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Modeling evapotranspiration for irrigation water management in a humid climate

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ABSTRACT

Quantifying evapotranspiration (ET, consumptive crop water requirement) is critical to managing limited water resources for crop irrigations. Agricultural system simulation models that realistically simulate the ET processes are potential tools for integration, synthesis, and extrapolation of location-specific water management research data across soils and climates for limited-water management in agriculture. The objective of this investigation was to evaluate the accuracy of the Root Zone Water Quality Model v2.0 (RZWQM2) simulated ET against ET measured in corn, soybean, and cotton cropping systems in a predominantly clay soil under humid climate in the Lower Mississippi (MS) Delta, USA, in 2016, 2017, and 2018. Energy balance (EB) and eddy covariance (EC) methods were used for measuring ET. The RZWQM2 parameters calibrated in previous studies at the location were used in the simulations. Potential evapotranspiration (PET) in the model was simulated using an extended approach based on the Shuttleworth and Wallace (SW) model. Water infiltration into the soil was simulated using the Green and Ampt approach, and its further movement in soil layers and contributions to soil evaporation using Richard's equation. Across the three crops and their crop-seasons, simulated daily ET deviated from EC and EB estimates with RMSEs between 0.09 and 0.14 cm and RRMSEs between 21 and 37%. On a weekly basis, accuracies in simulated ET (ET_S) improved significantly with RRMSEs between 9 and 17%, and on a seasonal basis RRMSEs were between -9 and 11%. The imbalance in incoming and outgoing energies accounted in the EC system varied between 2 to 12%; taking this uncertainty in estimated ET into account, the accuracies in weekly and seasonal ET simulations were reasonable for their use in irrigation management at these time-scales.

1. Introduction

The Lower Mississippi Delta (MS Delta) is one of the major agricultural production regions in the USA. Average annual precipitation of this region is about 1300 mm, of which only about 30% is received during the core crop growing periods from April to August (Saseendran et al., 2016a; Kebede et al., 2014). Soybean (*Glycine max* L.), cotton (*Gossypium hirsutum* L.), rice (*Oryza sativa* L.), and corn (*Zea mays* L.) are staple crops grown. While soybean represents the most irrigated acreage (53%), the remaining 47% is shared between rice, corn, cotton, and aquaculture (Heatherly, 2014; Powers, 2007). Rainfall received during the crop season is also characterized by large inter- and intra-seasonal variabilities in amounts and temporal distributions leading to unstable crop yield returns (Anapalli et al., 2016b). For optimum farm returns, currently, over sixty percent of all the crops grown in the MS Delta are irrigated. The shallow Mississippi (MS) River Valley Alluvial Aquifer provides most of these water (Powers, 2007; Clark and Hart, 2009). Overexploitation of this aquifer for water withdrawal, for example, irrigating crops, is causing its rapid decline, threatening sustainability of irrigated agriculture in this region. Lacking scientific research that integrates location and crop specific water demand information with available water resources for agricultural water management is ascribed to be one of the key reasons for this disturbing trend (Dalin et al., 2017; Heatherly, 2014; Clark and Hart, 2009). For reversing this aquifer decline for sustainable irrigated agriculture, exact estimation of the water use or evapotranspiration (ET) requirements of staple crops in this area is essential for guiding withdrawal of the right amount of water for irrigations commensurate with the aquifer's natural recharge levels. ET for a particular agroclimatic region can be derived using various methods, for example, soil water balance

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measurements, field lysimeters, eddy covariance (EC), residual energy balance (EB), Bowen ratio-energy balance (BR), sap flow measurements, and plant chambers (Shi et al., 2008; Wilson et al., 2001; Anapalli et al., 2018a, b). However, for crop irrigation scheduling applications, ET is often required at locations where such measurements may not be readily available. Also, highly technical, expensive facilities like large lysimeters and EC instrumentation are nonviable to have at every location where crops are cultivated, as is maintaining them for long-term data collection. In this context, state-of-the-science agricultural system models are cheap, viable, and widely accepted tools for developing location-specific ET data for irrigation scheduling and developing crop-ET response functions for predicting crop response to irrigation water (Okada et al., 2015; Saseendran et al., 2015a, b; McNider et al., 2015). In this context, the Root Zone Water Quality Model v2 (RZWQM2) is a process-oriented agricultural system model that was developed for simulating the effects of tillage, crop residue, water, fertilizers, and crop management practices on ET, crop production and water quality (Ahuja et al., 2000; Ma et al., 2009; Saseendran et al., 2014). The CSM-CERES-Maize, CSM-CROPGRO-Soybean, CSM-CROPGRO-Cotton are among the various crop modules available for simulations in RZWQM2 for simulations of corn, soybean, and cotton crops, respectively (Ma et al., 2006 and 2009; Hoogenboom et al., 1991; Jones et al., 2003). Several studies rigorously tested and combined the RZWQM2 with short-term (3 to 4 year) and long-term (14 to 17 year) field research conducted around the world for managing dryland and irrigated cropping systems (Sadhukhan et al., 2019; Ma et al., 2003; Saseendran et al., 2014a,b; 2005; 2009; Alves and Cameira, 2002). Saseendran et al. (2013) improved the water stress factor for photosynthesis and related processes in RZWQM2 and achieved improved simulations of water dynamics in agricultural systems; so, this version of the model was used for simulating ET in this study. Notwithstanding, there was only a study reported in the literature focused on assessing the accuracies of the ET simulations by RZWQM2 against field measured data as measured using large lysimeters grown to corn in a semi-arid climate (Saseendran et al., 2016c). Kimball et al. (2019) reported extensive differences among cropping system models in corn-ET simulations in an international agricultural system model intercomparison and improvement project (AgMIP). In that work, a single station experiment in a tile-drained soil in the Midwest, USA, was used but there were no attempts to simulate tile-water-nitrogen interactions in the models. Also, as pointed out in earlier works, one of the reasons that attributed for the divergence among models in simulations of ET in the Kimball et al. (2019) study was the unavailability of detailed crop growth and development, and ET data that are prerequisite for extensive testing and improvement of those ET modules used in the cropping systems models (Farahani and Bausch, 1995; Farahani and Ahuja, 1996). So, in order to validate and improve ET simulations, there is a need for further cautious evaluation of ET simulations of system models with quality measured data, for example, from large weighing lysimeters or EC systems (Saseendran et al., 2016c).

The objective of this study was to evaluate the ET simulations of RZWQM2 against eddy covariance and energy balance estimates of corn, soybean, and cotton ET in clay soils in a humid climate of the MS Delta in 2016, 2017, and 2018.

