water

MDPI

Article

Comparing CSM-CROPGRO and APSIM-OzCot Simulations for Cotton Production and Eddy Covariance-Based Evapotranspiration in Mississippi

Amitava Chatterjee [1,*] and Saseendran S. Anapalli [2]

[1] Water Quality & Ecology Research Unit, USDA-ARS, Oxford, MS 38655, USA
[2] Sustainable Water Management Research Unit, USDA-ARS, Stoneville, MS 38776, USA
* Correspondence: amitava.chatterjee@usda.gov

Abstract: Optimizing irrigation water use efficiency (WUE) is critical to reduce the dependency of irrigated cotton (*Gossypium* spp.) production on depleting aquifers. Cropping system models can integrate and synthesize data collected through experiments in the past and simulate management changes for enhancing WUE in agriculture. This study evaluated the simulation of cotton growth and evapotranspiration (ET) in a grower's field using the CSM-CROPGRO-cotton module within the Decision Support System for Agrotechnology Transfer (DSSAT) and APSIM (Agricultural Production Systems simulator)-OzCot during 2017–2018 growing seasons. Crop ET was quantified using the eddy covariance (EC) method. Data collected in 2017 was used in calibrating the models and in 2018 validating. Over two cropping seasons, the simulated seedling emergence, flowering, and maturity dates were varied less than a week from measured for both models. Simulated leaf area index (LAI) varied from measured with the relative root mean squared errors (RRMSE) ranging between 20.6% to 38.7%. Daily ET deviated from EC estimates with root mean square errors (RMSEs) of 1.90 mm and 2.03 mm (RRMSEs of 63.1% and 54.8%) for the DSSAT and 1.95 mm and 2.17 mm (RRMSEs of 64.7% and 58.8%) for APSIM, during 2017 and 2018, respectively. Model performance varied with growing seasons, indicating improving ET simulation processes and long-term calibrations and validations are necessary for adapting the models for decision support in optimizing WUE in cotton cropping systems.

Keywords: leaf area index (LAI); irrigation; Mississippi Delta region; eddy-covariance (EC); evapotranspiration (ET)

check for updates

Citation: Chatterjee, A.; Anapalli, S.S. Comparing CSM-CROPGRO and APSIM-OzCot Simulations for Cotton Production and Eddy Covariance-Based Evapotranspiration in Mississippi. *Water* **2022**, *14*, 4022. https://doi.org/10.3390/w14244022

Academic Editors: Xiukang Wang and Guang Yang

Received: 29 October 2022
Accepted: 6 December 2022
Published: 9 December 2022

1. Introduction

The United States of America (USA) remains a major producer and leading cotton exporter, ranking third in the world [1]. The lower Mississippi Delta (Delta) region generally ranks number two as a producer of US upland cotton (*Gossypium hirsutum*). Cotton is sensitive to water stress particularly during the flowering stage, and scheduling irrigation should consider crop evapotranspiration (ET) estimates [2,3]. In the Delta region, over-pumping (i.e., beyond natural discharge rates) for irrigation of over four million hectares of cropland is fast depleting the Mississippi River Valley alluvial aquifer, which provides 90% of the irrigation water applied [4,5]. Precise quantification and planning of crop water demand and supplies are necessary to protect against further groundwater depletion and sustain irrigated agricultural production in the region [6].

In the Delta region, although mean annual rainfall receipts were about 1306 mm; only about 30% of annual rainfall coincides with the growing season, forcing growers to irrigate with groundwater to achieve economic crop yields [7,8]. In addition, high intensity rainfall events are common during this period resulting in mostly surface run off. Only a small portion of the rainfall infiltrates into the soil profile and becomes available for plant use. Based on 1915–2015 weather data, cotton irrigation requirements in the Delta region ranged from 62 to 293 mm year^{-1} (mean value of 163 mm) in normal years, from 0 to 202 mm year^{-1} (mean value of 118 mm) in wet years, and from 144 to 353 mm year^{-1} (mean value of 233 mm) in dry years [9]. Major challenges in irrigated agriculture are to decide the time and quantity of irrigation based on the critical growth stage of the crop to irrigate and the optimum life cycle to take advantage of available soil water and precipitation [10].

Evapotranspiration (ET) is a multifaceted variable, comprises of interception loss, evaporation from soil and transpiration from the crop canopy. At a global scale, land ET significantly rise at a rate of 0.31 mm year^{-1} during 1982–2016 indicating a 2.2% increase over last 35 years [11]. Quantification of ET is an essential prerequisite for precise irrigation scheduling responding to weather [3,12]. Because direct measure of ET is challenging, alternatively ET can be physically derived as an energy variable [13]. Among various methods to quantify ET from cropping systems, eddy covariance (EC) has emerged as a scientifically sound method for continuous data collection. It provides reliable ET estimates for irrigation water scheduling [2,14]. The response of ET to crop management is dynamic, location-specific, and controlled by prevailing weather conditions, crop type, and cultivar characteristics [6]. However, applying EC for ET measurements involves deploying highly technical and expensive instrumentation. In this context, agricultural system models are inexpensive, viable, and widely recognized state of the science tools for estimating location-specific ET data for irrigation scheduling and crop response to irrigation. The crop simulation models available through the Decision Support System for Agrotechnology Transfer (DSSAT) and Agricultural Production System Simulator (APSIM) software packages allow simulations of crops across a wide range of soil-crop-water management systems [14–17]. Evaluation of these models must include verifications against experimental datasets for crop growth and water dynamics in agricultural systems over time and space [18]. However, most cropping system simulation model calibration and validation studies were limited to comparisons with small plot-scale data and attempts at collecting and using crop-ET responses to management in large-scale cotton fields are scarce [19]. The objectives of this study were to (i) compare cotton growth and yield simulations of DSSAT-CSM-CROPGRO-cotton and APSIM-OzCot-cotton models with observed values, and (ii) compare ET predictions from these two models with EC estimates, in a humid climate of the Lower Mississippi River Delta during 2017 and 2018 growing seasons.

