Received: 6 November 2020 | Accepted: 18 February 2021 | Published online: 1 April 2021

DOI: 10.1002/agj2.20644

Agronomy Journal

ARTICLE

Crop Economics, Production, and Management

Deriving genetic coefficients from variety trials to determine sorghum hybrid performance using the CSM–CERES–Sorghum model

Xi Liang[1,2] | **Gerrit Hoogenboom**[3,4] | **Stamatia Voulgaraki**[5] | **Kenneth J. Boote**[3] | **George Vellidis**[1]

[1] Dep. of Crop and Soil Sciences, Univ. of Georgia, 2329 Rainwater Road, Tifton, GA 31793, USA

[2] Dep. of Plant Sciences, Univ. of Idaho, Aberdeen Research and Extension Center, Aberdeen, ID 83210, USA

[3] Dep. of Agricultural and Biological Engineering, Univ. of Florida, Frazier Rogers Hall, Gainesville, FL 32611, USA

[4] Institute for Sustainable Food Systems, Univ. of Florida, Frazier Rogers Hall, Gainesville, FL 32611, USA

[5] Natural Resources Management and Agricultural Engineering Dep., Agricultural Univ. of Athens, 75 Iera Odos Str., Greece 11853

Correspondence
Xi Liang, Dep. of Crop and Soil Sciences, Univ. of Georgia, 2329 Rainwater Road, Tifton, GA, 31793, USA.
Email: xliang@uidaho.edu

Assigned to Associate Editor Rajan Ghimire

Abstract

Sorghum (*Sorghum bicolor* L.) is well-known to adapt to stressful environmental conditions. However, yield variability of sorghum has not been thoroughly investigated for different growing conditions in a subtropical climate. The overall goal of this study was to identify yield potential and management options for sorghum production in the southeastern United States. Specific objectives were to calibrate and evaluate the Cropping System Model (CSM)–CERES–Sorghum model with sorghum variety trial data and to apply the model for determining hybrid performance as a function of sowing date for different environments in Georgia. The model was calibrated and evaluated with data for six grain sorghum hybrids from 31 variety trials conducted in Georgia and Florida. Following calibration and evaluation, the model was used to simulate grain yield of the six hybrids in response to seven sowing dates under rainfed and irrigated conditions at 10 locations in Georgia using 40 yr of historical weather data. The results indicate that normalized root mean square error (RMSEn) between simulated and observed yield for the six hybrids ranged from 1.4 to 19% for model calibration and from 12 to 28% for model evaluation, suggesting that the model can be calibrated and evaluated using limited data from variety trials. For the long-term scenarios, differences in simulated grain yield were found for hybrids, sowing dates, and locations under both rainfed and irrigated conditions. This demonstrated that the CSM–CERES–Sorghum model can be used to investigate the effects of climate variability on crop yield and to develop management practices for optimizing sorghum production.

1 | INTRODUCTION

Sorghum (*Sorghum bicolor* L.) has been used widely for providing food, feed, fiber, and fuel (Rao et al., 2016; Saballos, 2008). In comparison to maize (*Zea mays* L.), sorghum can better withstand drought and heat stresses and can more easily adapt to various environmental conditions (Farre &

Abbreviations: CSM, Cropping System Model; DSSAT, Decision Support System for Agrotechnology Transfer; GDD, growing degree day; IQR, interquartile range; LAI, leaf area index; RMSEn, normalized root mean square error

Faci, 2006; Zegada-Lizarazu et al., 2012). For instance, under water-limited conditions, sorghum produces more biomass and grain yield compared to maize (Farre & Faci, 2006). Considering their similar end-use purposes, sorghum is able to replace maize under unfavorable conditions. Despite the adaptability of sorghum to environmental variability, there is still a need to develop best management practices for sorghum under different production conditions. The development of best management practices requires conducting experiments for a range of management factors, such as hybrid selection, sowing date, and irrigation, over multiple years and for different environments. However, such field experiments can be very resource-intensive and time consuming and may not provide recommendations in a timely manner. Alternatively, crop growth, development, and yield can be simulated over a range of growing conditions using crop models, which can then be used to develop best management practices for specific environments (Baumhardt & Howell, 2006; Hammer et al., 2014; Mauget et al., 2020; Tsuji et al., 1998; White et al., 2015).

The Cropping System Model (CSM)–CERES–Sorghum of the Decision Support System for Agrotechnology Transfer (DSSAT) (Hoogenboom et al., 2019; Jones et al., 2003; White et al., 2015) has been widely used for simulating sorghum production (Amouzou et al., 2018; MacCarthy et al., 2010; Mauget et al., 2020; Singh et al., 2014). The model enables the calibration of genotypic coefficients that are specific to each hybrid for defining crop growth, development, and yield (Table 2) (Hunt & Boote, 1998; White et al., 2015). Variation in grain yield among sorghum hybrids is related to differences in their physiological characteristics, for example, maturity group, plant architecture, and resource allocation to contribute to grain filling, and can be characterized in the CSM–CERES–Sorghum model (Baumhardt & Howell, 2006; Gambin & Borras, 2012; Hunt & Boote, 1998; Wade & Douglas, 1990). Following calibration of the model, the performance of sorghum can be simulated for various hybrids, environments, and management scenarios to understand the Genotype × Environment × Management interaction (G×E×M) effects on yield (Amouzou et al., 2018; Kothari et al., 2019; MacCarthy et al., 2010; Mauget et al., 2020; Singh et al., 2014; Tsuji et al., 1998).

The southeastern United States is subject to climate variability associated with the interannual fluctuation of the atmosphere–ocean system in the equatorial Pacific or El Niño-Southern Oscillation (ENSO) (AgroClimate, 2020; Fraisse et al., 2006; Garcia y Garcia et al., 2010; Mourtzinis et al., 2016; Paz et al., 2007). Georgia and especially southern Georgia is affected by ENSO and it has a wide range in environmental variability due to its spatially variable soils and the spatial and temporal variability of weather (Bao et al., 2017; Perkins et al., 1982, 1986; Salazar et al., 2012). In this region, irrigation and sowing dates are among the most important management practices in crop production. Despite the sometimes large amount of seasonal precipitation, there are still frequent dry spells and intermittent droughts that can cause yield loss if supplemental water through irrigation is lacking (Bao et al., 2017; Salazar et al., 2012). A suitable sowing window can minimize the gap between yield potential and the attainable yield (Mauget et al., 2020). For instance, crop production of sweet sorghum and maize was reduced with delayed sowing dates and differed among hybrids in southeastern United States and Brazil (Erickson et al., 2011; Soler et al., 2007). However, compared with early sowing dates, simulated grain yield from late sowing was greater in rainfed sorghum in the southwestern United States because it coincided with water availability during the critical growth phases, especially grain filling (Mauget et al., 2020). By adjusting the sowing date, a crop can reach timely maturity and can avoid unfavorable environments, especially droughts, during critical periods for yield formation during the growing season (Mauget et al., 2020; Soler et al., 2007).

Core Ideas

- CSM–CERES–Sorghum model can be calibrated and evaluated using limited data from variety trials.
- Locations, hybrids, and sowing dates contributing to high sorghum yield can be identified.
- The model can be used to study climate variability impacts and develop management practices.

Considering its tolerance and adaptation to environmental variability, sorghum can produce a relatively stable yield under different environmental conditions and in response to various management practices. However, sorghum yield variability in the southeastern United States so far has seldom been studied for multiple environments (e.g., different locations and multiple growing seasons) and in response to different management practices. Likewise, favorable conditions for high grain yield and low risk in yield loss have been rarely identified. Our hypothesis is that dynamic crop models can be complementary to variety trials to help provide guidance for selecting optimum management practices, especially as it relates to planting date selection for different hybrids. The objectives of the current study were, therefore, to determine the feasibility of using data from variety trials for calibration and evaluation of the CSM–CERES–Sorghum model and to estimate grain yield of sorghum for a range of sowing dates under rainfed and irrigated conditions, which would facilitate the evaluation of the risk in yield loss under environmental variability and different management practices.