2. Materials and methods

2.1. Eddy covariance and energy balance estimates of ET

For assessing the accuracies of RZWQM2 modeled ET, the ET measured using the EC method (ET_{EC}) in corn in 2017, soybean in 2016 and 2017, and cotton in 2017 and 2018, and ET measured using the EB method (ET_{EB}) in soybean in 2016 and in corn in 2017, were used. Corn, soybean, and cotton were grown under conventional tillage practices: deep tillage to break clay pans and overturn soils for burying of crop residue and killing of weeds in three passes, followed by another tillage to generate furrows and ridges for planting crops and to facilitate furrow irrigations. Corn (cv. DKC 66–97) was planted at 77,311 seeds ha^{-1} on March 23, 2016, and on March 21, 2017; soybean (cv. Progeny 4516) was planted on April 28, 2016, and on April 21, 2017, at 407,550 seeds ha^{-1}; and cotton (cv. Delta Pine Land 1522) was planted at 103,740 seeds ha^{-1} on April 22, 2017, and on May 10, 2018. All the experiments were conducted on large fields (25 ha–400 ha) with poorly-drained Tunica clay soils (clayey over loamy, montmorillonitic, non-acid, thermic Vertic Halaquepet) to a depth of about 1.2 m as measured. Crops were planted on ridges with 97-cm inter-row spacing. Fertilizer was applied, after plant emergence, at 225 kg N ha^{-1} in corn and 140 kg N ha^{-1} in cotton. No fertilizer was applied in soybean. A plant growth regulator, Mepiquat chloride, was applied to control cotton plant height and excessive vegetative growth. Irrigations were applied to maintain water content in a 30-cm soil layer above 65% of maximum plant available water. Water content and temperature at 8 and 30 cm soil layers were monitored using Stevens HydraProbe sensors (Stevens Water Monitoring Systems, Inc., Portland, OR USA). The sensors were installed three each in the north and south facing side of the ridges in all the fields. Combines were used to harvest and weigh seed-cotton and corn and soybean grains.

Table 1
RZWQM2 estimated soil parameters from field measured soil texture.

Soil Depth (cm)	Bulk Density, ρ_b (g cm^{-3})	θ_s ($cm^3\,cm^{-3}$)	Θ_{fc} ($cm^3\,cm^{-3}$)	Θ_{wp} ($cm^3\,cm^{-3}$)	h_b (cm)	λ
0-15	1.31	0.472	0.380	0.265	1.92	0.132
16-40	1.40	0.471	0.380	0.265	1.92	0.131
42-74	1.38	0.481	0.377	0.274	0.91	0.130
75-112	1.40	0.484	0.399	0.270	1.69	0.131
112-189	1.45	0.480	0.394	0.279	1.00	0.127

θ_s, θ_{fc} and θ_{wp} are soil water contents at field saturation, field capacity (drained upper limit) and plant wilting point (drained lower limit), respectively. h_b is the air entry water suction, and λ the pore size distribution index obtained by fitting the Brooks-Corey equation for obtaining the soil water retention curve (Brooks and Corey, 1964).

Detailed description of the instrumentation, data collection protocols, and data analysis of EC and EB estimations, and closure of energy measured were reported by Anapalli et al., 2018, 2019). Briefly, for estimating ET using the EC method, vertical transport of eddies from the cropping systems were measured at 10 Hz frequency using a Gill New Wind Master 3D sonic anemometer (Gill Instruments, Lymington, UK), and water vapor densities in those eddies measured using LI-7500-RS open-path infrared gas analyzers (LI−COR Inc., Lincoln, NE, USA). These sensors were maintained in the constant flux layer above the crop canopy by mounting the instrumentation on telescopic, height-adjustable towers. Sensors for measuring net radiation (NR-LITE2, Kipp & Zonen B.V., Delft, The Netherlands), infrared canopy surface temperature (SI-111 Standard View Infrared Sensor, Apogee Instruments, Inc, Logan, UT USA) from a view of the ground at a 60^{O} zenith angle, air temperature (T_a) and relative humidity (HMP 155, Vaisala, Helsinki, Finland), and wind direction and speed (Gill 2D-Sonic, Gill Instruments), were maintained at 2 m above the crop canopy within the cropped field along with the EC sensors. Three self-calibrating soil heat flux sensors (HP01SC, Hukseflux Thermal Sensors B.V., Delft, The Netherlands) were installed at 8-cm depth below the soil surface. HydraPobes were used to monitor water and temperature of the 8 cm soil layer above the flux plates. All measurements started at planting and continued until harvest. The data collected were processed in the field on a SmartFlux microprocessor (LI−COR Inc.) using the EddyPro software version 6.1.0 (LI−COR Inc.). In this processing, standardized correction procedures were applied to the high-frequency (10 Hz) data: anemometer tilt correction using double coordinate rotation, time-lag compensation, 30-min block averaging, and statistical tests and

Table 2
Calibrated crop parameters in CSM-CERES-Maize for simulating corn (cv. DKC 66–97) in the ET experiments at Stoneville, MS, in 2016 and 2017.

Acronyms used and definitions of cultivar traits.	Parameter values
P1 - Degree days (base temperature of 8 °C) from seedling emergence to end of the juvenile phase (thermal degree days).	260
P2 - Day length sensitivity coefficient [the extent (days) that development is delayed for each hour increase in photoperiod above the longest photoperiod (12.5 h) at which development proceeds at maximum rate].	0.12
P5 - Degree days (base temperature of 8 °C) from silking to physiological maturity (thermal degree days)	1130
G2 - Potential kernel number	880
G3 - Potential kernel growth rate (mg/(kernel d)	9.2
PHINT - Degree days required for a leaf tip to emerge (thermal degree days)	42

Table 3
Calibrated cultivar parameters for simulating Soybean (cv. Progeny 4516) and cotton (cv. Delta Pine Land 1522) using the CSM-CROPGRO- soybean and -cotton v4.6 models.

Parameters	Definitions	Soybean	Cotton
CSDL	Critical Short Day Length below which reproductive development progresses with no day in length effect (for short day plants) (hour)	13.1	23.0
PPSEN	Slope of the relative response of development to photoperiod with time (positive for short day plants) (hour $^{-1}$)	0.29	0.01
EM-FL	Time between plant emergence and flower appearance (R1) (photothermal days)	19.4	41.0
FL-SH	Time between first flower and first pod (R3) (photothermal days)	7.0	11.0
FL-SD	Time between first flower and first seed (R5) (photothermal days)	15.0	17.0
SD-PM	Time between first seed (R5) and physiological maturity (R7) (photothermal days)	34.0	40.0
FL-LF	Time between first flower (R1) and end of leaf expansion (photothermal days)	26.0	65.0
LFMAX	Maximum leaf photosynthesis rate at 30 C, 350 vpm CO2, and high light (mg CO_2/m^2s)	1.3	1.0
SLAVR	Specific leaf area of cultivar under standard growth conditions (cm^2/g)	360.0	170.0
SIZLF	Maximum size of full leaf (three leaflets) (cm^2)	250.0	200.0
XFRT	Maximum fraction of daily growth that is partitioned to seed + shell	1.2	0.50
WTPSD	Maximum weight per seed (g)	0.2	0.15
SFDUR	Seed filling duration for pod cohort at standard growth conditions (photothermal days)	20.0	35.0
SDPDV	Average seed per pod under standard growing conditions (#/pod)	2.2	20.0
PODUR	Time required for cultivar to reach final pod load under optimal conditions (photothermal days)	10.0	8.0

corrections for stationarity and steady state (Vickers and Mahrt, 1997); spike filtering and spectral correction (Moncrieff et al., 1997, 2004); anemometer temperature correction for humidity (Van Dijk et al., 2004); and compensation for air density fluctuations (Webb et al., 1980).

Further, the EddyPro processed data were filtered to remove fluxes with low-quality flags of 1 and 2 (Mauder and Foken, 2011). Also, turbulent flux data were confined within the possible range from -200 to 800 J m^{-2} s^{-1} for latent heat (LE) and -200 to 500 J m^{-2} s^{-1} for sensible heat (H) (Sun et al., 2010; Wagle et al., 2015). Gaps in flux data were filled using the REddyProc package, available online from the Max Planck Institute for Biogeochemistry (https://www.bgc-jena.mpg.de/bgi/index.php/Services/REddyProcWebRPackage).

