N, 82°8'30" W). Plants were sown in rows 0.76 m apart and the spacing within rows was 0.1 m. The soil was a deep, well drained Hague sand (Loamy, siliceous, semiactive, hyperthermic, Arenic Hapludalfs; NCRS, 2014). The study was conducted for two years and was planted on May 10th in 2012 and on May 15th in 2013. Liquid fertilizer (11-37-0) was applied at planting at a rate of 19 kg N ha⁻¹. The remainder of the fertilizer N was applied three and five weeks after planting at rates of 76 and 40 kg N ha⁻¹ respectively. A total of 135 kg K₂O was side dressed along with the second and third N applications. This level of fertility has been shown to not limit yield in this environment (Adams et al., 2015).

Destructive growth samples were collected at approximately 14 day intervals. At each sampling date, 1.5 m long rows were harvested from three (2012) or four (2013)

different locations in the field. Plants were divided into stem, panicle, and leaves and oven dried at 60 °C until the samples reached a constant weight. Leaf number, phenology, and leaf area index (LAI) were also measured each time. Leaf area was measured using a Li-3100 area meter (Li-Cor, Inc. Lincoln. Nebraska, U.S.A.). In 2013, root samples were collected using 3.8 cm diameter cores at 8 depths (15, 30, 60, 90, 120, 150, 180 and 210 cm.) at each harvest time. Samples were collected from within the row and between rows at each sampling location, giving a total of 8 samples per depth per harvest (4 sampling sites x 2 locations within sampling site). The roots were separated from the soil using water and a 2 mm screen, and scanned using an Epson Expression 1640 XL scanner. The images were analyzed with the WinRhizo software (Regent Instruments Inc., Canada), which provided root length. Root length density (RLD) was then calculated as the quotient of this root length (cm) and the respective soil volume (cm³) from which the roots were extracted to give RLD per soil depth layer.

2.2. Data Set for Model Calibration and Validation

We used global 'M 81E' sweet sorghum growth data from the literature to further refine model calibration and to validate the new sweet sorghum model used in this study. The global data set consisted of yield data from Citra, Live Oak, and Ona, Florida (Erickson et al., 2012, 2011), Tucson, Arizona (Miller and Ottman, 2010), Beijing, China (Zhao et al., 2009) and one unpublished observation from Jay, Florida. Out of the 39 observations of final biomass dry weight of the global data set, 35 also included stem dry weight at harvest and 28 included anthesis date.

The weather data required for the model was obtained from different sources. The Florida Automated Weather Network (FAWN, 2016) was used for all the Florida locations unless otherwise specified. Missing data was interpolated from nearby

weather stations. Weather data for the Citra location from 1990 to 2000 came from the National Aeronautics and Space Administration (NASA, 2014). Since there was no rainfall data available for Citra from 1990 to 1997, precipitation data from the National Climatic Data Center (NCDC, 2014) for Gainesville, Florida (about 40 km NW from Citra) was used. The Arizona Meteorological Network (AZMET, 2014) was the source of the weather data for the studies conducted in Tucson Arizona. Weather data from Beijing, China, was provided by the author through personal correspondence from a weather station adjacent to the experimental field (Zhao et al., 2009) with the exception of solar radiation, which was obtained from NASA.

The soil data required for the model included soil texture, organic matter content, pH, cation exchange capacity, drained lower and upper limit, bulk density, and saturated soil hydraulic conductivity per layer. Soil Data for the Florida locations was provided by the Agroclimate web resource (AgroClimate, 2014). Soil Data for Tucson Arizona was based on data from the National Resources Conservation Services of the USDA (NCRS, 2014) and author specifications (Miller and Ottman, 2010). The soil data from China was based on the author specifications (Zhao et al., 2009). Evapotranspiration (ET) was calculated using the Priestley Taylor equation (Priestley and Taylor, 1972).

2.3. CSM CERES Model Adjustment for Sweet Sorghum

The CSM CERES model within version 4.5 of DSSAT (Jones et al., 2003) has been adapted for simulating grain sorghum growth and yield (Ritchie et al., 1998). For details on the CSM CERES grain sorghum equations refer to White *et al.* (2015), Ritchie *et al.* (1998), and Robertson *et al.* (1993). Since carbohydrate partitioning in sweet sorghum differs in comparison to grain sorghum, two new equations were added to the model algorithm, as grain sorghum has been selected for its high biomass partitioning to

grain while sweet sorghum is valued for its high sugar concentration in the stem. For example, a grain sorghum breeding line (unpublished data) partitioned only 33% of its aboveground biomass to stem while sweet sorghum cultivar 'M 81E' allocated 81% of its aboveground biomass to stem at physiological maturity in the present study.

Therefore, the first new equation calculated stem growth rate (KGROSTM) as a linear function of thermal time. To parameterize this equation, we calculated observed KGROSTM in the growth sampling experiment using Eq. (1).

$$KGROSTM = \Delta SDW / \Delta TT2 \quad (1)$$

where ΔSDW and $\Delta TT2$ are the changes from one growth sampling date to the next in stem dry weight and thermal time two (TT2) respectively. Thermal time two are the cumulative growing degree days (DD) from the onset of stem growth (growth stage 2; GS2) to the beginning of grain filling (GS4). In contrast, TT1 refers to the cumulative DD between emergence (GS1) and the end of leaf expansion (GS3).