2. Materials and Methods

2.1. Field Experiment

The field experiment was conducted on grower's field (>25 ha) located near Stoneville, Mississippi (33.467, −90.875). The soil was a poorly drained, silty clay and classified as Forestdale, Fine, Smectitic, thermic, Typic Endoaqualfs. The soil was tilled to break clay pans and overturn soils for burying crop residues and killing weeds in three passes, followed by another tillage to generate furrows and ridges for planting to facilitate furrow irrigations. Cotton (cv. Deltapine 1522) was planted at 103,740 ha^{-1} on 22 April and 10 May during 2017 and 2018 growing seasons, respectively. Cotton was planted on ridges with 97 cm row spacing and fertilizer nitrogen (N) in the form of urea at the rate of 200 kg N ha^{-1} was applied after emergence. Irrigations (~400 mm) were applied on 24 July 2017, and 18 July 2018. A plant growth regulator, Mepiquat chloride, was applied to control plant stem elongation, leaf expansion, and excessive vegetative growth. Field combine was used to harvest and weigh seed-cotton on 18 September 2017, and 15 October 2018.

2.2. Eddy Covariance Estimates of Evapotranspiration (ET)

The EC instrumentation, data collection protocols, and data analysis were described in detail in [20]. The Eddy towers were located in the middle of cotton fields of over 250 ha, providing enough fetch for wind from all directions (an omnidirectional 3D anemometer was used in the EC system as well), there was no need for further 'footprint analysis' to justify the footprint of ET measurements. Vertical transport of eddies from the field was measured using a Gill New Wind Master 3D sonic anemometer at 10 Hz (Gill Instruments, UK). Water vapor densities in eddies were measured using LI-7500-RS open-path infrared gas analyzers (LI-COR Inc., Lymington, NE, USA). These sensors were placed in the constant flux layer above the canopy by mounting on the telescopic height adjustable quadrupled towers. Sensors for measuring net radiation (NR-LITE2, Kipp & Zonen B.V., Lincoln, The Netherlands), air relative humidity, temperature (Ta) (HMP 155, Vaisala, Helsinki, Finland), and wind direction and speed (Gill 2D-Sonic, Gill Instruments), were maintained 2 m above the canopy within the field along with EC sensor. Three self-calibrating soil heat flux sensors (HP01SC, Huskeflux Thermal Sensors B.V., Lincoln, The Netherlands) were installed at 8 cm depth below the soil surface. HydraProbes were used to monitor the water and temperature of the 8 cm soil layer above the flux plates. All measurements and data were from cotton planting to harvest. Collected data were processed on a SmartFlux microprocessor (LI-COR Inc.) with the EddyPro software Version 7.0 (LI-COR Inc.). Leaf area index (LAI) was measured at biweekly intervals using an AccuPAR LP 80 Ceptometer (Decagon Devices, Inc., Pullman, WA, USA). The soil heat flux (GO) was calculated by measuring heat flux at 8 cm depth and accounting for heat storage in the layer above it. The gaps in the flux and micrometeorological data were filled using the REddyProc package available online from the Max Planck Institute for Biogeochemistry (https://www.bgcjena.mpg.de/bgi/index.php/Services/REddyProcWebRPackage, accessed on 7 December 2022).

2.3. DSSAT-CSM-CROPGRO Cotton Module

The DSSAT is a modeling platform that ensembles the database management system (soil, climate, and management practices), crop models, and various programming applications including sensitivity analysis and spatial analysis [15,21]. The DSSAT CSM-CROPGRO-Cotton model simulates different cotton growth stages such as emergence, first leaf, first flower, first seed, first cracked boll, and 90% open boll based on the heat unit accumulation and photoperiod responses [17,22]. The soil water balance module is the driving component to estimate ET as it determines the amount of water uptake by plant roots. Two major steps in ET determination with the DSSAT system are calculating potential ET (PET) from weather data, then partitioning into potential soil evaporation and transpiration, and modifying of these two components from the feedback from crop growth and root water uptake modules.

The model has options for simulating PET using either Priestly-Taylor [23] or FAO-56 [24]. Water deficit stress is simulated when the potential demand for water lost through plant transpiration is greater than the amount of water supplied by the soil through the simulated root system. The amount of water soil supplies is a function of its water holding capacities, as defined by model inputs for the drained upper limit and lower limit. When DSSAT simulates PET with Priestly-Taylor and FAO-56 methods, FAO-56 was found to be more accurate in simulations [25]. We also obtained better simulation results with the FAO-56, which was used in the simulations.

The FAO-56 Penman-Monteith equation used was

$$ET_O = \frac{0.408\Delta(R_n - G) + \gamma\frac{900}{T+273}u_2(e_s - e_a)}{\Delta + \gamma(1 + 0.34u_2)}$$

ET_O = grass reference-crop evapotranspiration to which a model built-in crop coefficient was applied to get PET (mm d^{-1}), λ = latent heat of vaporization (kPa °C^{-1}), R_n = net radiation (MJ m^{-2} d^{-1}), γ = psychometric constant (kPa °C^{-1}), e_s = saturation vapor pressure (kPa), e_a = actual vapor pressure (kPa), Δ = slope of the vapor pressure-temperature curve (kPa °C^{-1}), T = air temperature, u_2 = wind speed at 2 m height (m s^{-1}).

The daily soil evaporation rate in the default DSSAT code follows the Suleiman-Ritchie method [26]. The SR method computes soil evaporation rate based on water loss from the entire soil profile depth based on transfer coefficients per layer dependent on soil texture and water contents. Actual soil evaporation is the minimum of either potential soil evaporations or SR computed evaporation.

2.4. APSIM-OzCot

Cotton growth and ET were simulated using the APSIM Version 7.10 r4220 (APSIM Initiative, CSIRO, Canberra, Australia) cotton module [14,27,28]. The APSIM modeling framework comprises cropping system biophysical modules, management modules, and a simulation engine. Plant modules simulate key processes on a daily time step in response to daily weather data, soil characteristics, and crop management actions. Leaf area production and senescence are simulated through relationships of leaf initiation rate, leaf appearance rate, and plant leaf area with temperature. Potential crop water uptake is simulated through relationships with root exploration and extraction potential, controlled by soil and crop characteristics. Soil water balance in the model is governed by two approaches, cascading layer, and Richard's equation methods. Evaporation is based on PET and modified according to the cover provided by surface residue or growing plant. For the calculation of soil evaporation, the Ritchie model separates into two stages as followed in DSSAT models. First, the evaporation rate equals the potential evaporation rate until a specified amount of water has evaporated (U or CONA, the upper limit of evaporation rate). Second, evaporation is proportional to the square root of time, and its rate is lower than the rate of potential evaporation. Crop transpiration in the APSIM is the Penman-Monteith water demand, derived from the energy balance equation of the crop canopy.