The procedure developed by Anapalli et al (2018a) was used in estimating ET from the EB method. In this method, all micro-meteorological data, excepting the latent and sensible heat fluxes measured on the EC towers, were used for estimating ET. And, actual ET is estimated (ET_{EB}) as the residual term of the energy balance equation from measurements of net solar irradiance (R_n) and computed sensible heat (H) and ground heat (G_o) fluxes. The H flux was computed from measurements of the air and crop canopy temperature differential and modeling the aerodynamic resistance to heat and water transport in the turbulent atmospheric boundary layer above the canopy. The G_o flux was estimated by measuring heat flux at 8 cm depth and accounting for heat storage in the soil layer above it. The developed EB procedure was tested using simultaneous measurements of EB data and lysimetric ET in a cotton (*Gossypium hirsutum* L.) field at Bushland, Texas, USA in 2008 (Anapalli et al., 2018a).

2.2. Simulating ET using RZWQM2 and computing of short grass reference ET (ET_O)

In RZWQM2, potential soil-evaporation (PE) and potential plant-transpiration (PT) were calculated using the Farahani and Ahuja (1996) extension of a Shuttleworth-Wallace (Shuttleworth and Wallace, 1985; S–W) model. In this approach, PET equations representing a partial-canopy-covered soil were extended to a complete range of soil-canopy-residue conditions. The computed *PT* and *PE* set the upper limits for actual transpiration (crop water uptake; *AT*) and actual evaporation (*AE*), respectively; plant water uptake was estimated by the Nimah and Hanks (1973) approach. Water infiltration during rainfalls or irrigation was simulated by the Green and Ampt (1911) approach, and water movement within the soil profile by the Richard's equation (Ahuja et al., 2000). The soil evaporation was calculated from the water re-distributed to the soil surface by the Richard's equation, with the flux of *PE* as the upper boundary condition initially until the soil water pressure head at the surface equaled −1500 kPa, which was then maintained as the constant head boundary.

PET is obtained by summing up the *PE* and *PT* estimates during a given time interval (Ahuja et al., 2000):

$$PET = PT + PE \tag{1}$$

$$PE = C_s\,PE_s + C_r PE_r \tag{2}$$

where, C_S and C_r are fractions of bare soil and residue covered soil surface areas, respectively, ($C_S + C_r = 1$); and PE_S and PE_r are evaporation fluxes from bare and residue covered soil areas, respectively.

$$PT = \left(\frac{\Delta[(R_n - G) - R_{nsub}] + \rho C_p (VPD_o)/r_a^c}{(\Delta + \gamma\left(1 + \frac{r_s^c}{r_a^c}\right))}\right)(1/\lambda) \tag{3}$$

where, R_n is the net incoming hemispherical radiation above the canopy; Δ is the slope of the saturation vapor pressure versus temperature curve; λ is the latent heat of evaporation of water; G is the heat flux into soil below the canopy with components G_s and G_r into the bare soil and into the residue-covered soil, respectively; R_{nsub} is the net radiation below the canopy (= $C_sR_{ns} + C_rR_{nr}$); pC_p the volumetric heat capacity of air; YPD_o is the air vapor pressure deficit at the measurement height; r_a^c is the bulk boundary layer resistance of the canopy elements within the canopy; r_s^c is the bulk stomatal resistance of the canopy; and γ is the

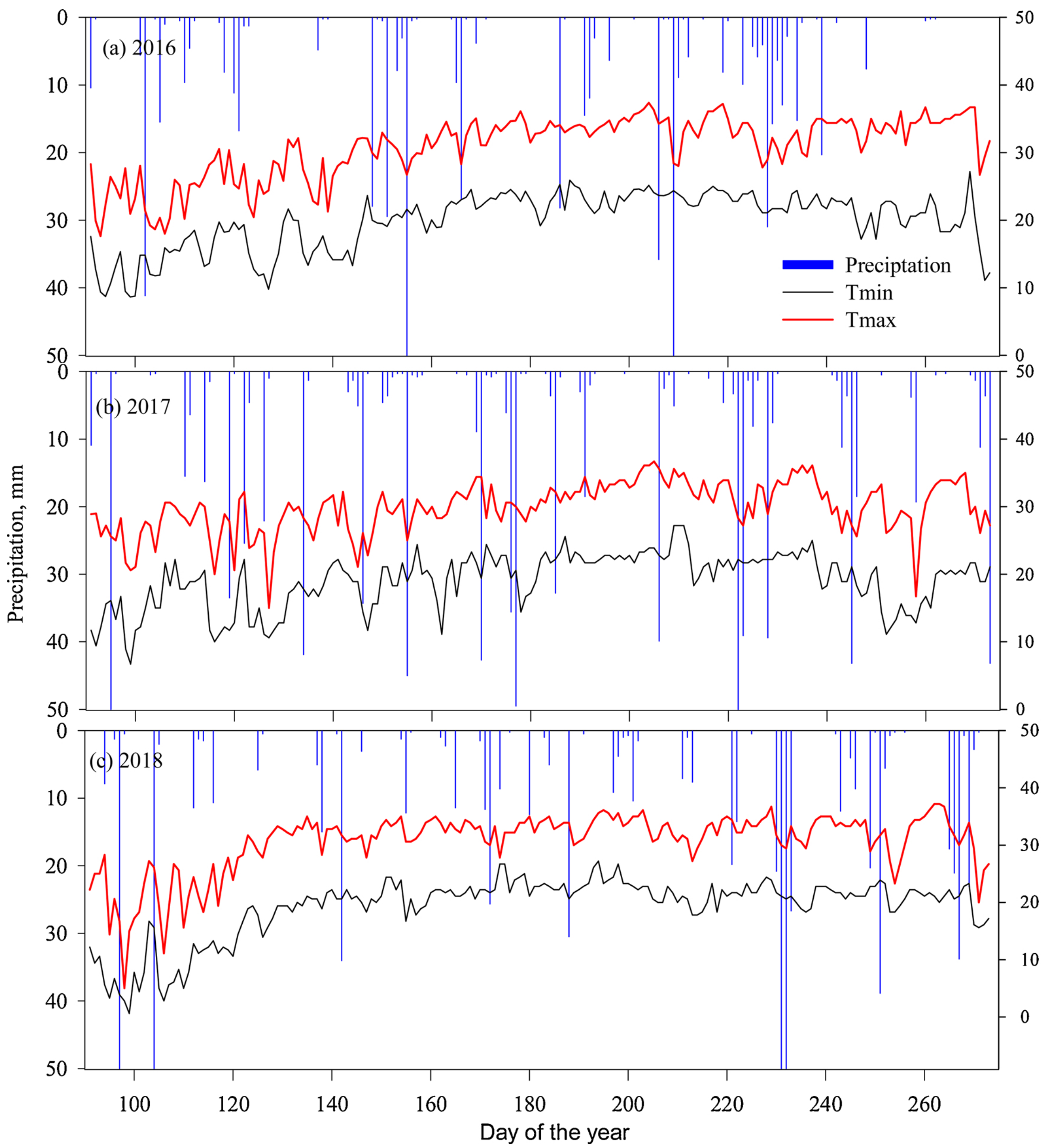

Fig. 1. Precipitation, maximum (Tmax) and minimum temperature (Tmin) at the experimental location during the crop growth seasons of 2016, 2017, and 2018.