Additionally, specific leaf weight (SLW) varies among sorghum genotypes and increases over time (Ferraris and Charles-Edwards, 1986). Therefore, the second equation added to the model algorithm calculated SLW as a function of TT1. We calculated observed SLW using Eq. (2):

$$SLW = LDW / LA \quad (2)$$

Where LDW is leaf dry weight (g) and LA is leaf area (cm²) measured using the LI-3100 (LI-COR, Inc., Lincoln, Nebraska USA). Specific leaf weight determines the amount of assimilates allocated to leaves as a result of leaf area expansion.

2.4. Model Calibration and Evaluation

An initial estimate of the phenology parameters for the duration of each growth stage in thermal time was made based on the observed phenology at each harvest time

during the 2012 and 2013 growing seasons in Citra, Florida. Subsequently, the KGROSTM and SLW equations were parameterized using the lm function in R (R Core Team, 2015), considering only the data points that fall within growth stages at which the model simulates stem and leaf growth, respectively (Fig. 1).

Next, we merged the global data sets with our Florida model development field trial data to further calibrate and validate the sweet sorghum model. The parameter that determines the effect of photoperiod on phenology was calibrated by optimizing the mean squared error (MSE) between the simulated and observed time interval between planting and maturity measured in days. The succeeding step was the calibration of radiation use efficiency (RUE) and canopy extinction coefficient (KCAN), as these parameters scored highest in the sensitivity analysis for optimal root depth (ORD; Table 1) and therefore are important for the estimation of ORD (see Sect. 2.5 for how ORD was determined). The default values of RUE (3.2 g MJ^{-1}) and KCAN (0.85) in the sorghum ecotype file in DSSAT v. 4.5, differ from experimentally determined values for sweet sorghum available in the literature. Measured values of RUE and KCAN for sweet sorghum range from 3.55 to 4.96 g MJ^{-1} and 0.57 to 0.65 , respectively (Curt et al., 1998; Dercas and Liakatas, 2007; Mastrorilli et al., 1995). By recursively calculating the MSE for observed and simulated total biomass weight data within the uncertainty limits (Table 2) for each RUE by KCAN combination in 0.10 and 0.01 intervals, respectively, we obtained values of RUE and KCAN within the range of observed literature values (Table 2).

Finally, to evaluate the predictive quality of the model, we estimated the mean squared error of prediction (MSEP) using a custom made implementation of the leave

one out cross validation algorithm described by Wallach *et al.* (2013) written in R. In short, we optimized RUE and KCAN for each n_k observation of final yield by minimizing the MSE, where n is the total number of final yield observations and k is each of the n possible $n-1$ subsamples that can be obtained from n . The MSEP estimate is the average of the optimization MSE from each subsample. Other parameters used to describe the relationship between the observed and simulated data are mean squared error (MSE), the root mean squared error (RMSE), and the relative root mean squared error (RRMSE; Wallach et al., 2013). Additionally, the coefficient of determination (R^2) was used to evaluate linear regressions.

2.5. Simulations of Root Depth by Planting Date

Following model calibration and validation, we simulated sweet sorghum growth and yield under rainfed conditions for nineteen hypothetical rooting depths. Root depth was increased from 30 to 210 cm in 10 cm intervals by changing the root growth factor (SGRF) of each simulated soil layer to either 1 or 0 depending on the root depth being simulated. Three planting dates (April 1, May 1, and June 1) appropriate for sweet sorghum in the southeastern U.S.A., were simulated to consider the interaction of planting date and rooting depth on sweet sorghum shoot dry matter yield. Each rooting depth by planting date combination was simulated for each of the 24 years of historic weather data collected for the Citra, Florida location. The simulations were carried out for rainfed production with the soil water characteristics of a Hague sand (Table 3). It was assumed that the soil was at field capacity at planting. This is a reasonable assumption for the production of sweet sorghum following a winter fallow because of the low water holding capacity of the soil (approx. 50 mm to a 1 m soil depth based on soil properties provided in Table 3) and a 10 year mean (2005-2015) precipitation of about

340 mm received at Citra, Florida from November to March (FAWN, 2016). The model simulations were also done assuming no nutrient stress. Subsequently, the yield gain attained by an increase per each 10 cm of root depth was calculated. The optimal root depth (ORD), defined as the root depth at which deeper rooting did not significantly increase simulated yields, was calculated with an analysis of variance approach (ANOVA) and Turkey's Honest Significant Difference (HSD) mean separation. This analysis was performed using proc GLIMMIX in SAS (Schabenberger, 2005) with planting date as a fixed effect and year as a random effect.

2.6. Model Sensitivity Analysis

Sensitivity analyses are used to study the effect of variation in some model parameters on the model output of interest (Wallach et al., 2013). As we were interested estimating optimal root depth (ORD), the output of interest was ORD. We used the elementary effects method with a one at a time based design with 8 levels and a grid jump of 4 (Campolongo et al., 2007; Morris, 1991; Pujol, 2009) using the package sensitivity (Pujol, 2009) in R (R Core Team, 2015) to rank the parameters based on their effect on ORD (Table 2). The minimum and maximum values evaluated for most model parameters correspond to increasing and decreasing the initial parameter estimates by 25%, except in the case of SRGF, where we chose values between 0.5 and 1, since this value had a default of 1, and could not be further increased (Table 2).