2.5. Cropping System Model Inputs

Daily maximum and minimum temperature, incoming solar radiation, and precipitation were obtained from the Stoneville Agricultural weather station (Delta Agriculture Weather Center, http://deltaweather.extension.msstate.edu/, accessed on 28 October 2022) close to the experimental site. The soil parameters for the Forestdale soil series of the experimental site were obtained from National Cooperative Soil Survey [29], presented in Table 1. The crop management related model inputs (plant population, row spacing, fertilizer, irrigation, tillage) were based on the actual practices followed in the field experiment. Irrigation was scheduled similar to the field study. For APSIM, the initial soil water storage was set at 50% of field capacity and filled from top. Cultivar parameters used in the simulations were parametrized by matching days of emergence, flowering, and maturity with the actual observations. Final calibrated values for the cultivar coefficients used in the simulations are listed in Table 2 for DSSAT-CSM-CROPGRO-cotton and Table 3 for APSIM-OzCot. For the calibration of the model parameters, we used 2017 growing season and 2018 growing season data for the validation. However, the calibration and validation did not vary substantially and only two growing season data were involved, we presented results together.

Table 1. Soil parameters for Forestdale soil series in the simulation for both growing seasons using CSM-CROPGRO-cotton and APSIM-OzCot-cotton models.

Soil Depth (cm)	Clay %	Silt %	OC %	Total N%	pH	CEC (cmol kg^{-1})	θ_{wp} (cm^3 cm^{-3})	θ_{fc} (cm^3 cm^{-3})	θ_S (cm^3 cm^{-3})	BD (Mg m^{-3})	K_S (cm h^{-1})
0–13	32.0	59.6	2.0	0.12	7.5	22.0	0.211	0.350	0.463	1.5	0.39
14–32	40.3	52.5	1.2	0.05	7.3	23.7	0.228	0.350	0.463	1.5	0.29
33–49	42.1	51.4	1.0	0.07	6.6	24.7	0.228	0.330	0.435	1.5	0.29
50–96	41.9	54.3	1.0	0.06	5.1	26.6	0.228	0.400	0.418	1.5	0.29
97–119	34.5	60.9	0.5	0.04	5.9	26.0	0.228	0.350	0.459	1.5	0.19
120–127	45.1	50.6	0.5	0.07	6.4	29.4	0.228	0.406	0.461	1.5	0.19
128–150	44.7	48.0	0.5	0.04	6.0	30.3	0.249	0.406	0.461	1.5	0.19

Note(s): OC: Soil organic carbon; CEC: cation exchange capacity; BD: soil bulk density; θS: saturated water content; θwp: drained lower limit, θfc: drained upper limit of water content, KS: Saturated Hydraulic conductivity.

Table 2. Cultivar parameters used for simulating cotton (cv. Deltapine Land 1522) using the CSM-CROPGRO-cotton v4.6.

Parameters	Definition	Value
CSDL	Critical short-day length below which reproductive development progress with no day in length effect (for short day plants) (h)	23.0
PPSEN	The slope of the relative response of development to photoperiod with time (positive for short-day plants) (h^{-1})	0.01
EM-FL	Time between plant emergence and flower appearance (R1) (photothermal days)	41.0
FL-SH	Time between first flower and first pod (R3) (photothermal days)	11.9
FL-SD	Time between first flower and first seed (R5) (photothermal days)	17.7
SD-PM	Time between first seed (R5) and physiological maturity (R7) (photothermal days)	32.81
FL-LF	Time between first flower (R1) and end of leaf expansion (photothermal days)	68.28
LFMAX	Maximum lead photosynthesis rate at 30 °C, 350 ppm CO_2, and high light (mg CO_2/m^2s)	1.00
SLVAR	Specific leaf area of cultivar under standard growth condition (cm^2/g)	180
SIZLF	Maximum size of full lead (three leaflets) (cm^2)	300
XFRT	Maximum fraction of daily growth that is partitioned to seed + shell	0.80
WTPSD	Maximum weight per seed (g)	0.180
SFDUR	Seed filling duration for pod cohort at standard growth conditions (photothermal days)	31.2
SDPDV	Average seed per pod under standard growing conditions (#/pod)	25.00
PODUR	Time required for cultivar to reach final pod load under optimal conditions (photothermal days)	14.2
THRSH	Threshing percentage. The maximum ratio of (seed/(seed + shell)) at maturity. Causes seed to stop growing as their dry weight increases until the shells are filled in a cohort.	70.0
SDPRO	Fraction protein in seeds (g(protein)/g(seed))	0.153
SDLIP	Fraction oil in seeds (g(oil)/g(seed))	0.120

Table 3. The main parameters of the APSIM-OzCot-cotton module used in the experiment.

Parameters	Definition	Value
PERCENT_I	The percent lint per boll	42.0
SCBOLL	The seed cotton per boll	4.0
RESPCON	Respiration constant	0.023
SQCON	Squaring constant for generating sites per day	0.021
FCUTOUT	Constant used to determine when site production stops due to boll load	0.45
FLAI	Varietal adjustment for the rate of LAI gain per fruiting site	0.87
DDISQ	Daydegrees accumulation to first square (°C d)	390
RLAI	Base rate of leaf growth pre-first square	0.015
BckGndRetn	Rate of underlying retention of fruit	0.9
FRUDD1	Cumulative day-degrees for each growth phase of fruit development	45
FRUDD2	Cumulative day-degrees for each growth phase of fruit development	169
FRUDD3	Cumulative day-degrees for each growth phase of fruit development	270
FRUDD4	Cumulative day-degrees for each growth phase of fruit development	290
FRUDD5	Cumulative day-degrees for each growth phase of fruit development	500
FRUDD6	Cumulative day-degrees for each growth phase of fruit development	630
FRUDD7	Cumulative day-degrees for each growth phase of fruit development	876
FRUDD8	Cumulative day-degrees for each growth phase of fruit development	1020

2.6. Statistics

The simulation accuracies of DSSAT and APSIM models were evaluated based on four variables (i) days after planting of three key developmental stages (emergence, flowering, and maturity), (ii) yield, (iii) LAI, and (iv) ET. The simulation results were evaluated using the root mean squared error (*RMSE*), relative RMSE (*RRMSE*), and percentage deviation (*PD*) using the following equations:

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(P_i - O_i)^2}$$
$$RRMSE = \frac{RMSE}{O_{avg}} \times 100$$
$$PD = \left\{\frac{(P_i - O_i)}{O_i}\right\} \times 100$$

where P_i is the ith simulated value, O_i is the ith observed values, O_{avg} is the average of the observed values, and n is the number of data pairs.