psychrometric constant.

$$E_s = \left(\frac{\Delta(R_{ns} - G_s) + \rho C_p (VPD_o)/r_a^s}{\Delta + \gamma(1 + \frac{r_s^s}{r_a^s})} \right)(1/\lambda) \tag{4}$$

where, R_{ns} is the net radiation absorbed by a unit area of bare soil; G_s is the heat flux into the bare soil; r_s^s is the soil surface resistance; r_a^s is the aerodynamic resistance between the ground surface and the mean canopy height.

$$E_r = \left(\frac{\Delta(R_{nr} - G_r) + \rho C_p (VPD_o)/r_a^s}{\Delta + \gamma[1 + (r_s^s + r_s^r)/r_a^s]} \right)(1/\lambda) \tag{5}$$

where, R_{nr} is the net radiation absorbed by a unit area of residue; G_s is the heat flux into the residue-covered soil; r_s^r is the residue evaporative resistance acting in series with r_s^s. Derivations and estimations of the parameters and inputs required for Eq. (1) through (5) can be found in Farahani and Ahuja (1996) and Farahani and DeCoursey (2000).

Inputs required for simulating crops using RZWQM2 include soil texture, bulk density, and organic matter content, saturated hydraulic conductivity and water retention curves of soil layers in the form of the Brooks and Corey equations, tillage dates and methods, crop planting date, density, depth, and row spacing; dates and amounts of irrigation; and amount and type of fertilizer applications. These soil water-nitrogen parameters were either measured in the field or estimated within the model, as such, they were not calibrated (Table 1). Weather variables needed for simulations are maximum and minimum air temperatures, solar irradiance, wind speed, relative humidity, and precipitation representing the experimental location: these data were obtained from the Mississippi State University Delta Research and Extension Center, Stoneville, MS weather station located within a mile of the experimental fields.

For simulations for corn (cv. DKC 66-77) using the CERES-Maize model, the cultivar parameters that were calibrated for simulating corn at the location in a previous study were used (Table 2; Anapalli et al., 2018). Similarly, for simulating cotton (cv. Delta Pine Land 1522) using the CSM-CROPGRO-Cotton model, the parameters calibrated for simulation of cotton at the location by Anapalli et al. (2016b) were used

Table 4
Measured and simulated seedling emergence, silking /flowering, and number of days to physiological maturity, grain yield, and soil water (SW) of corn, soybean, and cotton in the evapotranspiration -eddy covariance- experiments in 2016–2018.

Growth stage	Measured (m)	Simulated (s)	Error (s-m)
	2016 corn		
Emergence, DAP	9	11	2
Flowering, DAP	74	72	−2
Maturity, DAP	132	129	−3
Grain yield, kg ha^{-1}	10467	9994	−473
SW (RMSE), $cm^{3cm^{-3}}$	–	–	0.092
	2016 soybean		
Emergence, DAP	6	8	2
Flowering, DAP	41	47	−6
Maturity, DAP	122	126	4
Grain yield, kg ha^{-1}	4900	5183	283
SW (RMSE), $cm^{3cm^{-3}}$	–	–	0.069
	2017 corn		
Emergence, DAP	7	8	−1
Flowering, DAP	69	69	−2
Maturity, DAP	133	130	−4
Grain yield, kg ha^{-1}	11871	13600	1729
SW (RMSE), $cm^{3cm^{-3}}$	–	–	0.093
	2017 soybean		
Emergence, DAP	7	8	1
Flowering, DAP	48	47	−1
Maturity, DAP	133	130	−3
Grain yield, kg ha^{-1}	4260	4987	727
SW (RMSE), $cm^{3cm^{-3}}$	–	–	0.083
	2017 cotton		
Emergence, DAP	9	10	−1
Flowering, DAP	60	55	−5
Maturity, DAP	132	128	−4
Grain yield, kg ha^{-1}	3937	4133	196
SW (RMSE), $cm^{3cm^{-3}}$	–	–	0.079
	2018 cotton		
Emergence, DAP	10	11	1
Flowering, DAP	60	59	−1
Maturity, DAP	124	119	−5
Grain yield, kg ha^{-1}	4699	4205	−494
SW (RMSE), $cm^{3cm^{-3}}$	–	–	0.076

DAP = day after planting; Maturity = physiological maturity.

(Table 3). For simulating soybean (cv. Progeny 4516 - maturity group 4) using the CSM-CROPGRO-Soybean model, crop parameters for a maturity group 4 variety (soybean 990,004 M group 4) available in the DSSAT (Decision Support System for Agrotechnology Transfer) database were used with some adjustments for better match between measured and simulated crop growth (Table 3; Jones et al., 2003).

We computed reference evapotranspiration(ET_O) from weather data using the Allen et al. (1998) procedure. Weather data collected at 2 m height from the Delta Research and Extension Center weather station were used.

2.3. Statistics for model calibration and evaluations

The simulation results were evaluated using: (i) Root Mean Squared Error (*RMSE*), Eq. (6); (ii) Relative *RMSE* (*RRMSE*) that varies between 0 and 100%, Eq. (7); and (iii) Percentage Deviation (*PD*) that varies between 0 and 100%, Eq. (8) between simulated and observed values.

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(Pi - Oi)^2} \tag{6}$$

$$RRMSE = \frac{RMSE}{O_{avg}} 100\,\% \tag{7}$$

$$PD = ((Pi - Oi)/Oi\,)\,100\,\% \tag{8}$$

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

3. Results and discussion

The MS Delta region is characterized by a sub-tropical humid climate with mild winters and warm summers, Köppen-Geiger climate classification: warm temperate, fully humid with hot summer and precipitation evenly distributed throughout the year. Based on the 1960–2018 rainfall records available at the experiment site, the location's average annual rainfall is 130 cm. The growth season of corn, soybean, and cotton in the region falls roughly between April and September. During this period, the station receives an average seasonal total rainfall of 61 cm. During the same period during our experiments in 2016, 2017, and 2018, the location received significantly higher than normal rainfalls: 63, 98, and 79 cm, respectively. Maximum (Tmax) and minimum (Tmin) air temperature were, respectively, 37.4 and 8.7 ^{O}C in 2016, 36.77 and 6.7^{O}C in 2017, and 37.2 and 0.6^{O}C in 2018 (Fig. 1).

3.1. Calibration and validation of RZWQM2 for simulations of corn, soybean, and cotton

In addition to the water available in the system in terms of rain, irrigation, and soil profile water, ET loss from a cropping system to the atmosphere greatly depends upon the crop growth stage and leaf expansion and biomass growth. Accuracies in simulations of ET by a cropping system model depend upon how accurately the crop growth and development vis a vis the water dynamics in the soil-plant-atmosphere were simulated. In simulations of three crops in this experiment, corn plant-seedling emergence simulations in 2016 and 2017 were within -1 and +2 days. silking stages were simulated within -2 and 0 days, and physiological maturity stage between -4 and -3 days from the measured number of days after planting seeds in the experiment. Anapalli et al. (2018b) also observed similar error structures in simulation of phenological stages of corn cultivar DKC66-97 planted at the same location but in a different experiment, using the CSM-CERES-Maize model within RZWQM2 (Table 4 in Anapalli et al., 2018a). Simulation of different corn growth stages in Anapalli et al. (2018b) were between -3 and +4 days. Corn-grain yield simulations in our study were also comparable in accuracy with Anapalli et al., 2018 (Table 4).