3. Results

3.1. Model Modifications and Calibration

There was good agreement between simulated experiments using the new sweet sorghum model and observed sweet sorghum growth data from various experiments. Two new equations were added to the DSSAT grain sorghum model (White et al., 2015)

to estimate stem growth rate (KGROSTM) and specific leaf weight (SLW) in sweet sorghum, as a function of thermal time, as these variables were significantly correlated ($P < 0.001$) with thermal time in the growth study field trials (Fig. 1). Thermal time explained 81 and 42 % of the variation in KGROSTM and SLW, respectively. Simulations of growth across the 2012-2013 model development data set (Fig. 2) were strongly correlated with the observed sampling date means for stem dry weight (SDW; $R^2 = 0.97$) and total aboveground dry weight (TDW; $R^2 = 0.92$), but only moderately correlated with leaf area index (LAI; $R^2 = 0.47$) and leaf dry weight (LDW; $R^2 = 0.64$). The model simulations were further evaluated against various studies using the cultivar 'M 81E' in various environments across the globe. Across the global data set, days to maturity ranged from 115 to 168 days after planting (DAP); SDW from 13448 to 26600 kg ha⁻¹, and TDW from 15177 to 32796 kg ha⁻¹. When simulating the data from all sites and locations, the RRMSEP for TDW, days to maturity, and SDW were 21.4, 4.7, and 22.6 %, respectively (Table 4). The RRMSEP estimates are reliable as the standard deviations for the RRMSEP estimates were low (between 0.1 and 0.6 %).

In terms of measured RLD at the Citra, Florida location, 'M 81E' had a high RLD in the top two soil layers (0 to 30 cm) compared to RLD (<1 cm cm⁻³) in the deeper soil layers (Fig. 3a). This trend was captured relatively well by model simulations for 'M 81E' (Fig. 3b). However, in contrast with observed RLD for 'M 81E', the simulated 120 cm root depth sweet sorghum (Fig. 3c) had higher RLD at root depths from 30 to 120 cm (approx. 3 compared to less than 1 cm cm⁻³), especially later in the season. This resulted in greater rainfall water uptake later in the season for the simulated optimal root depth sorghum compared to the observed and simulated data for 'M 81E'.

3.2. Sweet Sorghum Rooting Depth Simulations

Simulated sweet sorghum rooting depth affected total aboveground dry matter production ranging from ca. 11,000 kg ha⁻¹ for the 30 cm rooting depth planted in April to >22,000 kg ha⁻¹ for deeper rooted genotypes (Fig. 6a). Simulated gains in yield were relatively large initially for shallow rooted sweet sorghum and diminished with depth (Fig. 6b). There was a significant interaction between rooting depth and planting date on simulated TDW, whereby the optimal root depth (ORD) was 120 cm for the May 1 and June 1 planting dates, but ORD was 140 cm for the April 1 planting date. The deeper ORD for April clearly reflects the drier growing season when the crop was planted in April, as the precipitation in April is on average 12.1 % less than the precipitation in May and 53.6 % less than the precipitation in June. Total aboveground dry weight simulations of the hypothetical 120 cm root depth sweet sorghum compared to 'M 81E' under rainfed conditions indicated mean yield enhancements from 27.9 % planted on June 1 planting compared to 48.2 % planted on April 1 (Fig. 8).

In addition to affecting ORD, planting date also affected the number of days to reach maturity, and seasonal potential evapotranspiration. Days to maturity averaged 125, 115, and 105 days for the April 1, May 1, and June 1 planting dates, respectively. Longer growing seasons were also associated with higher seasonal water requirements, as the seasonal potential evapotranspiration of the ORD sweet sorghum for the April, May, and June planting dates was 683, 626, and 573 mm, respectively. The irrigation requirements of the ORD sweet sorghum were estimated by calculating the average difference between the potential and actual simulated evapotranspiration across years, which was 234, 175, and 115 mm for the April, May and June planting dates, respectively. On average, the simulated ORD sweet sorghum required 25 % less

irrigation than 'M 81E' when planted in April, 26 % less irrigation when planted in May and 32 % less when planted in June.

The ratio of simulated daily actual ET to potential ET was used as an indicator of water deficit throughout the growing season. The simulated 24 year average of actual ET:potential ET for a select group of sweet sorghum hypothetical rooting depths (30, 90, 150, and 210 cm) indicated water deficit following emergence for all planting dates, dropping to <0.25 for all rooting depths within the first 10 DAP for the April and May planting dates, and to about 0.35 for the June planting date (Fig. 4). As the simulated sweet sorghum crop developed, differences in simulated actual ET:potential ET by rooting depth became more apparent. The gap between actual and potential ET decreased substantially from the 30 to 90 cm root depth. However, this gap only decreased marginally beyond the 90 cm root depth. For example, for the June planting date the maximum difference between simulated actual ET:potential ET between the 30 and 90 cm rooting depths was 0.34, but only 0.14 between the 90 and 150 cm rooting depths. These differences in actual ET:potential ET translated into differences in seasonal transpiration across rooting depths and planting dates (Fig. 5). The mean seasonal transpiration across planting dates and years for the 30, 90, 150, and 210 cm rooting depths was 220, 330, 364, and 375 mm respectively, following the overall trend of increased gain in soil water uptake for the deeper rooted sweet sorghums.

3.3. Uncertainty Associated with Model Parameters

The mean of the elementary effects (μ^* ; Table 1) indicated that the estimated ORD was sensitive to RUE and KCAN. Both RUE and KCAN affect canopy level photosynthetic and growth rate. Crops growing at a faster rate will have higher water

demands and therefore benefit more from access to water deeper in the soil than crops growing at a slower rate. The effect of maximum water uptake per unit root length (RWUMX) on ORD was negligible for all three planting dates, as the sweet sorghums had high RLD per layer and were able to mine enough water out of the soil even with low RWUMX. The rest of the evaluated crop model parameters had either a negligible effect or affected ORD only on specific planting dates (Table 1). Considering the uncertainty associated with model parameters, the ORD for rainfed sweet sorghum production across the evaluated planting dates in this environment was between 110 and 140 cm (Fig. 7).