TABLE 1 Variety trials of six grain sorghum hybrids in Georgia and Florida used for the Cropping System Model (CSM)–CERES–Sorghum model calibration and evaluation

Location	Sowing date	Water regime	Sorghum hybrid					
			A571	DKS51-90	DKS54-00	NK8416	NK8828	Pioneer 83G66
			Model calibration					
Griffin, GA	17 May 2001	Irrigated	√	√	√			√
Griffin, GA	21 June 2001	Irrigated	√	√	√			√
Griffin, GA	20 May 2002	Irrigated	√	√	√		√	√
Griffin, GA	21 June 2002	Irrigated	√	√	√		√	√
Griffin, GA	12 June 2003	Irrigated	√		√	√	√	√
Griffin, GA	10 July 2003	Irrigated	√		√	√	√	√
Griffin, GA	25 May 2004	Irrigated	√		√	√	√	√
Griffin, GA	14 July 2004	Irrigated	√		√	√	√	
Griffin, GA	19 May 2005	Irrigated	√		√			√
Griffin, GA	23 June 2005	Irrigated	√		√			√
Marianna, FL	21 Apr. 2003	Irrigated	√		√		√	√
Marianna, FL	15 Apr. 2004	Irrigated	√		√	√	√	√
Marianna, FL	21 Apr. 2005	Irrigated	√		√			√
Marianna, FL	27 June 2005	Irrigated	√		√			
Marianna, FL	7 Apr. 2006	Irrigated	√		√			√
Marianna, FL	27 June 2006	Irrigated						√
			Model evaluation					
Tifton, GA	25 Apr. 2001	Rainfed	√	√	√			√
Tifton, GA	22 June 2001	Rainfed	√	√	√			√
Tifton, GA	12 July 2002	Rainfed	√	√	√		√	√
Tifton, GA	15 July 2003	Rainfed			√	√	√	
Tifton, GA	26 Apr. 2004	Rainfed	√		√	√	√	√
Tifton, GA	14 May 2006	Rainfed	√		√			√
Tifton, GA	15 June 2006	Rainfed						√
Plains, GA	20 Apr. 2000	Rainfed	√	√				√
Plains, GA	23 Apr. 2001	Irrigated	√	√	√			√
Plains, GA	19 June 2001	Irrigated		√	√			√
Plains, GA	16 Apr. 2002	Rainfed	√	√	√			√
Plains, GA	17 June 2002	Rainfed	√	√	√			√
Plains, GA	23 Apr. 2003	Rainfed	√		√	√	√	√
Plains, GA	24 June 2003	Rainfed			√	√	√	√
			Growth experiment for model evaluation					
Tifton, GA	24 May 2012	Irrigated						√

TABLE 2 Cultivar coefficients of the Cropping System Model (CSM)–CERES-Sorghum model (Hoogenboom et al., 2014)

Parameter	Definition	Units
P1	Thermal time from seedling emergence to the end of the juvenile phase during which the plant is not responsive to photoperiod	degree days (GDD) above T_{Base} (8°C)
P2	Thermal time from the end of the juvenile stage to panicle initiation under short days	GDD above T_{Base}
P2O	Critical photoperiod or the longest day length at which development occurs at a maximum rate. At values higher than P2O, the rate of development is reduced	Hour
P2R	Extent to which phasic development leading to panicle initiation is delayed for each hour increase in photoperiod above P2O	GDD
PANTH	Thermal time from the end of panicle initiation to anthesis	GDD above T_{Base}
P3	Thermal time from the end of flag leaf expansion to anthesis	GDD above T_{Base}
P4	Thermal time from anthesis to beginning grain filling	GDD above T_{Base}
P5	Thermal time from beginning of grain filling to physiological maturity	GDD above T_{Base}
PHINT	Phyllochron interval; the interval in thermal time between successive leaf tip appearances	GDD
G1	Scaler for relative leaf size	–
G2	Scaler for partitioning of assimilates to the panicle (head)	–

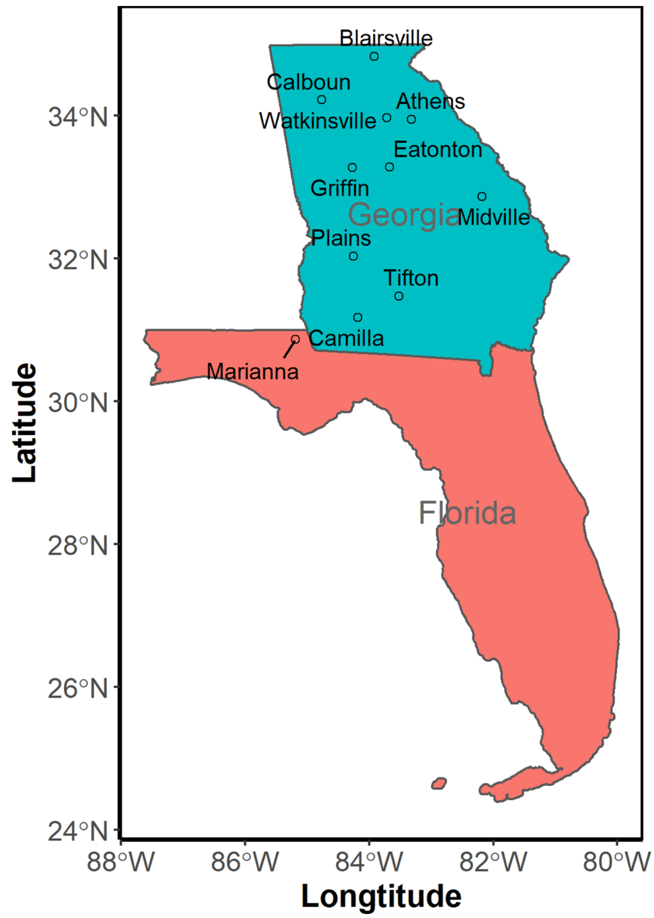

FIGURE 1 Locations of the variety trials and long-term simulations in Georgia and Florida

2 | MATERIALS AND METHODS

2.1 | Data collection

The data used in this study were obtained from the variety trials for rainfed and irrigated grain sorghum conducted in Griffin (33.26 ˚N, 84.28 ˚W), Plains (32.05 ˚N, 84.37 ˚W), and Tifton (31.49 ˚N, 83.53 ˚W) in Georgia, and Marianna in Florida (30.85 ˚N, 85.16 ˚W) (http://www.swvt.uga.edu/) (Table 1, Figure 1). The soil information and profile characteristics for these four locations were obtained from the soil surveys conducted by Perkins et al. (1982, 1986) and the Natural Resources Conservation Services (NRCS) of the United States Department of Agriculture (USDA). The soil types were a Cecil sandy clay loam (fine, kaolinitic, thermic Typic Kanhapludult) for Griffin, a Faceville sandy loam (fine, kaolinitic, thermic Typic Kandiudult) for Plains, a Tifton loamy sand (fine-loamy, kaolinitic, thermic Plinthic Kandiudult) for Tifton, and a Norfolk sandy loam (fine-loamy, kaolinitic, thermic Typic Kandiudult) for Marianna. Soil profiles were created using the soil utility program SBuild in DSSAT (ver. 4.7) (Hoogenboom et al., 2014) by importing the soil profile information from each location. The daily maximum and minimum air temperature, rainfall, and solar radiation were obtained from the Georgia Automated Environmental Monitoring Network (GAEMN, www.georgiaweather.net; Hoogenboom, 1993) and the Florida Automated Weather Network (FAWN, https://fawn.ifas.ufl.edu/).

Variety trials were conducted for both early and late sowing dates in Griffin from 2001 to 2005, in Plains from 2000 to 2003, in Tifton from 2001 to 2006, and in Marianna from 2003 to 2006 (Table 1). The seeding population ranged from 24.7 to 37.1 seeds m^{-2}, and row spacing was 76 cm in Griffin, Plains, and Tifton, and 91 cm in Marianna. The reported dates and irrigation quantity for each trial were also retrieved, and irrigation was applied via pivot irrigation systems.

Grain sorghum hybrids, Pioneer 83G66, DKS54-00, DKS51-90, A571, NK8416, and NK8828 were selected based on data availability from the variety trials (Table 1). The traits that were recorded for the variety trials included anthesis and harvest dates and grain yield. Anthesis dates were defined as 50% of plants at bloom in each plot. Since no observed maturity days were available, harvest dates were used as maturity dates. Grain yield was reported at 14% of moisture, which was converted to dry mass for model calibration and evaluation.