3. Results and Discussion

3.1. Climate

Lower Mississippi River Basin has a humid subtropical climate with mild winters and warm summers [30]. According to the Köppen-Geiger climate classification, this region is classified as humid temperate, with precipitation evenly distributed throughout the year. In April 2017 the average maximum and minimum air temperatures were 3.1 °C and 2.6 °C higher than normal. In 2018 April was cooler, but air temperature in May was significantly above normal (Table 4).

Table 4. Maximum and minimum air temperature (°C) and precipitation (mm) of the weather station (Stoneville, MS, USA) close to experimental field during 2017 and 2018 growing seasons, values in bracket indicate deviation from 30 yr. average.

Month	Max. Temp. (°C)	Min. Temp. (°C)	Precipitation (mm)
2017			
April	26.5 (3.1)	14.3 (2.6)	161 (25)
May	27.9 (0.2)	16.2 (−0.3)	97.5 (−28)
June	30.4 (−1.5)	20.0 (−0.6)	136 (38)
July	33.8 (0.7)	22.2 (0)	94.7 (6.9)
August	31.7 (−0.7)	21.6 (0.6)	260 (198)
September	31.1 (1.4)	17.3 (0.2)	21.6 (−62)
2018			
April	21.5 (−1.9)	8.9 (−2.8)	135 (−1.4)
May	31.9 (4.2)	19.6 (3.1)	55.9 (−70)
June	32.8 (0.9)	21.3 (0.7)	78.7 (−18.6)
July	33.2 (0.1)	22.2 (0)	68.3 (−19.5)
August	33.3 (0.9)	21.1 (0.1)	231 (170)
September	31.5 (1.8)	20.6 (3.1)	166 (82.5)

This difference facilitated earlier planting in 2017 than in 2018. For 2017 and 2018, the cumulative growing degree day (GDD) was 1386 °C-day (2526°F-day) and 1796 °C-day (3176 °F-day) based 15.6 °C-day (60 °F-day). Based on the average of the last three decades, the annual total rainfall is 1325 mm. The experimental site received 684 mm and 607 mm of rainfall from planting to harvest, during the 2017 and 2018 growing seasons. For both years, rainfall in May was lower than normal. For both years, August was extremely wet, as indicated by the above-normal monthly rainfall (Table 4).

3.2. Growth Parameters

Seedling emergence, flowering, and the number of days to physiological maturity dates showed a close association between observed and simulated, with error variations ranging from 8 d to 7 d (Table 5). Both models predicted similar seedling emergence for both growing seasons. For 2017, DSSAT and APSIM flowering day predictions were 6 d and 7 d late, respectively, whereas, in 2018, both models predicted 8 and 3 d earlier flowering. The DSSAT model predicted an early maturity by 2 d and 6 d and APSIM predicted a 4 d late and 4 d earlier maturity in 2017 and 2018, respectively. Using the Root zone Water Quality (RZWQM) model, Anapalli et al. (2019) also found days to seedling emergence, flowering, and physiological maturity varied between −5 and +1 days for this experiment [6]. Hussain et al. (2018) concluded that incorporated functions of photoperiod, cardinal temperature, and low temperature sensitivity within APSIM simulation might delay the maturity of wheat with late planting [31]. Response functions for rates and development and sensitivity to various stress factors at various stages are not parallel; the influence of various stress factors on phenology is needed to accurately predict cotton growth [32]. Results obtained in this study show that both the models need improvement in simulating phenology better for crop management applications.

Table 5. Measured and simulated seedling emergence, flowering, number of days to physiological maturity, and yield of cotton in the evapotranspiration-eddy covariance-experiments in 2017–2018.

Growth Stage	Measured (M)	DSSAT		APSIM	
		Simulated (S)	Error (S-M)	Simulated (S)	Error (S_M)
2017 (Calibration)					
Emergence, DAP	9	7	−2	7	−2
Flowering, DAP	60	66	6	67	7
Maturity, DAP	132	130	−2	136	4
Yield, kg ha^{-1}	3937	3973	36	3929	−8
2018 (Validation)					
Emergence, DAP	10	5	−5	5	−5
Flowering, DAP	60	52	−8	57	−3
Maturity, DAP	124	118	−6	120	−4
Yield, kg ha^{-1}	4699	4811	112	4610	−89

Note(s): DAP = days after planting.

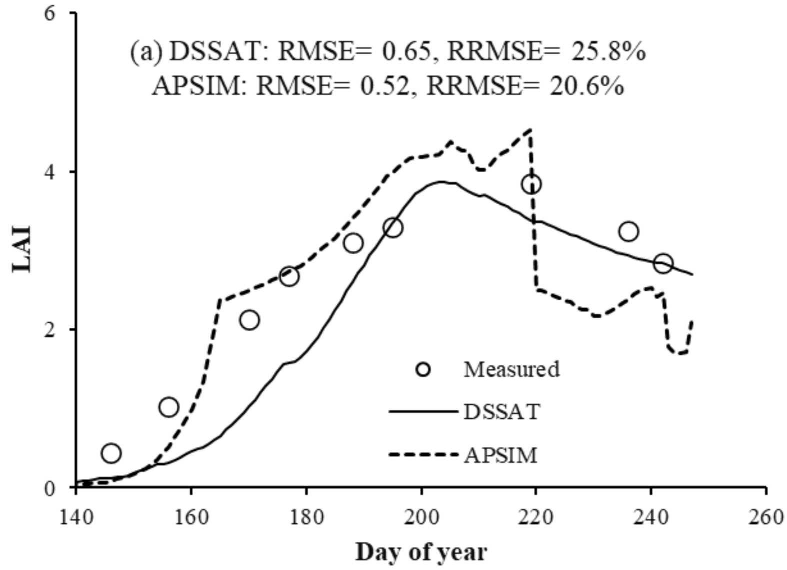
3.3. Yield

Comparing two models for yield, DSSAT overestimated yield by 0.91% and 2.38%, and APSIM underestimated yield by 0.20% and 1.89%, respectively, in the 2017 and 2018 growing seasons. Comparing the two models, APSIM simulation was better than DSSAT. Similarly, Li et al., 2022 also found that APSIM accurately predicted rainfed cotton biomass and lint yield in East-Central Texas [19]. They found the average difference between APSIM simulated values and field observations was 13.9% for cotton biomass production. In this experiment in grower's field, destructive-biomass samples were not collected for comparisons with simulations. Both simulated and observed yields were higher in 2018 than in 2017. Moreover, the GDD was higher in 2018 than in 2017, which might lead to a shorter growing season in 2018. Temperature is the most critical factor governing cotton phenological development; GDD could be used with other factors to predict cotton growth. Previous studies also reported that warming accelerated cotton growth, advanced cotton phenology, and shortened the growing period of cotton [33,34].