4. Discussion

4.1. Model Improvement

Two equations were modified in the CSM CERES grain sorghum algorithm to create a sweet sorghum model (Fig. 1). These equations update the values of the new state variables that determine specific leaf weight and stem growth rate, i.e. SLW and KGROSTM, within the daily time step of the model. Support for the modification of these equations in the grain sorghum model can be found in studies that reported that sweet sorghum stems grow at a higher rate (Li et al., 1991) than grain sorghum, and that SLW differs among sorghum genotypes and increases over time (Ferraris and Charles-Edwards, 1986). While the SLW and KGROSTM equations could be refined with additional data, the equations used for the simulations in the present study explained a large portion of the observed field variability in SLW ($R^2 = 0.42$) and KGROSTEM ($R^2 = 0.81$). Furthermore, the R^2 of the regression between the observed and simulated TDW and SDW in the growth sampling data set (Fig. 2) was similar to results obtained by others when simulating grain sorghum (White et al., 2015).

In addition to these equations, the parameters radiation use efficiency (RUE), and canopy extinction coefficient (KCAN) were calibrated based on the global data set. The parameter optimization algorithm suggested a RUE of 3.9 g DM MJ⁻¹ PAR for sweet sorghum, which is higher than the RUE of the default cultivars available in the DSSAT version 4.5 of 3.2 g DM MJ⁻¹ PAR for grain sorghum (Jones et al., 2003), but similar to high yielding grain sorghum cultivars calibrated using the same model by others, e.g. 4.0 g DM MJ⁻¹ PAR for ‘Tegemeo’ grain sorghum (Msongaleli et al., 2013). Both RUE and KCAN were within the range of measured values reported in the literature (Curt et al., 1998; Dercas and Liakatas, 2007; Mastrorilli et al., 1995).

The low RRMSE and RRMSEP for days to maturity for the simulations of the global data set (Table 4) provided strong evidence that the model simulations of crop phenology across planting dates and locations were accurate. Slightly higher values of RMSE and RRMSE for days to maturity, 6.6 days and 8% respectively, were observed by White *et al.* (2015) when simulating grain sorghum experiments planted at different planting dates in Maricopa, Arizona. Compared with days to maturity, the RRMSEP values for TDW and SDW were high (Table 4). Such results are not surprising considering that TDW and SDW are complex traits affected by virtually every environmental variable considered in the model while days to maturity depends only on thermal time, photoperiod, and light intensity (Murphy et al., 2011; Ritchie and Godwin, 1989; White et al., 2015). Likewise, the RRMSE for TDW of CERES rice across different locations in Asia and Australia was 23 % (Timsina and Humphreys, 2006), comparable to the RRMSE estimate for the CERES sweet sorghum model used in this study. However, CERES wheat performed better than the CERES sweet sorghum and CERES

rice when evaluated with global data sets (Timsina and Humphreys, 2006). A range of RMSE estimates for TDW for CERES grain sorghum ranging from 12 to 25 % were reported by White *et al.* (2015). Therefore, while TDW was not estimated as accurately as days to maturity, the RRMSE and RRMSEP for TDW of the simulations were comparable to the results obtained by others.

4.2. Root Depth Simulations

The simulations indicated the May planting date to be optimal for total biomass yield, consistent with field studies conducted across multiple locations and years in the region (Erickson *et al.*, 2011). June planting produced less biomass because of the shorter season, while planting in April increased the likelihood of suffering from drought stress during the first half of the growth cycle (Fig. 4). Because of the reduced water availability, the estimated optimal root depth (ORD) for April (140 cm) was higher than the estimated ORD for May and June (120 cm).

The simulations also indicated that even optimal-rooted varieties would require some level of irrigation because of the intermittent rainfall and low water holding capacity of the coarse-textured soils. The estimated seasonal irrigation requirement across planting dates was affected by the length of the growing season, the precipitation during the season, and the environmental water demand. Hence, optimal-rooted sweet sorghum required more irrigation when planted in April (234 mm) or May (175 mm) than when planted in June (115 mm). However, the hypothetical optimal-rooted sweet sorghums required between 25 and 32 % less irrigation than 'M 81E'. Therefore, in addition to improving biomass production in rainfed systems, deeper rooted cultivars would significantly reduce irrigation water requirements by increasing rainfall water uptake in irrigated systems.

By considering the uncertainty associated with model parameters, it was estimated that the ORD under rainfed production in the region was 110-140 cm. This indicates that breeding and selection for deeper rooting could enhance total biomass yield and reduce the quantity of irrigation needed compared to current commercial cultivars like M 81E. Similarly, increases in yield of other crops have been attributed to the unintentional selection of deeper rooted genotypes when selecting for yield. For example, modern high yielding wheat genotypes extract more water from deeper soil profiles (60 to 120 cm) than lower yielding varieties released in the 50s and 60s (Pask and Reynolds, 2013). Deeper root systems have also been suggested to explain why maize hybrids released in the 2000s have higher yields than maize hybrids released in the 1990s (Hammer et al., 2009).

The modeling experiments also provided insight on the relative importance of root length density at depth. The sensitivity analysis showed that changes in the SGRF parameter between 0.5 and 1 (Table 4), and therefore in root length density (RLD) across the whole soil profile, will have a negligible effect on the ORD estimation (Table 1). On the other hand, while the overall root depth of 'M 81E' was within the ORD range, its yield was up to 48% lower than the 120 cm ORD sweet sorghum in the long term simulations (Fig. 8) because it did not produce enough RLD deeper in the soil. Therefore, model simulations that predicted very low RLD in deep soil layers were not be enough to fulfill crop water demands, however, once RLD is high enough, further increases in RLD will have negligible effects on soil water uptake. This model finding is supported by Seetharama *et al.* (1990), who collected root cores from drought resistant and susceptible sorghum lines and found roots as deep as 150 cm in all lines,

but the drought resistant lines had higher RLD between 120 and 150 cm. However, the total RLD across the whole profile was not different between drought susceptible and adapted lines. Hence, root depth and rainfall water uptake can be improved by shifting the physical location of the roots without increasing overall root length density and therefore assimilate requirements. This is important because producing higher overall root length without significantly increasing water uptake would be a waste of assimilates (Lopes et al., 2011).