A field experiment with the hybrid Pioneer 83G66 was conducted in Tifton, GA (31.49 ˚N, 83.53 ˚W), during the growing season of 2012. The experimental plots were established with three replicates on 24 May 2012. The row spacing was 91 cm with a seeding population of 21.5 seeds m^{-2}. Irrigation was applied via a center pivot system, and the plots were harvested on 12 Sept. 2012. In addition to anthesis and maturity dates, one representative plant from each plot was harvested every 2 wk until the final harvest. The leaf area was measured using a leaf area meter (model LI-3100, LI-COR), while the leaf area index (LAI) was calculated by multiplying the leaf area for each plant by the number of plants per m^2. The sample plants from each harvest were dried in an oven at 70 ˚C until constant weight was achieved to estimate aboveground biomass.

2.2 | Model calibration and evaluation

Model calibration and evaluation were conducted by comparing model simulations with observations (Table 1). Cultivar coefficients were adjusted to minimize the error between simulations and observations. The CSM–CERES–Sorghum model has 11 cultivar coefficients that define the growth and development characteristics of a grain sorghum hybrid (Table 2). In this study, six cultivar coefficients, that is, P1, P2O, P2R, P5, G1, and G2 were calibrated. Cultivar coefficients of P2, PANTH, P3, P4, and PHINT were set as default at 102, 617.5, 152.5, 81.5, and 49, respectively.

In the model calibration procedure, parameters were calibrated using the Genotype Coefficient Calculator (GENCALC) in DSSAT (ver. 4.7) with the designated dataset (Table 1). The process of anthesis is controlled by the P1, P2O, and P2R coefficients, which are grouped for the calculation. In GENCALC, the cultivar coefficients of a genotype are estimated by running the model with approximate coefficients and comparing the model outputs to observed data (Anothai et al., 2008; Hunt et al., 1993). For each successive run of GENCALC, the selected coefficients were automatically inserted into the simulation runs and the procedure was repeated until the simulated anthesis dates were similar to the observed anthesis dates (Buddhaboon et al., 2018). When the normalized root mean square error (RMSEn) (Equation 2) reached its lowest value, ideally lower than 5%, the calibration of the coefficients for a particular target trait was ended and switched to the calibration of the next target trait by updating the calibration rules for that specific trait. The use of RMSEn is superior to root mean square error (RMSE) (Equation 1) for determining the goodness of fit for multiple target traits (Anothai et al., 2008), as RMSE only represents the deviation between the simulated and measured values of different target traits. Maturity is controlled by the coefficient P5, and the calibration was the same as the process of coefficients controlling the anthesis date.

Grain yield is influenced by coefficients G1 (associated with leaf size) and G2 (partitioning of assimilates to the panicle). The calibration of coefficient G2 was the same as the process of coefficients controlling anthesis and maturity dates. Considering that there were no observed data available for LAI, the G1 coefficient was calibrated using the Sensitivity Analysis program of DSSAT and setting the initial value at 1.0, with the target of final grain yield. The coefficient G1 was incremented by 1.0 until the simulated grain yield fell into a reasonable range. Then, G1 coefficient was adjusted by 0.5 until the simulated and measured grain yields were matched visually. Since the G1 and G2 coefficients interactively influence grain yield, the calibrated G1 coefficient was incorporated into the calibration of the G2 coefficient in the GENCALC program.

The accuracy of the procedure for evaluating the generated cultivar coefficients was determined by comparing simulated and observed values using the determination coefficient (R^2, Equation 3) and RMSEn (Equation 2) (Anothai et al., 2008). The R^2 was obtained from the linear regression between the simulated and observed values. A high value of R^2 and a low value of RMSEn indicate goodness of fit between the simulated and observed values (Anothai et al., 2008).

Calibrated cultivar coefficients were evaluated against independent datasets from variety trials and the growth experiment (Table 1). The Index of Agreement (*d*-stat, Equation 4) and RMSEn were used to evaluate the agreement between simulated and observed values (Willmott et al., 1985). The *d*-stat ranges from 0 to 1 and the best fit is with the index close to 1. The simulation is considered excellent with an RMSEn lower than 10%, good if RMSEn is between 10 and 20%, fair if RMSEn is between 20 and 30%, and poor if RMSEn is greater than 30% (Equation 2) (Soler et al., 2007; Yang et al., 2014).

$$\text{RMSE} = \sqrt{\frac{\sum_{i=1}^{n}\left(P_i - O_i\right)^2}{n}} \tag{1}$$

$$\text{RMSEn} = \frac{\text{RMSE} \times 100}{\bar{O}} \tag{2}$$

$$R^2 = \frac{\sum_{i=1}^{n}\left(P_i - \bar{P}\right)\left(O_i - \bar{O}\right)}{\sqrt{\sum_{i=1}^{n}\left(P_i - \bar{P}\right)^2 \sum_{i=1}^{n}\left(O_i - \bar{O}\right)^2}} \tag{3}$$

$$d - stat = 1 - \frac{\sum_{i=1}^{n}\left(P_i - O_i\right)^2}{\sum_{i=1}^{n}\left(\left|P_i - \bar{O}\right| + \left|O_i - \bar{O}\right|\right)^2} \tag{4}$$

where n is the number of observations; P_i is the simulated value for the ith measurement; O_i is the observed value for the ith measurement; $\bar{P}$ is the overall mean of simulated values; and $\bar{O}$ the overall mean of observed values.

2.3 | Long-term simulation scenarios

Following calibration and evaluation, the model was used to predict yield under both irrigated and rainfed conditions using long-term historical weather data from 1966 to 2005 for four regions in Georgia. The selection of this period was due to the availability of long-term weather data for 10 locations in Georgia that represent the Research and Education Centers of the University of Georgia Agricultural Experiment Station. From North to South, Calhoun represents the Limestone Valley; Blairsville represents the Blue Ridge Mountains; Athens, Watkinsville, Griffin, Eatonton represent the Piedmont; and Midville, Plains, Tifton, and Camilla represent the Coastal Plain (Figure 1). The average maximum and minimum temperature, rainfall, and solar radiation during the growing season from 1966 to 2005 for the 10 locations are presented in Table 3. The simulation was conducted using seven sowing dates, that is, 15 April, 1 May, 15 May, 1 June, 15 June, 1 July, and 15 July, to cover the possible sowing window in Georgia and to determine the yield response of each hybrid to sowing date. For this analysis, the most common soil type was used for each location, including an Etowah loam (fine-loamy, siliceous, semiactive, thermic Typic Paleudult) for Calhoun, a Bradson clay loam (clayey, parasesquic, mesic Typic Hapludult) for Blairsville, a Cecil sandy clay loam for Athens, Watkinsville, Eatonton, and Griffin, a Faceville sandy loam for Plains, and a Tifton loamy sandy for Midville, Tifton, and Camilla (Bao et al., 2017; Perkins et al., 1982, 1986). In the simulation, initial soil condition was assumed at 100% of plant available water, and N was applied at 100 kg N ha^{-1} at pre-sowing, 75 kg N ha^{-1} at 30 d and 75 kg N ha^{-1} at 60 d after sowing, which was similar to the crop management of the variety trials. Under irrigated conditions, a fixed amount of 25 mm was applied whenever the irrigation threshold was below 60% of plant available water in the top of the soil profile (Salazar et al., 2012). Soil organic matter mineralization was simulated using the CERES-Goodwin method (Godwin & Singh, 1998), and potential evapotranspiration was simulated using the Priestley-Taylor (1972) method.

An ANOVA (one-way ANOVA) was conducted to determine whether simulated grain yield was affected by sorghum hybrid, location, and sowing date. Multiple comparisons were conducted when the p value was <.05. All statistical analyses were conducted using R 3.6.0 (R Core Team, 2018).