In the case of soybean in 2016 and 2017, seedling emergence, flowering, and physiological maturity simulations deviated from those measured by -6 to +4 days (Table 4). Soybean grain yields measured in 2016 and 2017 were 4900 and 4260 kg ha^{-1}, while corresponding simulated values were 5183 and 4987 kg ha^{-1}, respectively.

Accuracies in simulations of cotton (cv. Delta Pine Land 1522), in 2017 and 2018, also were reasonable, comparable to Anapalli et al. (2016a) simulations of cotton (cv. ST5599BR) at the same location in plantings from 2005 to 2008 (Table 4). Anapalli et al. (2016b) plant parameters of cotton (cv. ST5599BR) were used in this study without further changes (Table 3). Seed cotton yields also were simulated well, within -494 and +196 kg ha^{-1} from measured values (Table 4). Days to seedling emergence, flowering, and physiological maturity were also reasonable, with errors within -5 and +1 days from the measured values. Some flood events and rodent related damages to sensor cables rendered soil water measurements sporadic or unusable. However, with the few measurements available, the error in simulations of soil water at 15, 30, and 60 cm depths across the three years and three crops were within RMSEs between 0.069 and 0.092 cm^3 cm^{-3}, which are reasonably accurate for applications in irrigation water applications (Table 3).

3.2. Uncertainties in measurements of ET

The EC method for estimating ET, which is based on the eddy transport theories representing the lower boundary layer of the atmosphere, is known to have inherent inaccuracies due to both theoretical and sensor limitations in measurements, data analysis, and

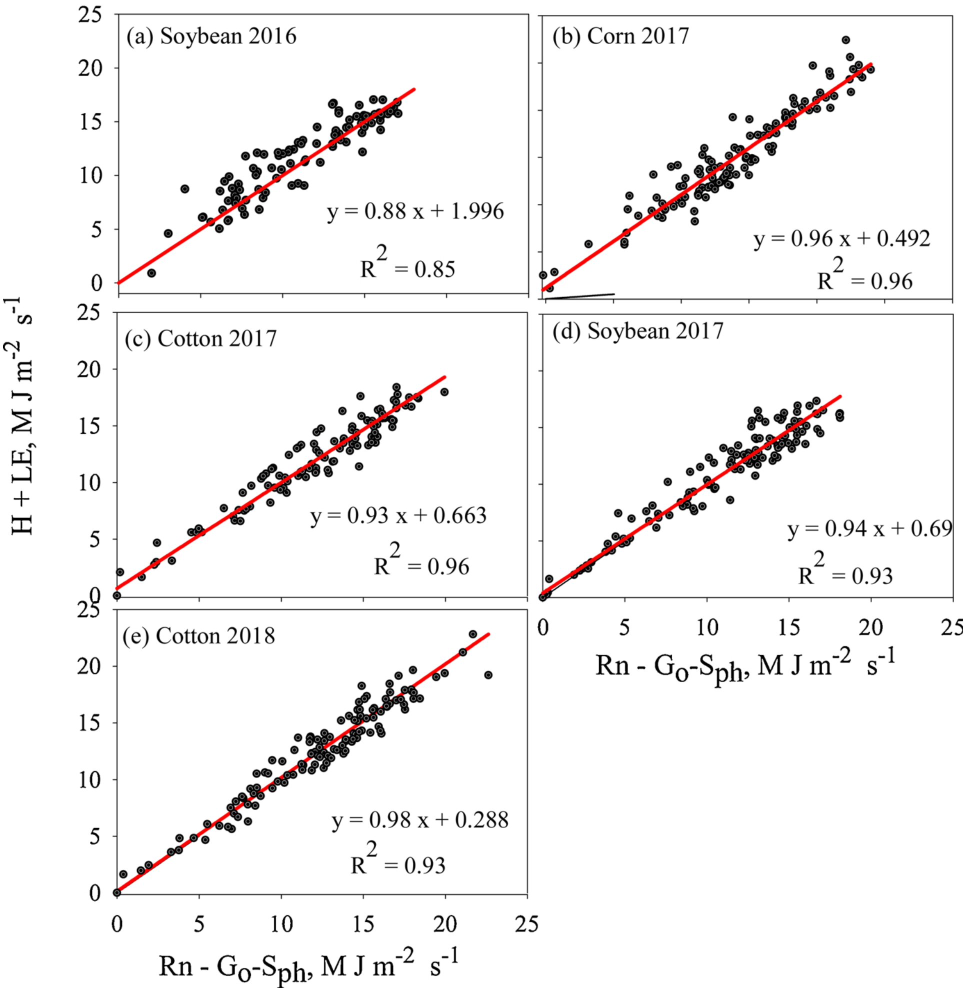

Fig. 2. Regression between measured or estimated energy input ($R_n - G_0 - S_{ph}$) and energy use/output (H + LE), at daily intervals, using the eddy covariance system in corn, soybean, and cotton cropping sytems in 2016, 2017, and 2018. Rn = net solar radiation, Go = ground heat flux, Sph = energy used in photosynthesis, H = sensible heat flux, and LE = latent heat flux. R^2 is the coefficient of determination of linear regression.

interpretation (Mauder and Foken, 2011; Gao et al., 2017; Leuning et al., 2012; Liu et al., 2017; Mauder et al., 2007). These limitations are often reported in the literature as an energy balance closure problem (EBC), the inability of the total measured or computed energy output (turbulent fluxes of sensible (H) and latent heat (L) energies) to balance the total measured or computed input energies (net solar radiation (Rn), ground heat flux (G_o), and energy used in photosynthesis (S_{ph}) in the system). In order to quantify the degree of uncertainty in the measured ET using the EC method in this study, we compared the energy inputs and outputs from the three copping systems, across three years by taking a linear regression between energy inputs ($R_n - G_o - S_{ph}$, the energies available in the system for conversion to H and LE) and actual sums of measured turbulent (H + LE) fluxes realized on a daily basis during the crop growth period. Slope of this least-square regression between the energy inputs and outputs (EBR, energy balance ratio) were used as a measure of this uncertainty (Liu et al., 2017). In the EB method for quantifying ET, the EBR is always assumed to be one as all the energy available, that is, $R_n - G_o - S_{ph} - H$ within the system was accounted for calculating LE flux from the cropping system (LE, the latent heat of vaporization of water, represents the ET from the system) (Anapalli et al., 2018b).

In this study, first we analyzed EC data for ET in 30-min time periods, and then their cumulative values over daily time periods were calculated and compared with simulated daily ET outputs from RZWQM2. The EBR achieved on a daily basis in corn, soybean, and cotton varied between 0.88 (12% of the input energy was unaccounted for in the output energies from the system) in soybean in 2016, and 0.98 (2% of the energy unaccounted for) in cotton in 2018 (Fig. 2). The EBR computed for the same data in half hour time periods exhibited EBRs between 0.84 and 0.88 (data not shown). EBR reported from across FLUXNET research sites in various climate regimes across the world varied between 0.70 and 0.90 (Wilson et al., 2001).