5. Conclusions

The Cropping System Model CERES grain sorghum was successfully adapted to simulate sweet sorghum by modifying the equations that allocate assimilates to the stems and leaves based on observed field data. The relatively low MSEP for TDW, SDW, and days to maturity observed in the model validation against the global data set support the claim that the new sweet sorghum model can be used to simulate sweet sorghum growth and yield. In the current study, the simulations of cultivar root depth on coarse-textured sandy soils in a sub-tropical environment indicated an optimal sweet sorghum rooting depth of 110 to 140 cm to maximize aboveground biomass yield. The superior performance of the simulated lines compared to the widely grown cultivar 'M 81E' indicated that breeding programs in the southeastern USA should invest in developing sorghum lines with greater rooting depth. However, model simulations also indicated that, even with optimal rooting depth and density, irrigation would be needed to achieve optimal yields due to the low water holding capacity of the soil, erratic precipitation throughout the season, and less abundant precipitation early in the growing season. Sowing later reduced the need for supplemental water, but sowing too late resulted in quicker maturity and reduced TDW.

408

6. Acknowledgements

409

This manuscript is based upon work that was supported by the National Institute of

410

Food and Agriculture, U.S. Department of Agriculture, under competitive award No.

411

2011-10006-30358.

412

7. References

- Acuña, C.A., Sinclair, T.R., Mackowiak, C.L., Blount, A.R., Quesenberry, K.H., Hanna, W.W., 2010. Potential root depth development and nitrogen uptake by tetraploid bahiagrass hybrids. *Plant Soil* 334, 491–499.
- Adams, C.B., Erickson, J.E., Singh, M.P., 2015. Investigation and synthesis of sweet sorghum crop responses to nitrogen and potassium fertilization. *F. Crop. Res.* 178, 1–7.
- AgroClimate, 2014. Tools for managing climate risk. <http://www.agroclimate.org/> (accessed 1.1.14).
- Ali, M.A., Niaz, S., Abbas, A., Sabir, W., Jabran, K., 2009. Genetic diversity and assessment of drought tolerant sorghum landraces based on morph-physiological traits at different growth stages. *Plant Omics* 2, 214–227.
- Al-Shugeairy, Z., Islam, M.S., Shrestha, R., Al-Ogaidi, F., Norton, G.J., Price, A.H., 2014. High throughput screening of rooting depth in rice using buried herbicide. *Ann. Appl. Biol.* 165, 96–107.
- AZMET, 2014. The Arizona Meteorological Network. <http://ag.arizona.edu/azmet>. URL <http://ag.arizona.edu/azmet/> (accessed 1.1.14).
- Boote, K.J., Kropff, M.J., Bindraban, P.S., 2001. Physiology and modelling of traits in crop plants: implications for genetic improvement. *Agric. Syst.* 70, 395–420.
- Brown, K., McIntosh, J., Rademacher, L., Lohse, K., 2011. Impacts of agricultural irrigation recharge on groundwater quality in a basalt aquifer system (Washington, USA): a multi-tracer approach. *Hydrogeol. J.* 19, 1039–1051.
- Brunel-Muguet, S., Aubertot, J.-N., Dürr, C., 2011. Simulating the impact of genetic diversity of *Medicago truncatula* on germination and emergence using a crop emergence model for ideotype breeding. *Ann. Bot.* 107, 1367–1376.
- Campolongo, F., Cariboni, J., Saltelli, A., 2007. An effective screening design for sensitivity analysis of large models. *Environ. Model. Softw.* 22, 1509–1518.
- Curt, M.D., Fernandez, J., Martinez, M., 1998. Productivity and radiation use efficiency of sweet sorghum (*Sorghum bicolor* (L.) Moench) cv. *Keller* in central Spain. *Biomass and Bioenergy* 14, 169–178.
- Dercas, N., Liakatas, A., 2007. Water and radiation effect on sweet sorghum productivity. *Water Resour. Manag.* 21, 1585–1600.
- Donald, C.M. t, 1968. The breeding of crop ideotypes. *Euphytica* 17, 385–403.
- Dupuy, L., Gregory, P.J., Bengough, A.G., 2010. Root growth models: towards a new generation of continuous approaches. *J. Exp. Bot.* 61, 2131–2143.
- Erickson, J.E., Helsel, Z.R., Woodard, K.R., Vendramini, J.M.B., Wang, Y., Sollenberger, L.E., Gilbert, R.A., 2011. Planting Date Affects Biomass and Brix of Sweet Sorghum Grown for Biofuel across Florida. *Agron. J.* 2011, 1827–1833.

451 Erickson, J.E., Woodard, K., Sollenberger, L., 2012. Optimizing Sweet Sorghum
452 Production for Biofuel in the Southeastern USA Through Nitrogen Fertilization and
453 Top Removal. *BioEnergy Res.* 5, 86–94.

454 Evans, J.M., Cohen, M.J., 2009. Regional water resource implications of bioethanol
455 production in the Southeastern United States. *Glob. Chang. Biol.* 15, 2261–2273.