3 | RESULTS

3.1 | Calibration of cultivar coefficients

The phenology and growth coefficients of the CSM–CERES–Sorghum model were calibrated for six sorghum hybrids (Table 4). The P1 coefficient (thermal time from seedling emergence to the end of the juvenile phase) was similar among hybrids with a narrow range from 205 to 227 GDD, except for the hybrid DKS54-00 that had a higher P1 of 282 GDD. The values for the P2O coefficient (critical photoperiod or the longest day length at which development occurs at a maximum rate) ranged from 12.6 to 13.4 h. The P2R coefficient (extent to which phasic development leading to panicle initiation is delayed for each hour increase in photoperiod above P2O) ranged from 14.4 to 16.3 GDD. The values for the P5 coefficient (thermal time from beginning of grain filling to physiological maturity) ranged from 657 GDD for the hybrid NK8416 to 789 GDD for the hybrid Pioneer 83G66. The G2 coefficient (scaler for partitioning of assimilates to the panicle) ranged from 4.07 to 6.90. The values for the G1 coefficient (scaler for relative leaf size) ranged from 5.00 for the hybrid DKS51-90 to 15.0 for the hybrid NK8416.

Simulated grain yield was compared with observed yield for each hybrid (Table 5). For hybrids DKS51-90, A571, NK8416, and NK8828, simulated yield was very similar to the observed yield (with the average difference below 0.1 t ha^{-1}). Grain yield was slightly underestimated for hybrids DKS54-00 and Pioneer 83G66. The slope of linear regression of simu-

TABLE 3 Average monthly maximum and minimum temperature, total rainfall, and solar radiation (± SD) during the growing season from 1966 to 2005 for the 10 locations in Georgia

Location	Growing season							
	Apr.	May	June	July	Aug.	Sept.	Oct.	Nov.
	Maximum temperature, ˚C							
Calhoun	23.2 ± 4.51	26.4 ± 3.32	29.8 ± 2.83	31.5 ± 2.69	30.8 ± 2.52	27.9 ± 3.62	22.9 ± 3.95	17.3 ± 5.04
Blairsville	19.9 ± 5.13	23.6 ± 3.68	27.0 ± 2.92	28.8 ± 2.78	28.3 ± 2.52	25.4 ± 3.27	20.6 ± 4.04	15.4 ± 5.39
Athens	22.9 ± 4.60	26.7 ± 3.68	30.2 ± 3.27	32.0 ± 3.23	31.0 ± 3.05	28.0 ± 3.80	22.9 ± 4.22	17.7 ± 5.04
Watkinsville	23.2 ± 4.51	26.7 ± 3.41	30.1 ± 3.00	31.6 ± 3.05	30.9 ± 2.78	27.7 ± 3.45	22.7 ± 3.86	17.6 ± 4.77
Eatonton	23.8 ± 4.42	27.3 ± 3.41	30.5 ± 3.09	32.2 ± 2.69	31.4 ± 2.69	28.8 ± 3.62	23.8 ± 3.86	18.9 ± 4.77
Griffin	22.6 ± 4.48	26.2 ± 3.41	29.7 ± 3.01	31.3 ± 2.71	30.6 ± 2.63	27.8 ± 3.62	22.9 ± 4.03	17.9 ± 5.08
Midville	24.8 ± 4.15	28.5 ± 3.32	31.6 ± 2.92	33.1 ± 2.69	32.1 ± 2.78	29.7 ± 3.45	25.2 ± 3.77	20.6 ± 4.51
Plains	25.0 ± 4.15	28.6 ± 3.14	31.4 ± 2.83	32.6 ± 2.61	32.0 ± 2.52	29.8 ± 3.45	25.4 ± 3.95	20.2 ± 4.77
Tifton	24.9 ± 4.07	28.6 ± 3.14	31.2 ± 2.74	32.5 ± 2.25	32.0 ± 2.43	30.0 ± 3.18	25.7 ± 3.86	20.9 ± 4.77
Camilla	26.2 ± 3.80	29.7 ± 2.87	32.1 ± 2.74	33.1 ± 2.52	32.6 ± 2.43	30.8 ± 3.00	26.5 ± 3.50	21.6 ± 4.51
	Minimum temperature, ˚C							
Calhoun	8.56 ± 5.33	13.1 ± 4.49	17.2 ± 3.09	19.4 ± 2.07	19.0 ± 2.16	15.9 ± 3.98	9.41 ± 5.58	4.65 ± 6.19
Blairsville	4.79 ± 5.15	9.51 ± 4.55	14.0 ± 3.36	16.4 ± 2.16	15.8 ± 2.43	12.5 ± 4.24	5.64 ± 5.79	1.19 ± 6.11
Athens	9.72 ± 4.47	14.4 ± 3.59	18.7 ± 2.65	20.8 ± 1.71	20.3 ± 1.89	17.0 ± 3.36	10.7 ± 4.76	5.65 ± 5.29
Watkinsville	8.18 ± 4.59	12.7 ± 3.77	16.8 ± 2.83	19.1 ± 1.80	18.8 ± 2.07	15.8 ± 3.53	9.70 ± 4.81	4.83 ± 5.42
Eatonton	9.51 ± 4.75	13.9 ± 3.77	18.4 ± 2.65	20.5 ± 1.71	20.0 ± 1.98	16.9 ± 3.62	10.5 ± 4.94	5.42 ± 5.53
Griffin	9.53 ± 4.69	13.9 ± 3.68	17.8 ± 2.67	19.8 ± 1.66	19.3 ± 2.01	16.1 ± 3.62	9.79 ± 4.81	5.39 ± 5.43
Midville	10.8 ± 4.42	15.2 ± 3.50	19.1 ± 2.56	20.8 ± 1.80	20.1 ± 1.98	17.4 ± 3.27	11.4 ± 5.12	6.63 ± 5.71
Plains	10.2 ± 4.67	14.9 ± 3.50	18.8 ± 2.30	20.7 ± 1.53	20.2 ± 1.71	17.5 ± 3.45	11.5 ± 5.03	6.39 ± 5.58
Tifton	12.0 ± 4.15	16.3 ± 3.23	19.9 ± 2.21	21.5 ± 1.53	21.2 ± 1.53	18.7 ± 2.92	12.9 ± 4.85	8.23 ± 5.52
Camilla	11.9 ± 4.51	16.2 ± 3.41	20.0 ± 2.30	21.5 ± 1.44	21.2 ± 1.53	18.9 ± 3.18	12.9 ± 5.39	8.08 ± 6.02
	Rainfall, mm							
Calhoun	100 ± 59.5	92.9 ± 60.6	86.9 ± 52.4	114 ± 86.6	79.0 ± 45.7	86.7 ± 53.6	65.0 ± 55.9	92.7 ± 51.6
Blairsville	117 ± 55.9	120 ± 58.9	119 ± 63.0	120 ± 63.4	122 ± 68.1	114 ± 68.5	89.5 ± 55.8	124 ± 50.2
Athens	85.4 ± 53.9	102 ± 60.5	110 ± 79.3	120 ± 66.8	96.2 ± 48.4	93.3 ± 67.6	83.5 ± 58.4	95.9 ± 46.7
Watkinsville	101 ± 57.4	113 ± 71.7	98.3 ± 62.7	108 ± 78.4	99.5 ± 62.0	98.7 ± 72.0	91.1 ± 63.8	99.1 ± 44.6
Eatonton	87.1 ± 57.3	92.0 ± 54.7	96.5 ± 60.3	118 ± 73.1	104 ± 60.0	84.4 ± 64.3	70.3 ± 50.6	86.6 ± 48.5
Griffin	103 ± 62.8	106 ± 50.1	106 ± 65.6	124 ± 88.4	104 ± 54.1	85.2 ± 51.4	78.1 ± 53.6	96.9 ± 55.9
Midville	73.4 ± 47.7	84.4 ± 56.5	102 ± 58.1	113 ± 67.9	130 ± 82.3	85.9 ± 62.7	73.2 ± 76.1	70.9 ± 51.3
Plains	87.2 ± 66.5	88.9 ± 53.2	116 ± 62.0	146 ± 130	103 ± 59.2	91.2 ± 84.5	50.1 ± 44.2	88.8 ± 59.0
Tifton	80.6 ± 65.1	85.5 ± 56.0	109 ± 60.6	126 ± 59.1	112 ± 59.9	87.3 ± 69.5	65.7 ± 61.8	76.9 ± 49.2
Camilla	90.8 ± 73.5	92.5 ± 64.0	136 ± 78.6	154 ± 72.0	117 ± 64.2	93.7 ± 82.1	60.0 ± 52.4	80.1 ± 52.8

(Continues)

TABLE 3 (Continued)