3.4. LAI

In 2017, the maximum observed LAI value was 3.85 at 107 days after planting or 219 day of year (DOY); DSSAT and APSIM simulated maximum LAI values of 3.38 and 4.52, respectively (Figure 1a). In 2018, the maximum observed LAI value was 4.17; DSSAT and APSIM predicted maximum LAI of 4.72 and 3.80, respectively. Simulation of LAI with DSSAT and APSIM resulted in RMSE values of 0.65 and 0.52, respectively, in 2017 and 1.02 and 0.85, respectively, in 2018.

Cotton is a perennial crop with indeterminate growth characteristics; for that reason, cotton leaf area development typically follows a sigmoid curve; it increases slowly during the first 6–7 weeks and rapidly during early fruiting and canopy closure, approximately 75 days after planting [35]. LAI closely follows crop biomass, and the larger the LAI greater the radiation use efficiency. In corn, Saadi et al., 2022 observed that maximum light interception (90%) reached an LAI value of about 4; beyond this threshold, the increase in light interception was minimal (less than 5%) and the impact on biomass and grain formation are very small [18]. As discussed above, the differences between simulated and observed LAI were not large enough to influence cotton yield prediction in this study. Thorp et al., 2020 found that leaf growth or development simulation by the CSM-CROPGRO-cotton model was sensitive to three cultivar-specific parameters that were used for simulating the crop, (i) maximum photosynthesis rate (mg CO_2 m^{-2} s^{-1}, LFMAX), (ii) specific leaf area for standard conditions (cm^2 g^{-1}, SLVAR), and (iii) leaf appearance rate (# $°C^{-1}$ d^{-1}, TRIFL) [22]. However, in APSIM, leaf expansion, photosynthesis and fruiting cotton module are controlled by plant water supply and uptake [14].



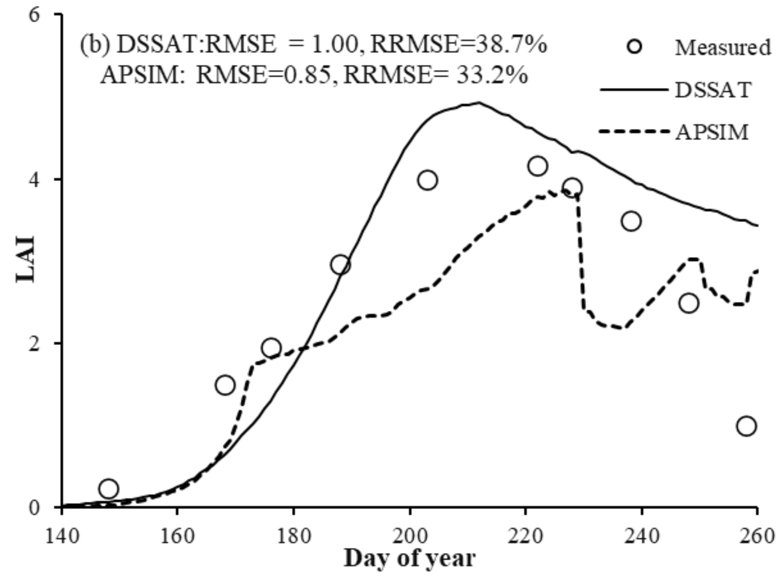


Figure 1. Observed and simulated leaf area index under cotton production for the calibration during (**a**) 2017 and validation during (**b**) 2018 growing seasons.

3.5. ET

The cumulative ET (DOY:126-247) quantified using the EC method was 368 mm, whereas the simulated values were 484 mm and 485 mm (+32% for both) for DSSAT and APSIM, respectively, during the 2017 growing seasons (Figure 2a,b). Average observed ET values were 3.01 mm, and DSSAT and APSIM had average values of 3.97 mm and 3.98 mm, respectively. The highest observed ET was 5.67 mm; DSSAT and APSIM had the highest values of 6.79 mm and 7.23 mm, respectively. In 2018, cumulative measured ET was 429 mm, DSSAT and APSIM simulated cumulative ET values of 464 and 469 mm, respectively. Simulations of 1915–2015 weather data using RZWQM, Tang et al., 2018 found that average cotton evapotranspiration in the Delta region was 552 mm during growing season; the mean water requirement for cotton during the growing season totaled 649 mm, average deficit of 395 mm year^{-1} [9].