456 FAWN, 2016. Florida Automated Weather Network. URL <http://fawn.ifas.ufl.edu>
457 (accessed 7.30.16).

458 Ferraris, R., Charles-Edwards, D.A., 1986. A comparative analysis of the growth of
459 sweet and forage sorghum crops. I. Dry matter production, phenology and
460 morphology. *Crop Pasture Sci.* 37, 495–512.

461 Hammer, G.L., Dong, Z., McLean, G., Doherty, A., Messina, C., Schussler, J.,
462 Zinselmeier, C., Paszkiewicz, S., Cooper, M., 2009. Can Changes in Canopy
463 and/or Root System Architecture Explain Historical Maize Yield Trends in the U.S.
464 Corn Belt? *Crop Sci.* 49, 299–312.

465 Hoogenboom, G., Jones, J.W., Wilkens, P.W., Porter, C.H., Boote, K.J., Hunt, L.A.,
466 Singh, U., Lizaso, J.L., White, J.W., Uryasev, O., Royce, F.S., Ogoshi, R., Gijsman,
467 A.J., Tsuji, G.Y., Ko, J., 2012. Decision Support System for Agrotechnology
468 Transfer (DSSAT) Version 4.5.1.023.

469 Jones, J.W., Hoogenboom, G., Porter, C.H., Boote, K.J., Batchelor, W.D., Hunt, L.A.,
470 Wilkens, P.W., Singh, U., Gijsman, A.J., Ritchie, J.T., 2003. The DSSAT cropping
471 system model. *Eur. J. Agron.* 18, 235–265.

472 Kashiwagi, J., Krishnamurthy, L., Crouch, J.H., Serraj, R., 2006. Variability of root length
473 density and its contributions to seed yield in chickpea (*Cicer arietinum* L.) under
474 terminal drought stress. *F. Crop. Res.* 95, 171–181.

475 Koehler, A., Challinor, A., 2011. Developing spring wheat ideotypes for India using a
476 regional crop model, in: AGU Fall Meeting Abstracts. p. 412.

477 Li, H.B., Zhai, W.X., Yu, G.R., Wang, S.C., Guo, H.L., Wu, Y.L., 1991. A comparative
478 study of the accumulation and distribution of dry matter and formation of yield in
479 sweet sorghum and grain sorghum. *Acta Agron. Sin.* 17, 204–212.

480 Lopes, M.S., Araus, J.L., Van Heerden, P.D.R., Foyer, C.H., 2011. Enhancing drought
481 tolerance in C4 crops. *J. Exp. Bot.* 62, 3135–3153.

482 MacCarthy, D.S., Vlek, P.L.G., Bationo, A., Tabo, R., Fosu, M., 2010. Modeling nutrient
483 and water productivity of sorghum in smallholder farming systems in a semi-arid
484 region of Ghana. *F. Crop. Res.* 118, 251–258.

485 Manschadi, A.M., Christopher, J., deVoi, P., Hammer, G.L., 2006. The role of root
486 architectural traits in adaptation of wheat to water-limited environments. *Funct.*
487 *Plant Biol.* 33, 823–837.

488 Mastorilli, M., Katerji, N., Rana, G., Steduto, P., 1995. Sweet sorghum in
489 Mediterranean climate: radiation use and biomass water use efficiencies. *Ind.*
490 *Crops Prod.* 3, 253–260.

491 Miller, A.N., Ottman, M.J., 2010. Irrigation Frequency Effects on Growth and Ethanol
 492 Yield in Sweet Sorghum All rights reserved. No part of this periodical may be
 493 reproduced or transmitted in any form or by any means, electronic or mechanical,
 494 including photocopying, recording, or any inf. Agron. J. 60–70.

495 Morris, M.D., 1991. Factorial sampling plans for preliminary computational experiments.
 496 Technometrics 33, 161–174.

497 Msongaleli, B., Rwehumbiza, F.B.R., Tumbo, S.D., Kihupi, N., 2013. Investigation of
 498 sorghum yield response to variable and changing climatic conditions in semi-arid
 499 central Tanzania: Evaluating crop simulation model applications. pp. 899–909.

500 Murphy, R.L., Klein, R.R., Morishige, D.T., Brady, J.A., Rooney, W.L., Miller, F.R.,
 501 Dugas, D. V, Klein, P.E., Mullet, J.E., 2011. Coincident light and clock regulation of
 502 pseudoresponse regulator protein 37 (PRR37) controls photoperiodic flowering in
 503 sorghum. Proc. Natl. Acad. Sci. 108, 16469–16474.

504 NASA, 2014. Climatology Resource for Agroclimatology. URL
 505 <http://power.larc.nasa.gov/cgi-bin/cgiwrap/solar/agro.cgi> (accessed 1.1.14).

506 NCDC, 2014. National Climatic Data Center. URL <http://www.ncdc.noaa.gov/> (accessed
 507 1.1.14).

508 NCRS, 2014. National Resource and Conservation Service. Web Soil Survey.
 509 <http://websoilsurvey.sc.egov.usda.gov> (accessed 1.1.14).

510 Pask, A.J.D., Reynolds, M.P., 2013. Breeding for yield potential has increased deep soil
 511 water extraction capacity in irrigated wheat. Crop Sci. 53, 2090–2104.

512 Priestley, C.H.B., Taylor, R.J., 1972. On the assessment of surface heat flux and
 513 evaporation using large-scale parameters. Mon. Weather Rev. 100, 81–92.

514 Pujol, G., 2009. Simplex-based screening designs for estimating metamodels. Reliab.
 515 Eng. Syst. Saf. 94, 1156–1160.