Location	Growing season							
	Apr.	May	June	July	Aug.	Sept.	Oct.	Nov.
	Solar radiation, MJ/(m^2 day)							
Calhoun	19.6 ± 5.30	22.1 ± 5.12	22.9 ± 4.60	21.6 ± 4.22	18.8 ± 3.95	15.0 ± 4.51	12.9 ± 4.22	9.79 ± 3.58
Blairsville	18.9 ± 5.83	21.3 ± 6.38	22.1 ± 6.01	20.8 ± 5.48	18.3 ± 4.94	14.7 ± 5.30	12.8 ± 4.67	9.44 ± 3.76
Athens	19.5 ± 4.60	22.3 ± 4.13	22.9 ± 3.98	21.9 ± 3.59	18.7 ± 3.77	15.2 ± 4.33	13.0 ± 3.95	10.2 ± 3.34
Watkinsville	20.0 ± 4.60	22.5 ± 4.58	23.3 ± 4.24	21.6 ± 3.95	18.7 ± 3.95	14.9 ± 4.33	12.7 ± 3.86	10.1 ± 3.38
Eatonton	19.9 ± 4.51	22.8 ± 3.86	23.0 ± 4.07	22.0 ± 3.50	19.1 ± 3.77	15.6 ± 4.24	13.4 ± 3.95	10.7 ± 3.36
Griffin	19.2 ± 4.74	21.8 ± 4.64	23.0 ± 4.13	21.9 ± 3.59	19.1 ± 3.68	15.7 ± 4.22	13.5 ± 4.03	10.3 ± 3.45
Midville	19.4 ± 4.86	22.3 ± 4.40	23.2 ± 4.07	22.6 ± 3.32	19.5 ± 4.04	15.8 ± 4.24	13.5 ± 4.04	10.7 ± 3.53
Plains	20.3 ± 4.51	22.7 ± 4.40	22.9 ± 4.42	21.8 ± 3.59	19.1 ± 3.86	15.8 ± 4.33	13.8 ± 4.04	11.2 ± 3.36
Tifton	20.1 ± 4.42	22.7 ± 4.13	23.2 ± 3.98	22.7 ± 3.14	19.7 ± 3.50	16.1 ± 4.24	14.1 ± 3.86	11.3 ± 3.45
Camilla	20.2 ± 4.60	23.1 ± 4.13	23.4 ± 3.89	22.6 ± 3.41	19.8 ± 3.50	16.0 ± 4.15	14.0 ± 4.13	11.3 ± 3.62

TABLE 4 Cultivar coefficients for six grain sorghum hybrids in the Cropping System Model (CSM)–CERES–Sorghum model calibrated in Georgia and Florida

Coefficient[a]	A571	DKS51-90	DKS54-00	NK8416	NK8828	Pioneer83G66
P1	221	218	282	220	227	205
P2	102	102	102	102	102	102
P2O	13.4	13.2	12.9	13.1	12.6	13.0
P2R	16.0	16.3	15.7	14.4	16.2	15.9
PANTH	618	618	618	618	618	618
P3	152	152	152	152	152	152
P4	81.5	81.5	81.5	81.5	81.5	81.5
P5	777	777	728	657	690	789
PHINT	49.0	49.0	49.0	49.0	49.0	49.0
G1	6.00	5.00	6.00	15.0	6.00	6.00
G2	5.45	6.52	4.07	6.90	4.79	6.86

[a]See Table 2 for the definitions of the cultivar coefficients.

TABLE 5 Average observed and simulated grain yield for the six grain sorghum hybrids for the Cropping System Model (CSM)–CERES–Sorghum model for the calibration and evaluation phases

Hybrid	Observed	Simulated	Slope[a]	R^2	*d*-stat	RMSEn
	t ha^{-1}					%
Calibration						
A571	4.18	4.12	0.695 (15)[b]	.728	0.912	18.7
DKS51-90	5.50	5.51	0.947 (4)	1.00	0.999	1.44
DKS54-00	4.97	4.77	0.890 (15)	.778	0.933	13.2
NK8416	5.35	5.39	1.41 (5)	.729	0.958	12.9
NK8828	4.20	4.27	0.736 (8)	.409	0.785	23.5
Pioneer 83G66	4.84	4.62	0.695 (14)	.759	0.913	17.0
Evaluation						
A571	4.32	4.18	1.09 (10)	.820	0.936	18.1
DKS51-90	4.14	4.25	0.907 (8)	.704	0.913	20.7
DKS54-00	4.68	4.51	0.952 (12)	.738	0.920	15.8
NK8416	5.55	5.10	0.679 (4)	.805	0.891	11.8
NK8828	3.90	3.80	1.21 (5)	.626	0.847	28.4
Pioneer 83G66	4.54	4.36	0.747 (13)	.528	0.842	21.6

Note. RMSEn, normalized root mean square error.

[a]The slope of the linear regression was between simulated (x) and observed (y) grain yield.

[b]Number in parentheses indicates the number of observations for the linear regression.

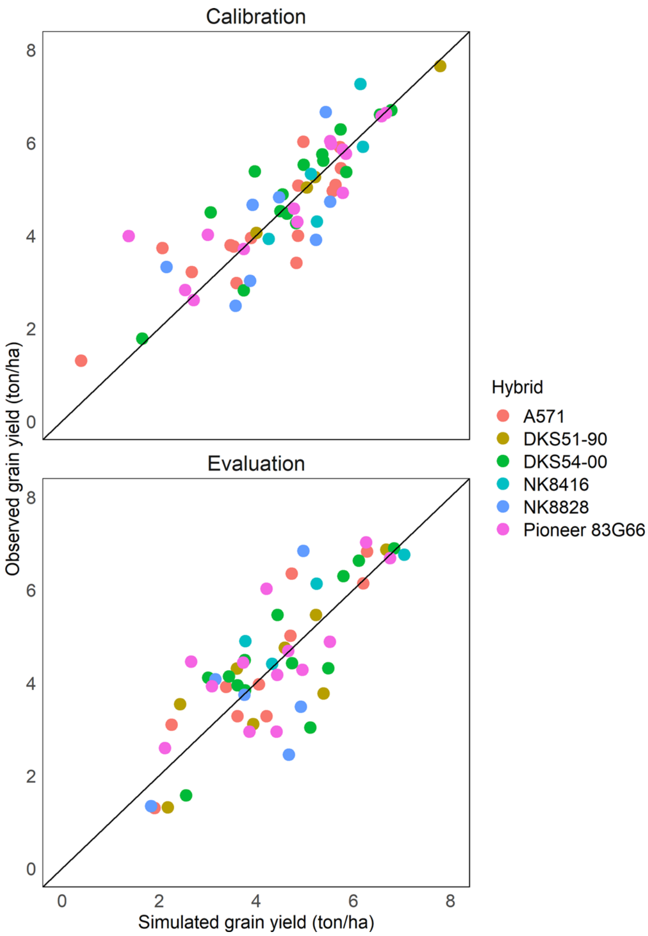

FIGURE 2 Observed vs. simulated grain yield for model calibration and evaluation based on the variety trial data of six grain sorghum hybrids conducted in Georgia and Florida from 2000 to 2006. For model calibration, $y = 0.795x+1.04$, $R^2 = .727$, $d = 0.919$, RMSEn = 16.2%. For model evaluation, $y = 0.909x+0.474$ $R^2 = .626$, $d = 0.852$, RMSEn = 24.1%. In each figure, the line is 1:1

lated and observed yield ranged from 0.695 for hybrids A571 and Pioneer 83G66 to 1.41 for the hybrid NK8416, while the hybrid DKS51-90 had a slope (0.947) closest to 1 among the six hybrids. The value for R^2 ranged from .409 for the hybrid NK8828 to 1.00 for the hybrid DKS51-90, while the *d*-stat ranged from 0.785 for the hybrid NK8828 to 0.999 for the hybrid DKS51-90. The RMSEn ranged from 1.44% for the hybrid DKS51-90 to 23.5% for the hybrid NK8828. When combining all data for different hybrids for model calibration, the slope of linear regression was 0.795 with a value for R^2 of .727, while the *d*-stat was 0.919 and the RMSEn was 16.2% (Figure 2).