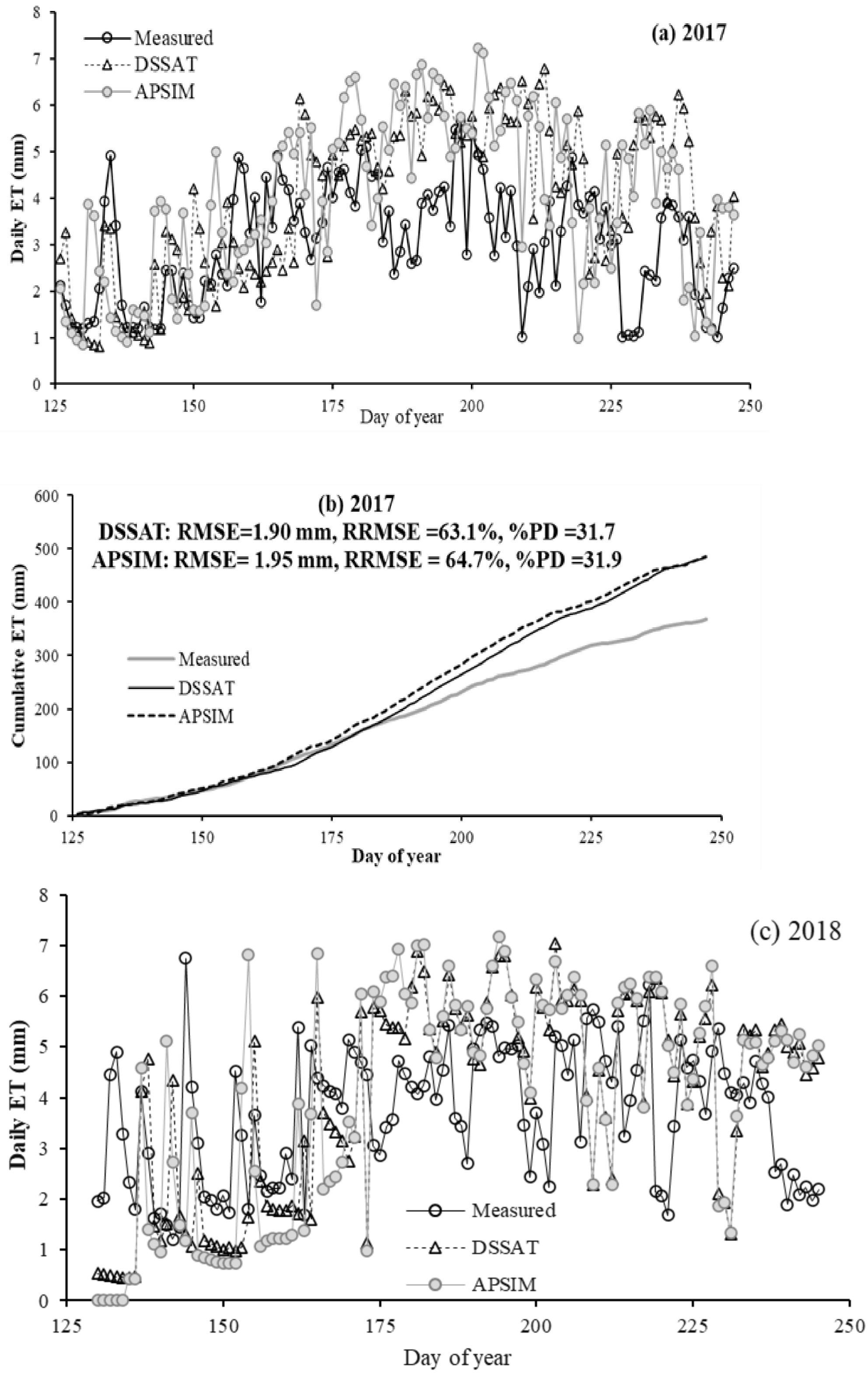


Figure 2. *Cont.*

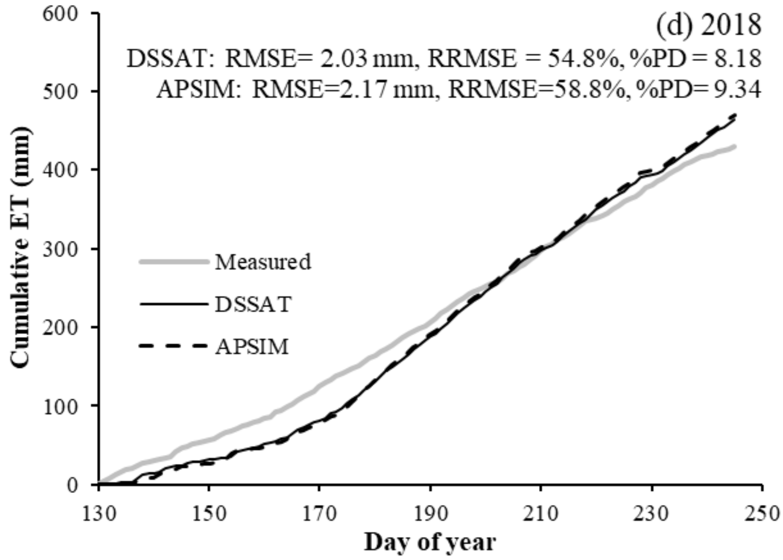


Figure 2. Comparisons of daily and cumulative seasonal ET-measured with eddy covariance (EC)-simulated by DSSAT and APSIM for calibration (**a**,**b**) during 2017 and validation (**c**,**d**) during 2018 growing seasons.

Over two years, the RMSE of daily simulated values of ET ranged between 1.90 to 2.17 mm (Figure 2a,c). For this experiment, Anapalli et al., 2019 reported that RMSEs of daily ET simulations were 1.1 and 1.0 mm and RRMSE values of 37% and 30% for 2017 and 2018, respectively, using the RZWQM model [20]. The value of RRMSEs for DSSAT and APSIM were 63% and 65% in 2017, and 55 and 59% in 2018, respectively. It seems that both models did not perform well when ET decreased in certain periods (DOY 185–200 and 226–235 in 2017). This might be due to simulation of soil moisture by these models because low ET values without any reduction in LAI might indicate low soil evaporation due to moisture stress. Percentage deviation differed between 2017 (32%) and 2018 (9%). Saadi et al., 2022 reported that overall ET predictions were slightly higher than observed variations by 3%, while the FAO-56 method overestimated ET by 18% [18]. Menefee et al., 2020 also observed an average overestimation of ET and concluded that possible errors might be associated with DSSAT's PET estimations, crop coefficient estimation, and the simulation of soil water balance in vertisols with high swell-shrink clay minerals [36]. Menefee et al., 2020 concluded that the inaccuracies with ET simulation in the DSSAT based models were contributed by issues with PET calculation, crop coefficient (kC), in addition to soil characteristics, especially clay contents, altering soil water movement in their experiment [36]. Thorp et al., 2020 noted that leaf growth and expansion parameters (LFMAX and TRIFL) influenced soil evaporation (EVPH) [37]. Estimation errors when evaporation is dominant mainly caused by the heterogeneity of water vapor transport within plant and soil media [18]. Deviations of LAI simulations from the observed prediction also affected the observed deviations in ET predictions. Finally, the imbalance in energy flux accounted in the EC system varied between 2% to 12%. Considering all uncertainties in measured and simulated ET, the accuracies in ET simulations, especially daily values of ET, both the cropping system models-need further improvement for precision irrigation management applications for enhanced WUE [20].