516 R Core Team, 2015. R: A language and environment for statistical computing. R
 517 Foundation for Statistical Computing, Vienna, Austria.

518 Ritchie, J.T., Godwin, D.C., 1989. Soil water balance and weather generation, in:
 519 Virmani S.M., Tandon H.L.S, Alagarswamy G. (Eds.), Model. Growth Dev.
 520 Sorghum Pearl Millet. p. 14.

521 Ritchie, J.T., Singh, U., Godwin, D.C., Bowen, W.T., 1998. Cereal growth, development
 522 and yield, in: Tsuji, G.Y., Hoogenboom G., Thornton, P.K. (Eds.), Understanding
 523 Options for Agricultural Production. p. 79.

524 Robertson, B.M., Hall, A.E., Foster, K.W., 1985. A field technique for screening for
 525 genotypic differences in root growth. Crop Sci. 25, 1084–1090.

526 Robertson, M.J., Fukai, S., Hammer, G.L., Ludlow, M.M., 1993. Modelling root growth of
 527 grain sorghum using the CERES approach. F. Crop. Res. 33, 113–130.

528 Sarlikioti, V., de Visser, P.H.B., Buck-Sorlin, G.H., Marcelis, L.F.M., 2011. How plant
 529 architecture affects light absorption and photosynthesis in tomato: towards an

ideotype for plant architecture using a functional–structural plant model. *Ann. Bot.* 108, 1065–1073.

Schabenberger, O., 2005. Introducing the GLIMMIX procedure for generalized linear mixed models. *SUGI 30 Proc.* 130–196.

Seetharama, N., Flower, D.J., Jayachandran, R., Krishna, K.R., Peacock, J.M., Singh, S., Soman, P., Rani, A.U., Wani, S.P., 1990. Assessment of genotypic differences in sorghum root characteristics.

Sinclair, T.R., Muchow, R.C., 2001. System analysis of plant traits to increase grain yield on limited water supplies. *Agron. J.* 93, 263–270.

Singh, P., Nedumaran, S., Traore, P.C.S., Boote, K.J., Rattunde, H.F.W., Prasad, P.V.V., Singh, N.P., Srinivas, K., Bantilan, M.C.S., 2014. Quantifying potential benefits of drought and heat tolerance in rainy season sorghum for adapting to climate change. *Agric. For. Meteorol.* 185, 37–48.

Staggenborg, S.A., Vanderlip, R.L., 2005. Crop simulation models can be used as dryland cropping systems research tools. *Agron. J.* 97, 378–384.

Stanhill, G., 1986. Water use efficiency. *Adv. Agron.* 39, 53–85.

Timsina, J., Humphreys, E., 2006. Performance of CERES-Rice and CERES-Wheat models in rice–wheat systems: A review. *Agric. Syst.* 90, 5–31.

Trachsel, S., Kaeppler, S.M., Brown, K.M., Lynch, J.P., 2011. Shovelomics: high throughput phenotyping of maize (*Zea mays* L.) root architecture in the field. *Plant Soil* 341, 75–87.

Vadez, V., 2014. Root hydraulics: The forgotten side of roots in drought adaptation. *F. Crop. Res.* 165, 15–24.

Wallach, D., Brun, F., Jones, J.W., Makowski, D., 2013. Working with Dynamic Crop Models Methods, Tools and Examples for Agriculture and Environment, 2nd ed. ed. Elsevier Science, Burlington.

White, J.W., Alagarswamy, G., Ottman, M.J., Porter, C.H., Singh, U., Hoogenboom, G., 2015. An Overview of CERES–Sorghum as Implemented in the Cropping System Model Version 4.5. *Agron. J.* 107, 1987–2002.

Wong, M.T.F., Asseng, S., 2007. Yield and environmental benefits of ameliorating subsoil constraints under variable rainfall in a Mediterranean environment. *Plant Soil* 297, 29–42.

Zhao, Y.L., Dolat, A., Steinberger, Y., Wang, X., Osman, A., Xie, G.H., 2009. Biomass yield and changes in chemical composition of sweet sorghum cultivars grown for biofuel. *F. Crop. Res.* 111, 55–64.

Table 1. Distribution of the elementary effects of the parameters mKGROSTM (Slope of the linear model used to calculate stem growth rate), mSLW (Slope of the linear model used to calculate specific leaf weight), radiation use efficiency (RUE), canopy extinction coefficient (KCAN), maximum water uptake per unit root length (RWUMX), and soil root growth factor (SRGF) on the optimal root depth (ORD).

Parameter	μ^{*a}			σ^b		
	April	May	June	April	May	June
mKGROSTM (g plant ⁻¹)	0.00	0.00	4.50	0.00	0.00	8.33
mSLW (g cm ⁻²)	0.00	4.50	6.75	0.00	8.33	9.32
RUE (g MJ ⁻¹ PAR)	15.75	11.25	13.50	11.54	9.32	12.73
KCAN	11.25	4.50	6.75	9.32	8.33	9.32
RWUMX (cm ³ water cm ⁻¹ root)	0.00	2.25	2.25	0.00	6.36	6.36
SGRF	6.75	0.00	2.25	9.32	0.00	6.36

^a Mean of the elementary effects. High values indicate an important effect on ORD.