3.2 | Model evaluation

For model evaluation, simulated grain yield was compared with observed values from an independent set of variety trial data (Table 5). For the hybrid NK8828, the simulated yield was very similar to the observed yield. For the hybrid DKS51-90, grain yield was slightly overestimated, while it was underpredicted for the other four hybrids. The slope of the linear regression ranged from 0.679 for the hybrid NK8416 to 1.21 for the hybrid NK8828, while the hybrid DKS54-00 had a slope of 0.952 that was closest to 1 among the six hybrids. The value for R^2 ranged from .528 for the hybrid Pioneer 83G66 to .820 for the hybrid A571, and the value for *d*-stat ranged from 0.842 for the hybrid Pioneer 83G66 to 0.936 for the hybrid A571. The RMSEn ranged from 11.8% for the hybrid NK8416 to 28.4% for the hybrid NK8828. When combining the set of data for all six hybrids for model evaluation, the slope of linear regression was 0.909 with the R^2 value of .626. The *d*-stat was 0.852, and the RMSEn was 24.1% (Figure 2).

Using the genetic coefficients derived from the variety trial data (Table 4), the model was used to simulate crop growth of the hybrid Pioneer 83G66 for the growth analysis experiment conducted in Tifton in 2012 (Table 1). The LAI and aboveground biomass that were collected during the growing season were compared with the observed values. For LAI, the *d*-stat was 0.986 and the RMSEn was 7.95% (Figure 3a). For aboveground biomass, the *d*-stat was 0.939 and the RMSEn was 26.9% (Figure 3b).

3.3 | Long-term simulation scenarios

Under rainfed conditions, simulated grain yield in the Blue Ridge Mountains (i.e., 5.42 t ha^{-1} at Blairsville) was the highest, followed by the Limestone Valley (i.e., 4.84 t ha^{-1} at Calhoun) and the Coastal Plain, including Camilla (4.14 t ha^{-1}), Plains (4.03 t ha^{-1}), Tifton (4.02 t ha^{-1}), and Midville (3.85 t ha^{-1}) (Figure 4). The lowest grain yield was simulated in the Piedmont, including Watkinsville (2.86 t ha^{-1}), Athens (2.83 t ha^{-1}), and Eatonton (2.78 t ha^{-1}). Despite the higher mean grain yield, yield variability at Blairsville was the highest with the distance between the 75th and 25th percentiles (i.e., interquartile range [IQR]) of 4.46 t ha^{-1}. For the low-yielding locations in the Piedmont, the IQR of simulated grain yield ranged from 1.86 to 1.98 t ha^{-1}.

Simulated grain yield under rainfed conditions generally decreased with delayed sowing dates (Figure 4). For the Blue Ridge Mountains (i.e., Blairsville), simulated grain yield with the sowing date of 15 May was greater than the other sowing dates, while sowing sorghum before mid-May was associated with high yield variability (the IQR ranged from 3.60 to 4.61 t ha^{-1}) and possibly subject to a high risk for seasons with a low yield. For the Limestone Valley (i.e., Calhoun), the Piedmont (i.e., Athens, Watkinsville, Eatonton, Griffin), and Plains, sorghum planted between 15 April and 15 May (the IQR ranged from 2.03 to 4.06 t ha^{-1}) had a higher grain yield than the sowing dates of 1 and15 July (the IQR ranged

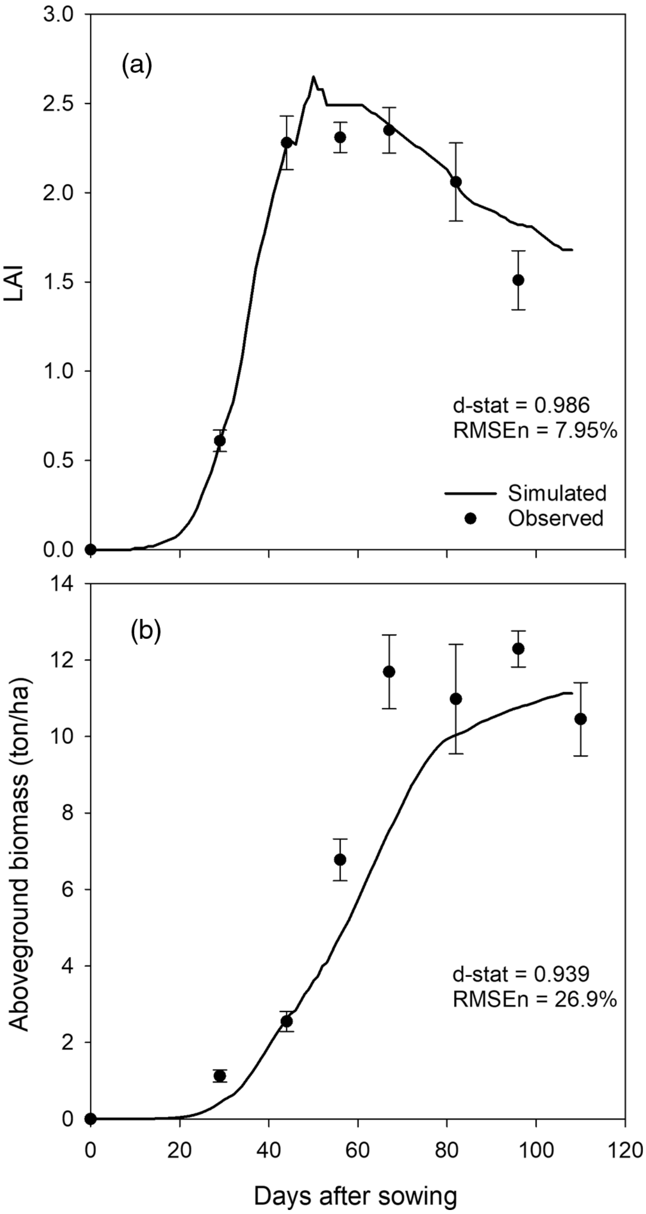

FIGURE 3 (a) Simulated and observed leaf area index (LAI) and (b) aboveground biomass as a function of days after sowing for the grain sorghum hybrid Pioneer 83G66 for the experiment conducted in Tifton, GA, in 2012 (Table 1)

from 1.08 to 2.05 t ha^{-1}). For the Coastal Plain (e.g., Midville, Tifton, and Camilla), grain sorghum planted on 1 and 15 July (the IQR ranged from 1.49 to 2.03 t ha^{-1}) had a lower grain yield than the sowing dates between 15 April and 1 June (the IQR ranged from 2.01 to 3.18 t ha^{-1}). Rainfed sorghum with early sowing dates produced high grain yields but they were associated with a large yield variability (i.e., IQR).

Under irrigated conditions, the highest simulated grain yield was in Griffin (7.27 t ha^{-1}), followed by Calhoun (7.00 t ha^{-1}), Watkinsville (6.97 t ha^{-1}), Blairsville (6.82 t ha^{-1}), and Eatonton (6.81 t ha^{-1}); the lowest grain yield was for Plains (5.76 t ha^{-1}) (Figure 5). In addition to the higher mean grain yield, the yield variability for Griffin was among the smallest with an IQR of 2.17 t ha^{-1}. By contrast, the IQR of simulated grain yield at Blairsville was the highest at 5.47 t ha^{-1}. For the other locations, the IQR ranged from 2.13 t ha^{-1} for Plains to 2.72 t ha^{-1} for Calhoun.

Simulated grain yield under irrigated conditions significantly decreased with delayed sowing dates (Figure 5). Simulated grain yield for the sowing dates of 15 and 1 July was below the 25th percentile for all 10 locations. For Blairsville, simulated grain yield with the sowing date of 1 May was higher than 15 April, and the IQR ranged from 1.15 for the 15 July sowing date to 2.20 t ha^{-1} for the 15 April sowing date. For the other nine locations, the IQR for each sowing date was <2.0 t ha^{-1}.

Under both rainfed and irrigated conditions, the hybrids DKS51-90, NK8416, and Pioneer 83G66 had a higher simulated grain yield than the hybrids NK8828 and DKS54-00 for all 10 locations and seven sowing dates (Figures 4 and 5). The higher grain yield potential of the hybrids DKS51-90, NK8416, and Pioneer 83G66 agrees with their high values of G2 that controls assimilate allocation to reproductive growth (Table 4). Under irrigated conditions, hybrid DKS54-00 exhibited a IQR of 1.51 t ha^{-1}, and for the other five hybrids, the IQR ranged from 2.38 t ha^{-1} for hybrid NK8828 to 3.33 t ha^{-1} for hybrid Pioneer 83G66. Under rainfed conditions, the IQR ranged from 2.62 to 2.74 t ha^{-1} for the six hybrids.