In our study, no crop or season specific trends in the computed EBR were noted: crop-wise, EBR varied between 0.9 and 0.94 across years in soybean in 2016 and 2017, 0.96 in corn in 2017, between 0.92 and 0.98 in cotton across 2017 and 2018 (Fig. 2). From our analysis, it is evident that the uncertainties in measured ET_{EC} in corn, soybean, and cotton should, at the location of this study, reflect uncertainties between 2% and 12%, averaging 7%, as reflected in the EBR. Leuning et al. (2012) observed that the EBR computed over daily time periods can be better than those computed over half-hourly time periods as temporary storages and their releases of heat energy within the copping system cancel out over diurnal periods. Anderson and Wang (2014) reported EBRs between 0.75 and 1.05 in irrigated sugarcane fields in Maui, Hawaii USA, under varying atmospheric turbulence and advection conditions. The EBRs achieved in corn, soybean, and cotton in our study, therefore, are comparable to and better than those reported by Anderson and Wang (2014). Coefficient of determination of the computed EBR in our study were between 0.85 and 0.96 across the three crops and three crop seasons (Fig. 2).

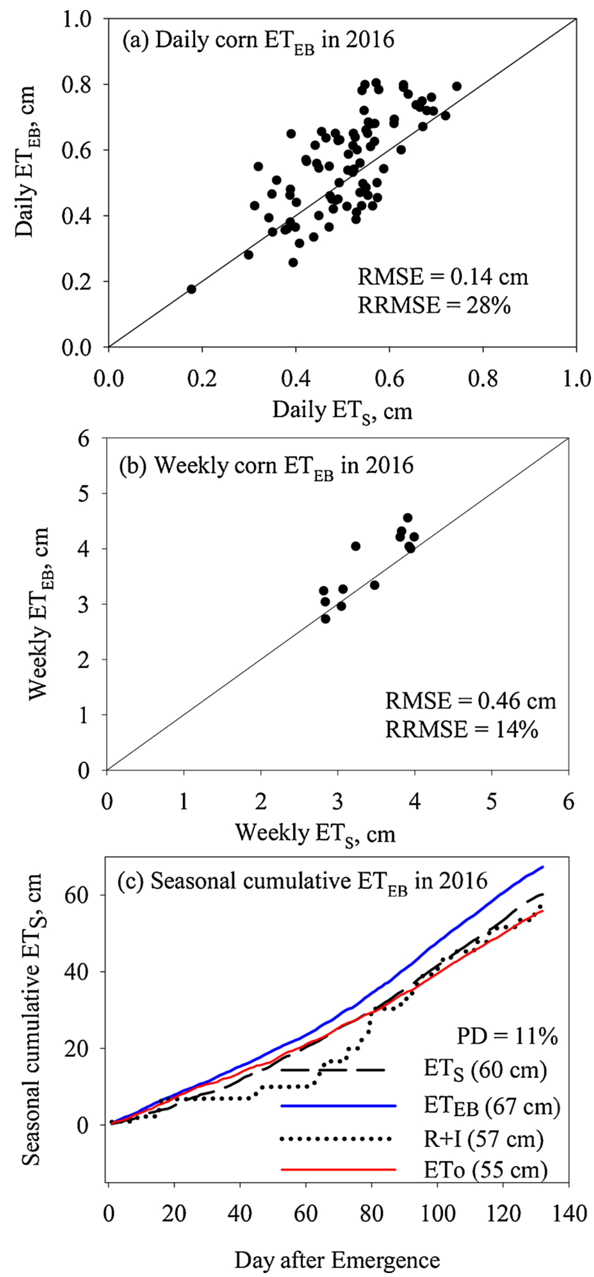

Fig. 3. Comparison between simulated (ET_S) and eddy covariance-measured (ET_{EB}): total (a) daily and (b) weekly ET, and (c) seasonal cumulative ET_{EB}, grass reference-crop ET (ET_O), and rainfall in corn in 2016. R + I is total water input from rainfall and irrigation.

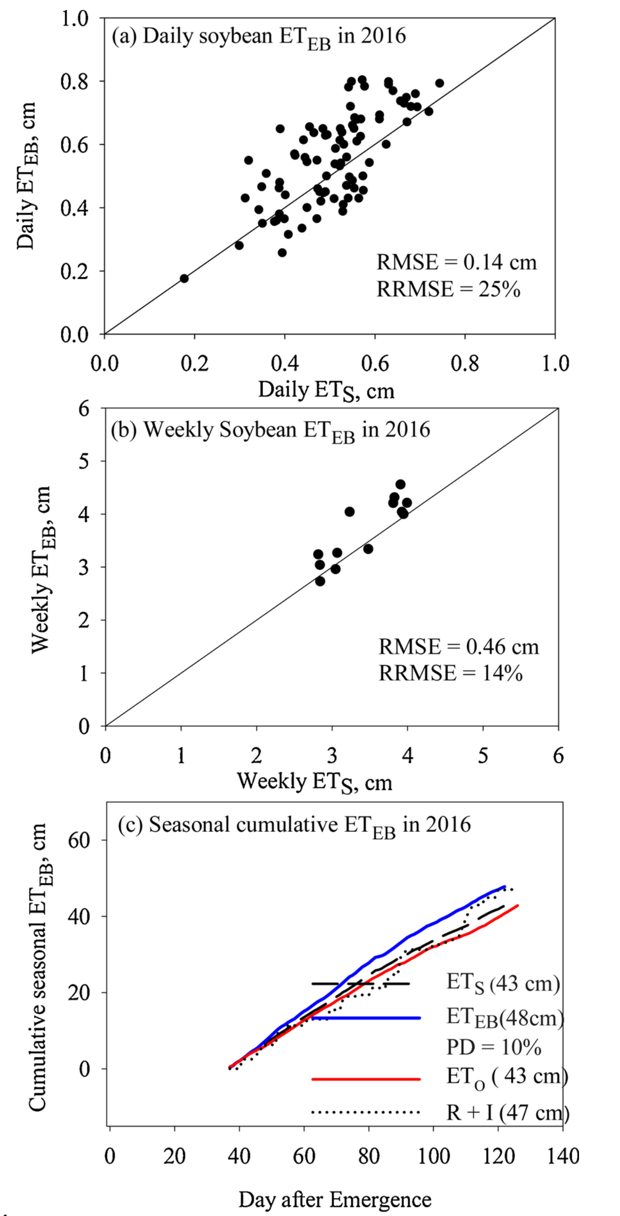

Fig. 4. Comparison between simulated (ET_S) and eddy covariance-measured (ET_{EB}): total (a) daily and (b) weekly ET, and (c) seasonal cumulative ET_{EB}, grass reference-crop ET (ET_O), and rainfall in soybean in 2016. R + I is total water input from rainfall and irrigation.

3.3. Comparison between EB or EC estimated and simulated ET

3.3.1. Comparison between estimated EB (ET_{EB}) and simulated ET (ET_S)

The ET_{EB} estimates in corn and soybean in 2016 were compared with ET_S simulated by RZWQM2 in Figs. 3 and 4. The RMSEs in daily ET simulations were 0.14 cm in both corn and soybean in the same year (Figs. 3a and 4 a). Comparing other RZWQM2 simulations with lysimetric ET data collected in corn under both rainfed and irrigated conditions in a semi-arid environment, Anapalli et al. (2016a) and Zhang et al. (2018) reported RMSEs between 0.1 and 0.15 cm. These results show that both the EB estimates of corn and soybean ET and the RZWQM2 simulated values are comparable to literature reported data. The RRMSE of these daily simulations were 28% in corn and 25% in soybean. Errors of these magnitude can be a deterrent in using these simulation outputs of ET for computing irrigation water requirements for managing limited-water irrigation in these cropping systems. In irrigated agriculture, especially in the MS Delta, farmers look for a non-rainy period of a week or more for water stress to develop to make an irrigation decision. So, we examined the error structure in simulated ET in comparison with ET_{EB} at weekly intervals. The RRMSEs of weekly ET simulations in both corn and soybean were found to be reduced to 14%, which is a more tolerable accuracy level for irrigation applications (Figs. 3b and 4 b). Annually, ET_{EB} deviated from ET_S with PD of 11%.