4. Conclusions

Irrigation water management based on location-specific crop water demands (ET) vs. supply situations can significantly help enhance WUE for sustainable irrigated crop production systems. Cropping system models are easy to implement tools for estimating location-specific ET and crop production responses from soil and weather information. In this study comparing models for predicting location-specific simulation of cotton, overall, the DSSAT-CROPGRO and APSIM-OzCot models demonstrated the potential to reasonably estimate cotton yields under irrigated conditions in the Mississippi Delta region. Both models showed similar performance predicting LAI and ET, but the prediction varied between observed and simulated over two growing seasons. The simulation error statistics show that the models need improvement in simulating daily ET demands for applications in enhancing WUE in irrigated cotton systems in the Delta region.

Author Contributions: Conceptualization, A.C. and S.S.A.; methodology, A.C. and S.S.A.; software, A.C. and S.S.A.; formal analysis, A.C. and S.S.A.; investigation, S.S.A.; resources, S.S.A.; data curation, S.S.A.; writing—original draft preparation, A.C.; writing—review and editing, A.C. and S.S.A.; project administration, S.S.A. All authors have read and agreed to the published version of the manuscript.

Funding: This research received no external funding.

Data Availability Statement: Experimental data and information associated with model validation will be available upon request.

Conflicts of Interest: The authors declare no conflict of interest.

References

1. Khan, M.A.; Wahid, A.; Ahmad, M.; Tahir, M.T.; Ahmed, M.; Ahmad, S.; Hasanuzzaman, M. World Cotton Production and Consumption: An Overview. In *Cotton Production and Uses: Agronomy, Crop Protection, and Postharvest Technologies*; Ahmad, S., Hasanuzzaman, M., Eds.; Springer: Singapore, 2020; pp. 1–7. ISBN 9789811514722.
2. Anapalli, S.S.; Fisher, D.K.; Reddy, K.N.; Wagle, P.; Gowda, P.H.; Sui, R. Quantifying Soybean Evapotranspiration Using an Eddy Covariance Approach. *Agric. Water Manag.* **2018**, *209*, 228–239. [CrossRef]
3. Koudahe, K.; Sheshukov, A.Y.; Aguilar, J.; Djaman, K. Irrigation-Water Management and Productivity of Cotton: A Review. *Sustainability* **2021**, *13*, 10070. [CrossRef]
4. Marston, L.; Konar, M.; Cai, X.; Troy, T.J. Virtual Groundwater Transfers from Overexploited Aquifers in the United States. *Proc. Natl. Acad. Sci. USA* **2015**, *112*, 8561–8566. [CrossRef] [PubMed]
5. Reba, M.L.; Massey, J.H. Surface Irrigation in the Lower Mississippi River Basin: Trends and Innovations. *Trans. ASABE* **2020**, *63*, 1305–1314. [CrossRef]
6. Anapalli, S.S.; Fisher, D.K.; Reddy, K.N.; Krutz, J.L.; Pinnamaneni, S.R.; Sui, R. Quantifying Water and CO2 Fluxes and Water Use Efficiencies across Irrigated C3 and C4 Crops in a Humid Climate. *Sci. Total Environ.* **2019**, *663*, 338–350. [CrossRef] [PubMed]
7. Kebede, H.; Fisher, D.K.; Sui, R.; Reddy, K.N. Irrigation Methods and Scheduling in the Delta Region of Mississippi: Current Status and Strategies to Improve Irrigation Efficiency. *Am. J. Plant Sci.* **2014**, *05*, 2917–2928. [CrossRef]
8. Anapalli, S.S.; Pettigrew, W.T.; Reddy, K.N.; Ma, L.; Fisher, D.K.; Sui, R. Climate-Optimized Planting Windows for Cotton in the Lower Mississippi Delta Region. *Agronomy* **2016**, *6*, 46. [CrossRef]
9. Tang, Q.; Feng, G.; Fisher, D.; Zhang, H.; Ouyang, Y.; Adeli, A.; Jenkins, J. Rain Water Deficit and Irrigation Demand of Major Row Crops in the Mississippi Delta. *Trans. ASABE* **2018**, *61*, 927–935. [CrossRef]
10. Sau, F.; Boote, K.J.; McNair Bostick, W.; Jones, J.W.; Inés Mínguez, M. Testing and Improving Evapotranspiration and Soil Water Balance of the DSSAT Crop Models. *Agron. J.* **2004**, *96*, 1243–1257. [CrossRef]
11. Ma, N.; Szilagyi, J.; Zhang, Y. Calibration-Free Complementary Relationship Estimates Terrestrial Evapotranspiration Globally. *Water Resour. Res.* **2021**, *57*, e2021WR029691. [CrossRef]
12. Ghiat, I.; Mackey, H.R.; Al-Ansari, T. A Review of Evapotranspiration Measurement Models, Techniques and Methods for Open and Closed Agricultural Field Applications. *Water* **2021**, *13*, 2523. [CrossRef]
13. Fisher, J.B.; Melton, F.; Middleton, E.; Hain, C.; Anderson, M.; Allen, R.; McCabe, M.F.; Hook, S.; Baldocchi, D.; Townsend, P.A.; et al. The Future of Evapotranspiration: Global Requirements for Ecosystem Functioning, Carbon and Climate Feedbacks, Agricultural Management, and Water Resources: The Future of Evapotranspiration. *Water Resour. Res.* **2017**, *53*, 2618–2626. [CrossRef]
14. Yang, Y.; Yang, Y.; Han, S.; Macadam, I.; Liu, D.L. Prediction of Cotton Yield and Water Demand under Climate Change and Future Adaptation Measures. *Agric. Water Manag.* **2014**, *144*, 42–53. [CrossRef]
15. Hoogenboom, G.; Porter, C.H.; Shelia, V.; Boote, K.J.; Singh, U.; White, J.W.; Pavan, W.; Oliveira, F.A.A.; Moreno-Cadena, L.P.; Lizaso, J.I.; et al. *Decision Support System for Agrotechnology Transfer (DSSAT) Version 4.8*; DSSAT Foundation: Gainesville, FL, USA, 2021.
16. Modala, N.R.; Ale, S.; Rajan, N.; Munster, C.L.; DeLaune, P.B.; Thorp, K.R.; Nair, S.S.; Barnes, E.M. Evaluation of the CSM-CROPGRO-Cotton Model for the Texas Rolling Plains Region and Simulation of Deficit Irrigation Strategies for Increasing Water Use Efficiency. *Trans. ASABE* **2015**, *58*, 685–696.
17. Thorp, K.R.; Barnes, E.M.; Hunsaker, D.J.; Kimball, B.A.; White, J.W.; Nazareth, V.J.; Hoogenboom, G. Evaluation of CSM-CROPGRO-Cotton for Simulating Effects of Management and Climate Change on Cotton Growth and Evapotranspiration in an Arid Environment. *Trans. ASABE* **2014**, *57*, 1627–1642.