4 | DISCUSSION

Our results indicate that the CSM–CERES–Sorghum model can be calibrated and evaluated using limited data from variety trials that were conducted at multiple locations over several growing seasons. The RMSEn between the simulated and observed grain yield ranged from 1.4 to 19% for model calibration and from 12 to 22% for model evaluation, except for the hybrid NK8828 (Table 5), suggesting a good match between simulated and observed yield (Soler et al., 2007). The hybrid NK8828 exhibited larger discrepancies between simulated and observed grain yield, which probably resulted from a smaller dataset that was available for model calibration and evaluation compared to the other hybrids.

For the long-term scenarios, variability (i.e., IQR) of the simulated grain yield under rainfed conditions was large (Figure 4), suggesting a larger year-to-year variation in weather variables, mostly due to the annual variation for the rainfall amount and distribution (Table 3). In contrast, the IQRs were smaller under irrigated conditions as irrigation removes the variability due to rainfall (Figure 5). Additionally, simulated grain yield in the Piedmont was among the lowest under rainfed conditions, but the highest under irrigated conditions (Figures 4 and 5). Thus, applying irrigation signifi-

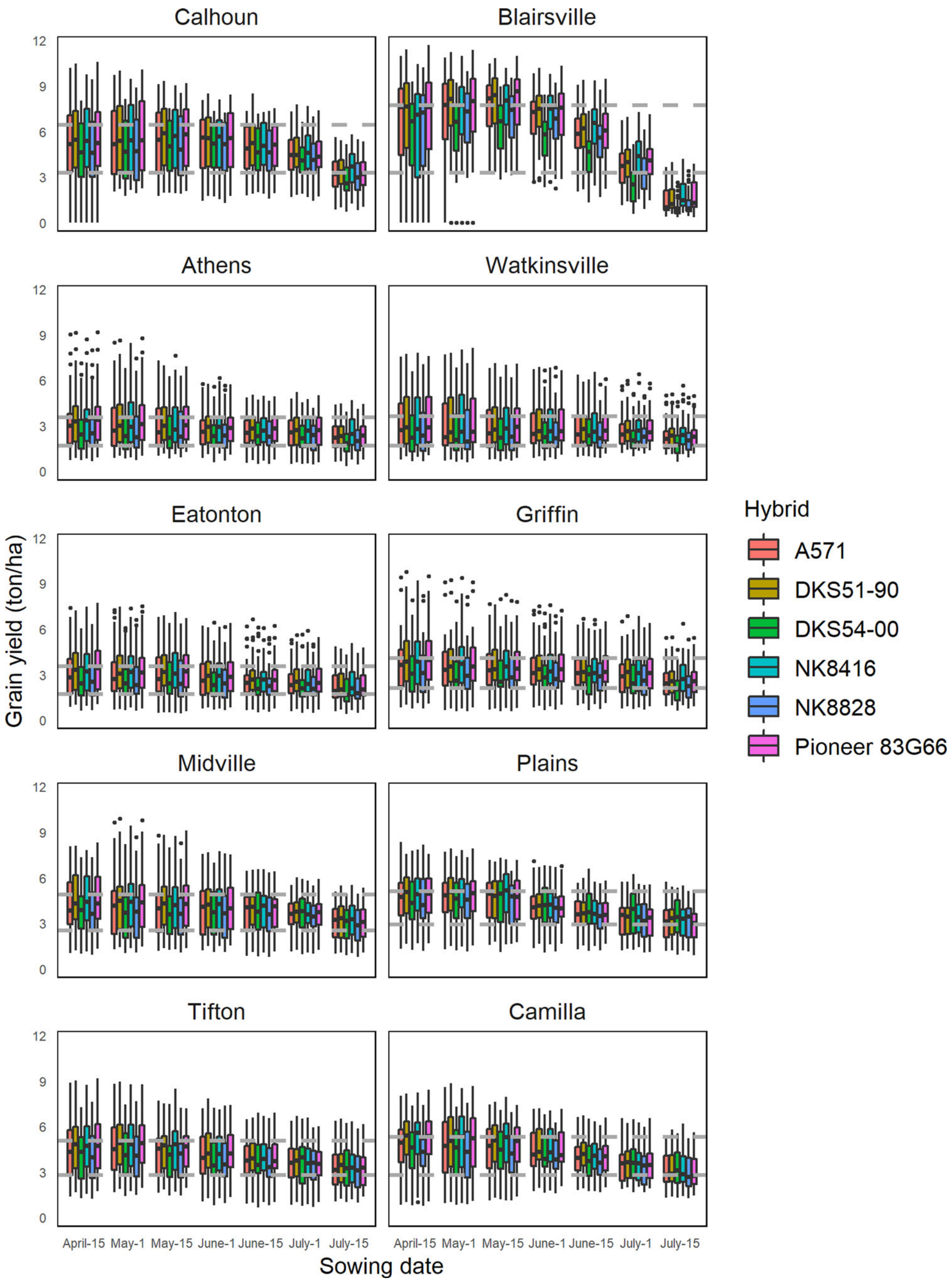

FIGURE 4 Simulated grain yield for the six grain sorghum hybrids under rainfed conditions from 1966 to 2005 for 10 locations in Georgia. The dashed lines indicate the 25th and 75th percentiles of simulated grain yield at each location across all hybrids and sowing dates. The lower and upper ends of the box indicate the 25th and 75th percentiles of grain yield, respectively, and the line inside the box indicates the median. The lower and upper whiskers represent the lower and upper 25% of grain yield, respectively

cantly reduces the impact of rainfall variability and ensures a higher crop yield. Simulated grain yield in the Limestone Valley (e.g., Blairsville) and Blue Ridge Mountains (e.g., Calhoun) was among the highest under both rainfed and irrigated conditions (Figures 4 and 5). The high grain yield for these two regions could be related to the lower daily maximum air temperature that results in less heat stress (Table 3) (Manunta & Kirkham, 1996; Prasad et al., 2015). The soil textures at Blairsville and Calhoun are clay loam and loam, respectively, which have more plant available water than the sandy clay loam in the Piedmont, and the sandy loam and loamy sand in the Coastal Plain (Liang et al., 2016; Perkins et al., 1982, 1986). These fine textures enable the soil to store more moisture rather than draining rapidly out of the root zone after rainfall and irrigation inputs, which maintains crop growth during dry spells between rainfall and/or irrigation events. However, we need to acknowledge the limitations in our simulations that only one soil type was used at each location, which might not