^b Standard deviation of the elementary effects. High values indicate an important interaction with another variable or that effect on the evaluated parameter is not linear

Table 2. Crop model parameters bounds for mKGROSTM (Slope of the linear model used to calculate stem growth rate), mSLW (Slope of the linear model used to calculate specific leaf weight), radiation use efficiency (RUE), canopy extinction coefficient (KCAN), maximum water uptake per unit root length (RWUMX), and soil root growth factor (SRGF) used in the sensitivity analysis

Parameter name	Calibrated values	Min	Max
mKGROSTM (g plant ⁻¹ DD ⁻¹)	8.83 * 10 ⁻⁵	6.80 * 10 ⁻⁵	1.13 * 10 ⁻⁷
mSLW (g cm ⁻²)	3.42 * 10 ⁻³	2.33 * 10 ⁻³	3.88 * 10 ⁻³
RUE (g MJ ⁻¹ PAR)	3.90	2.93	4.88
KCAN	6.50 * 10 ⁻¹	4.33 * 10 ⁻¹	7.63 * 10 ⁻¹
RWUMX (cm ³ H ₂ O cm ⁻¹ root)	3.00 * 10 ⁻²	2.25 * 10 ⁻²	3.75 * 10 ⁻²
SRGF	1.00	5.00 * 10 ⁻¹	1.00

583 Table 3. Volumetric fraction of soil water content for the lower limit (LL) of plant
 584 available water, for the drained upper limit (DUL), and for field saturation
 585 (SSAT) for each soil depth layer (SLB) of the Hague sand soil used for the
 586 CSM CERES model simulations. The soil is characteristic of soils in the
 587 region and for the field data collected in the study at Citra, Florida.

SLB (cm)	LL	DUL	SSAT
20	0.066	0.120	0.376
30	0.060	0.107	0.396
43	0.060	0.107	0.396
61	0.066	0.111	0.418
69	0.128	0.180	0.350
102	0.144	0.197	0.361
124	0.118	0.167	0.376
210	0.096	0.141	0.355

588

589

590 Table 4. Mean squared error (MSE), root mean square error (RMSE), relative root
 591 mean square error (RMSE), mean squared error of prediction (MSEP), root
 592 mean squared error of prediction (RMSEP), and relative root mean squared
 593 error of prediction (RRMSEP) of the CSM CERES model simulations of 'M
 594 81E' sweet sorghum total aboveground dry weight (TDW), days to maturity,
 595 and stem dry weight (SDW).

Statistic	TDW (kg ha ⁻¹)	Days to Maturity	SDW (kg ha ⁻¹)
Locations	6	6	5
N ^a	39	39	35
Range observed values	15177 - 32796	115 - 168	13448 ± 26600
MSE	26477311	39.9	19659077
RMSE	5146	6.3	4434
RRMSE (%)	21	4.7	23
MSEP	26593739 ± 662562 ^b	39.9 ± 1.7	19407556 ± 944968
RMSEP	5157 ± 65	6.3 ± 0.1	4404 ± 108
RRMSEP (%)	21 ± 0.3	4.7 ± 0.1	22.6 ± 0.6

596 ^a Sample size.

597 ^b Standard deviation.

598

Fig. 1. (a) Regression between stem growth rate (KGROSTM) and thermal time from the end of the juvenile stage until the beginning of grain filling (TT2) under well-watered conditions. $KGROSTM = 8.83 \times 10^{-5} TT2$; $R^2 = 0.81$. (b) Regression between specific leaf weight (SLW) and thermal time from emergence until the end of leaf growth (TT1). $SLW = 3.42 \times 10^{-3} + 1.64 \times 10^{-6} TT1$; $R^2 = 0.42$. Solid lines indicate the expected values for SLW and KGROSTM derived from the adjusted equations for the growth stages were SLW and KGROSTM are a function of thermal time. Dotted lines represent the default model values for SLW and KGROSTM in growth stages were they remain constant. Squares and triangles are observed KGROSTM and SLW values respectively.

Fig. 2. Simulated and observed values of total above ground dry weight (TDW), stem dry weight (SDW), leaf dry weight (LDW), and leaf area index (LAI) for sweet sorghum cultivar 'M 81E' throughout the growing season at Citra, Florida in 2012 and 2013. Closed circles represent observations. Error bars are the standard errors of the observations. Solid lines represent CERES CSM sweet sorghum model simulations.

Fig. 3. Average root length density (RLD) observed in 2013 (a), and simulated for 24 years of historic weather across three planting dates for genotypes 'M 81E' (b) and for the 120 cm deep rooted sweet sorghum (c). Different grey shades in bars represent different soil depths. Error bars represent standard errors across observations (a) or standard deviations across simulations (b and c).

Fig. 4. Ratio of daily actual evapotranspiration to potential evapotranspiration simulated using the CERES CSM crop model for different sweet sorghum rooting depths (30, 90, 150, and 210 cm). Data are derived from mean ($n = 24$) daily averages from simulations using 24 years of weather data for sweet sorghum planted on April 1 (top), May 1 (middle), and June 1 (bottom) at Citra, Florida.

Fig. 5. Simulated mean seasonal transpiration (Ta) by planting date across 24 years of historic weather data for 19 sweet sorghum root depths.

636

637 Fig. 6. (a) Simulation of mean total aboveground dry weight (TDW) for differing sweet
 638 sorghum root depths across three planting dates. Error bars represent
 639 standard errors of the mean for the 24 years of simulation. (b) Mean DW gain
 640 for each 10 cm increase in root depth. Error bars represent standard errors of
 641 the mean for the 24 years of simulation.

642

Fig. 7. Simulated distribution of the optimal root depth (ORD) obtained in a sensitivity analysis for the three planting dates.

Fig. 8. Simulated average total aboveground biomass dry weight (TDW) of sweet sorghum for 24 years of weather data at Citra, Florida, for sweet sorghum cultivar 'M 81E' and a hypothetical sweet sorghum with a 120 cm root depth planted in April, May, and June. Bars represent standard errors of the mean across years.