In 2016, both crops were irrigated twice during the cropping season, and each irrigation added 3 cm, totaling 6 cm of water seasonally; this supplemented the rainfall realized during the same time period for stress-free plant growth. In the case of corn, R (rainfall) + I (irrigation) was 57 cm against an ET_{EB} estimate of 67 cm (Fig. 3c). As we had not noticed any significant drought stress in the crop at any time during the crop season, we assume that the 10 cm shortage in the R + I for this crop in this season was compensated by water drawn from the soil water storage. The seasonal (133 days from seedling emergence to

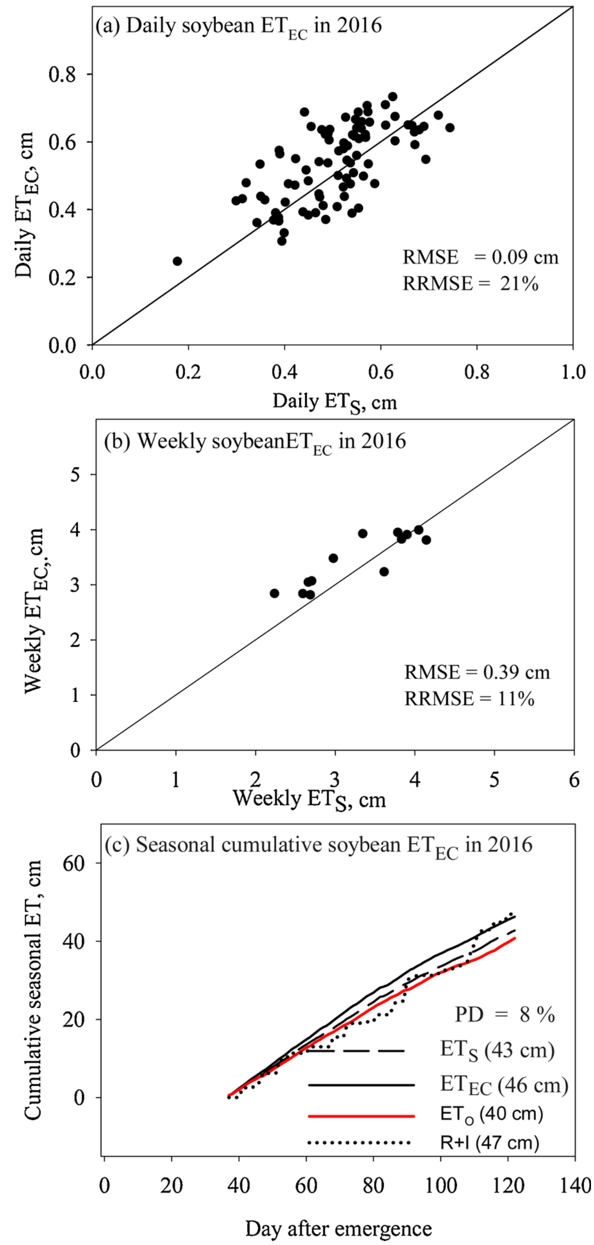

Fig. 5. Comparison between simulated (ET$_S$) and eddy covariance-measured (ET$_{EC}$): total (a) daily and (b) weekly ET, and (c) seasonal cumulative ET$_{EC}$, grass reference-crop ET (ET$_O$), and rainfall in soybean in 2016. R + I is total water input from rainfall and irrigation.

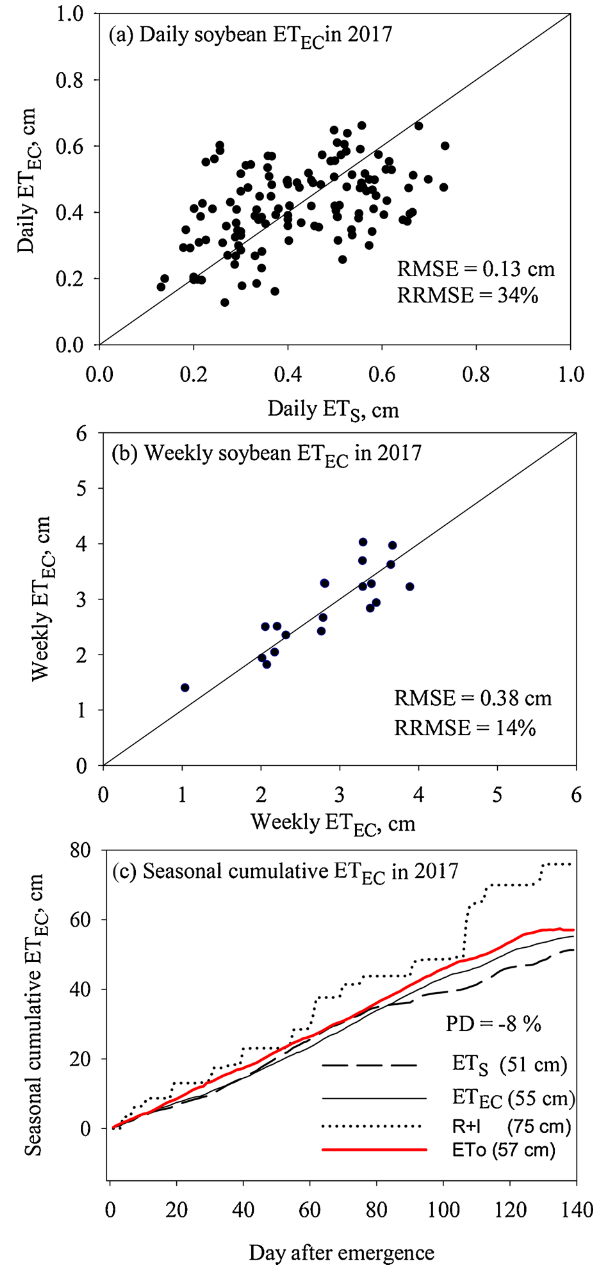

Fig. 6. Comparison between simulated (ET$_S$) and eddy covariance-measured (ET$_{EC}$): total (a) daily and (b) weekly ET, and (c) seasonal cumulative ET$_{EC}$, grass reference-crop ET (ET$_O$), and rainfall in soybean in 2017. R + I is total water input from rainfall and irrigation.

harvest) totals of corn ET$_S$, ET$_{EB}$, R + I, and ET$_O$ were 60, 67, 57, and 55 cm, respectively.

In the case of 2016 soybean, starting from the 37th day after seedling emergence (due to inclement weather conditions, EC data could not be collected during the initial 36 days after planting), the seasonal cumulative (85 days) ET$_S$ and ET$_{EB}$ were 43 and 48 cm, respectively (Fig. 4c). The PD of the ET$_S$ from ET$_{EB}$ was 11% in the case of corn and 10% in the case of soybean in 2016 (Figs. 3c and 4 c).