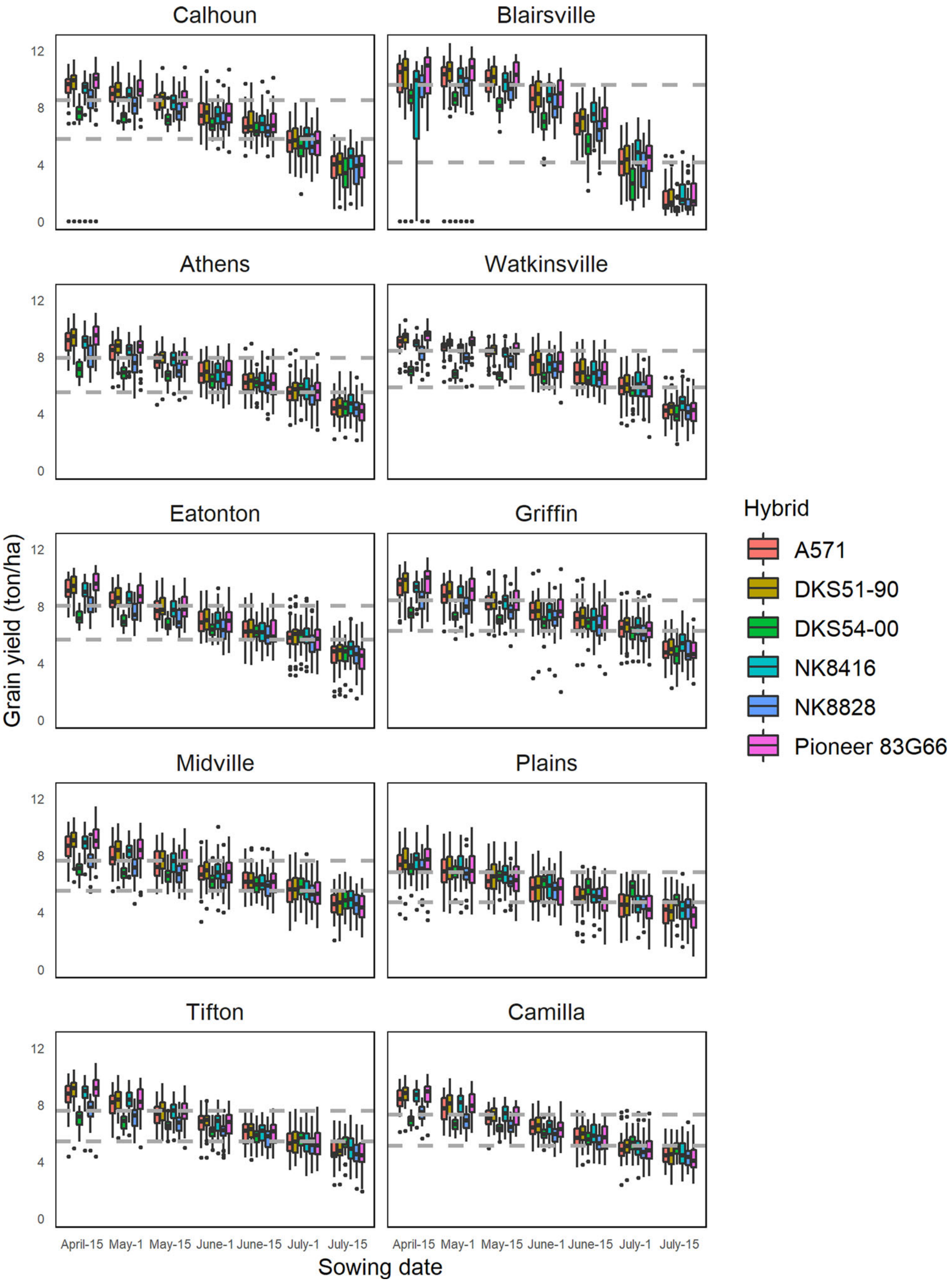

FIGURE 5 Simulated grain yield for six grain sorghum hybrids under irrigated conditions from 1966 to 2005 for 10 locations in Georgia. The dashed lines indicate the 25th and 75th percentiles of simulated grain yield at each location across all hybrids and sowing dates. The lower and upper ends of the box indicate the 25th and 75th percentiles of grain yield, respectively, and the line inside the box indicates the median. The lower and upper whiskers represent the lower and upper 25% of grain yield, respectively

be representative of all soil types in a certain region. The crop yield may be subject to change in simulations using a different soil type, especially under rainfed conditions.

Simulated grain yield generally decreased with a delay in sowing for both rainfed and irrigated conditions (Figures 4 and 5), suggesting that late sowing dates increase the risk of low grain yield. For the latest sowing dates, that is, 1 and 15 July, the anthesis phase ranged from late August to mid-September. Daily solar radiation gradually declined from August to September (Table 3), which decreases the crop growth rate and assimilate accumulation for yield formation (Muchow et al., 1990; Seshu & Cady, 1984). Besides solar radiation, daily minimum temperature also decreased in September (Table 3). Low temperatures (e.g., 13–15 ˚C) during flowering are reported to significantly reduce the number of grains per panicle and hence grain yield (Maulana & Tesso, 2013). Furthermore, for late planting dates, sorghum might not reach physiological maturity before the occurrence of the first fall freeze (Mauget et al., 2020). Delayed sowing sorghum could be even worse for more northern locations in Georgia such as the Limestone Valley and the Blue Ridge Mountains that have earlier first frost dates compared to the other regions of Georgia and Florida.

Early sowing, for example, before 1 May, is susceptible to total yield loss under extreme weather conditions and associated with a large year-to-year variability (Figure 4–5). For instance, for Blairsville, the lowest grain yield was simulated when planted on 15 April in 1976, 1977, 1979, 1984, 1988, and 2002, as well as on 1 May in 1979, 1984, and 1988 (Figures 4 and 5). Simulated grain yield was also close to zero for the 15 April sowing date in 2003 at Calhoun. The failure in grain production for early sowing in these years could be due to low temperatures below the T_{base}, which causes a slow development rate and a low crop growth rate. This results in small LAI and aboveground biomass production, and thus a significant reduction in grain filling (Maulana & Tesso, 2013; Maulana et al., 2017; Yu et al., 2004). Therefore, a high yield could be achieved via adjusting sowing dates. Early sowing dates in mid-April are more suitable for the southern regions in Georgia, whereas postponing sowing until early May could reduce the risk of yield loss due to early-season low temperatures in northern areas (e.g., the Limestone Valley and Blue Ridge Mountains).

Some sorghum hybrids, that is, DKS51-90, NK8416, and Pioneer 83G66 had a high simulated yield under both rainfed and irrigated conditions (Figures 4 and 5). This could be attributed to their higher values for the G2 cultivar coefficient that controls the allocation to reproductive growth, resulting in a higher grain yield potential (Table 4) (Adam et al., 2018). Despite differences in grain yield among the six hybrids that were tested in this study, they are generally high-yielding hybrids in Georgia, Texas, and the mid-Atlantic area, for example, Virginia, South Carolina, and North Carolina, and have a medium to late maturity (State Grain Sorghum Hybrid Yield Performance Results of 2010 and State Grain Sorghum Hybrid Yield Performance Results of 2013). Late-maturity hybrids are more suitable for favorable environments such as irrigated conditions and early sowing dates (Baumhardt & Howell, 2006; Wade & Douglas, 1990), which enable these hybrids to approach their yield potential with sufficient thermal time and little impact of drought stress during their reproductive growth. That could explain the large variation in grain yield under rainfed conditions and the low yield from delayed sowing dates of the current study (Figures 4 and 5). On the other hand, early-maturity hybrids may be superior in environments subject to drought stress, for example, rainfed and dryland, and may complete grain filling prior to severe drought stress later during the growing season when grain filling occurs (Wade & Douglas, 1990). Hybrid selection should thus consider the compatibility with environmental conditions and management practices.

Our study exhibited sorghum yield variability in the southeastern United States and identified the potential locations, hybrids, and sowing dates that can obtain a high sorghum yield under either rainfed or irrigated conditions. The results demonstrate a model-based approach for estimating the impact of climate variability on crop production as well as optimizing management practices for improving crop yield and reducing risks of yield losses. Such approaches could also be applied to other crops and crop production in other areas and assist in decision making to optimize farming outcomes.

ACKNOWLEDGMENTS

This work was supported by the Southeast Climate Consortium. We are grateful to Dr. Yawen Bao for providing the historical weather data, Mr. Herman Henry and Rodney Hill, and Dr. Vasilis Liakos for their laboratory and field support.

AUTHORSHIP CONTRIBUTIONS

Xi Liang: Conceptualization, Data curation, Formal analysis, Methodology, Writing - original draft, Writing - review & editing. **Gerrit Hoogenboom**: Funding acquisition, Conceptualization, Methodology, Writing - review & editing. **Stamatia Voulgaraki**: Investigation, Data curation. **Kenneth J. Boote**: Conceptualization, Methodology, Writing - review & editing. **George Vellidis**: Funding acquisition, Project administration, Supervision, Resources.

CONFLICT OF INTEREST

The authors declare no conflict of interest.

ORCID

Xi Liang https://orcid.org/0000-0001-8749-8267
Gerrit Hoogenboom https://orcid.org/0000-0002-1555-0537

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How to cite this article: Liang, Xi, Hoogenboom, G., Voulgaraki, S., Boote, K. J., & Vellidis, G.. Deriving genetic coefficients from variety trials to determine sorghum hybrid performance using the CSM-CERES-Sorghum model. *Agronomy Journal*. 2021;*113:*2591–2606. https://doi.org/10.1002/agj2.20644