18. Saadi, S.; Pattey, E.; Jégo, G.; Champagne, C. Prediction of Rainfed Corn Evapotranspiration and Soil Moisture Using the STICS Crop Model in Eastern Canada. *Field Crops Res.* **2022**, *287*, 108664. [CrossRef]
19. Li, Z.; Menefee, D.; Yang, X.; Cui, S.; Rajan, N. Simulating Productivity of Dryland Cotton Using APSIM, Climate Scenario Analysis, and Remote Sensing. *Agric. For. Meteorol.* **2022**, *325*, 109148. [CrossRef]
20. Anapalli, S.S.; Fisher, D.K.; Reddy, K.N.; Rajan, N.; Pinnamaneni, S.R. Modeling Evapotranspiration for Irrigation Water Management in a Humid Climate. *Agric. Water Manag.* **2019**, *225*, 105731. [CrossRef]
21. Jones, J.W.; Hoogenboom, G.; Porter, C.H.; Boote, K.J.; Batchelor, W.D.; Hunt, L.A.; Wilkens, P.W.; Singh, U.; Gijsman, A.J.; Ritchie, J.T. The DSSAT Cropping System Model. *Eur. J. Agron.* **2003**, *18*, 235–265. [CrossRef]
22. Thorp, K.R.; DeJonge, K.C.; Marek, G.W.; Evett, S.R. Comparison of Evapotranspiration Methods in the DSSAT Cropping System Model: I. Global Sensitivity Analysis. *Comput. Electron. Agric.* **2020**, *177*, 105658. [CrossRef]
23. Priestley, C.H.B.; Taylor, R.J. On the Assessment of Surface Heat Flux and Evaporation Using Large-Scale Parameters. *Mon. Weather Rev.* **1972**, *100*, 81–92. [CrossRef]
24. Allen, R.G. *Crop Evapotranspiration: Guidelines for Computing Crop Water Requirements*; Food and Agriculture Organization of the United Nations, Ed.; FAO Irrigation and Drainage Paper; Food and Agriculture Organization of the United Nations: Rome, Italy, 1998; ISBN 978-92-5-104219-9.
25. Cuadra, S.V.; Kimball, B.A.; Boote, K.J.; Suyker, A.E.; Pickering, N. Energy Balance in the DSSAT-CSM-CROPGRO Model. *Agric. For. Meteorol.* **2021**, *297*, 108241. [CrossRef]
26. Suleiman, A.A.; Ritchie, J.T. Modeling Soil Water Redistribution during Second-Stage Evaporation. *Soil Sci. Soc. Am. J.* **2003**, *67*, 377–386. [CrossRef]
27. Hearn, A.B. OZCOT: A Simulation Model for Cotton Crop Management. *Agric. Syst.* **1994**, *44*, 257–299. [CrossRef]
28. Holzworth, D.P.; Huth, N.I.; deVoil, P.G.; Zurcher, E.J.; Herrmann, N.I.; McLean, G.; Chenu, K.; van Oosterom, E.J.; Snow, V.; Murphy, C.; et al. APSIM—Evolution towards a New Generation of Agricultural Systems Simulation. *Environ. Model. Softw.* **2014**, *62*, 327–350. [CrossRef]
29. National Cooperative Soil Survey (NCSS) Advanced Query, National Cooperative Soil Survey Soil Characterization Database. Available online: https://ncsslabdatamart.sc.egov.usda.gov/advquery.aspx (accessed on 28 October 2022).
30. Kottek, M.; Grieser, J.; Beck, C.; Rudolf, B.; Rubel, F. World Map of the Köppen-Geiger Climate Classification Updated. *Meteorol. Z.* **2006**, *15*, 259–263. [CrossRef]
31. Hussain, J.; Khaliq, T.; Ahmad, A.; Akhtar, J. Performance of Four Crop Model for Simulations of Wheat Phenology, Leaf Growth, Biomass and Yield across Planting Dates. *PLoS ONE* **2018**, *13*, e0197546. [CrossRef]
32. Reddy, K.; Reddy, V. Cotton Phenology and Growth Processes: Model Development. In Proceedings of the World Cotton Research Conference-2, Athens, Greece, 6–12 September 1998; pp. 526–529.
33. Luo, Q.; Bange, M.; Johnston, D.; Braunack, M. Cotton Crop Water Use and Water Use Efficiency in a Changing Climate. *Agric. Ecosyst. Environ.* **2015**, *202*, 126–134. [CrossRef]
34. Wang, D.; Wang, C.; Xu, L.; Bai, T.; Yang, G. Simulating Growth and Evaluating the Regional Adaptability of Cotton Fields with Non-Film Mulching in Xinjiang. *Agriculture* **2022**, *12*, 895. [CrossRef]
35. Oosterhuis, D.M. Growth and Development of a Cotton Plant. In *Nitrogen Nutrition of Cotton: Practical Issues*; John Wiley & Sons, Ltd.: Hoboken, NJ, USA, 1990; pp. 1–24. ISBN 978-0-89118-244-3.
36. Menefee, D.; Rajan, N.; Cui, S.; Bagavathiannan, M.; Schnell, R.; West, J. Simulation of Dryland Maize Growth and Evapotranspiration Using DSSAT-CERES-Maize Model. *Agron. J.* **2021**, *113*, 1317–1332. [CrossRef]
37. Thorp, K.R.; Thompson, A.L.; Bronson, K.F. Irrigation Rate and Timing Effects on Arizona Cotton Yield, Water Productivity, and Fiber Quality. *Agric. Water Manag.* **2020**, *234*, 106146. [CrossRef]