3.3.2. Comparison between ET$_{EC}$ and ET$_S$

ET$_{EC}$ measurements were available in soybean in 2016 and 2017, corn in 2017, and cotton in 2017 and 2018 (Figs. 5–9). In general, simulated ET$_S$ corresponded better with EC estimated ET than EB estimated ET (discussed above), across corn, soybean, and cotton and their cropping seasons in 2016, 2107, and 2018. This is possibly due to the fact that the EC method has less uncertainty compared to EB methods in their abilities to quantify ET in cropping systems in this area. RMSE of daily soybean ET$_S$ when compared against ET$_{EC}$ in 2016 was 0.09 cm (Fig. 5a), and in 2017 was 0.13 cm (Fig. 6 a). RMSE of simulated corn ET (only one crop season's EC data was available for comparison) during the 2017 crop season was 0.13 cm (Fig. 7 a). In the case of cotton in 2017 and 2018, RMSEs of ET simulations were 0.11 and 0.10 cm, respectively. These errors in ET$_S$ simulations were equal to or less than the accuracies in ET$_S$ when compared with lysimeter ET data in a semiarid climate (Anapalli et al., 2016b; Zhang et al., 2018). This also means that the accuracies of the ET quantified using the EC method in this study are comparable to those measured using the lysimeters.

The above daily ET$_S$ simulations across EB soybean and corn in 2016, EC soybean in 2016 and 2017, EC corn in 2017, and EC cotton in 2017 and 2018 had RRMSEs values of 28, 25, 21, 34, 32, 37, and 30% (Figs. 3a, 4 a, 5 a, 6 a, 7 a, 8 a, and 9 a), respectively. Nonetheless, when

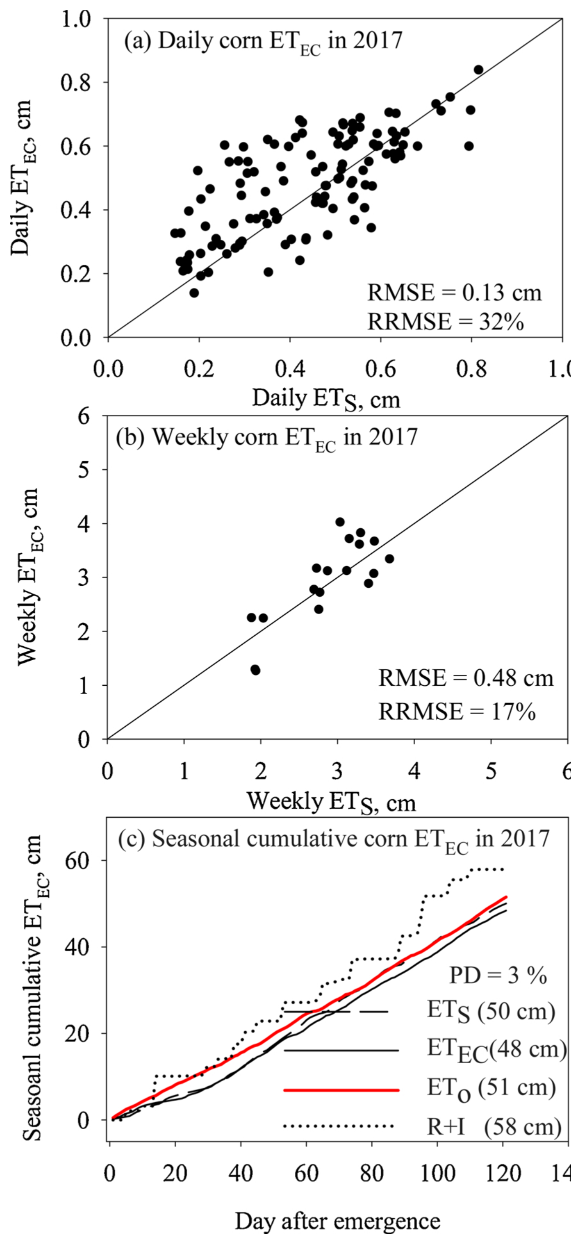

Fig. 7. Comparison between simulated (ET_S) and eddy covariance-measured (ET_{EC}): total (a) daily and (b) weekly ET, and (c) seasonal cumulative ET_{EC}, grass reference-crop ET (ET_O), and rainfall in corn in 2017. R + I is total water input from rainfall and irrigation.

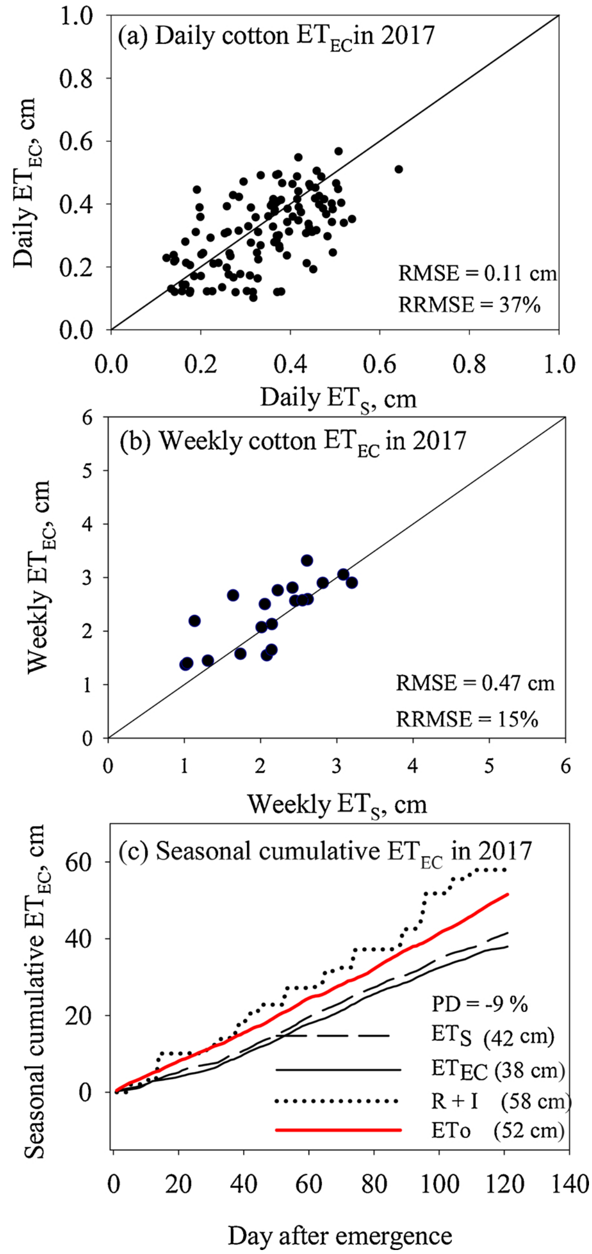

Fig. 8. Comparison between simulated (ET_S) and eddy covariance-measured (ET_{EC}): total (a) daily and (b) weekly ET, and (c) seasonal cumulative ET_{EC}, grass reference-crop ET (ET_O), and rainfall in cotton in 2017. R + I is total water input from rainfall and irrigation.

these simulations were accumulated weekly, a time-interval more practical in irrigation applications, RRMSEs were reduced to 14, 14, 11, 14, 17, 15, and 16% (Figs. 3b, 4 b, 5 b, 6 b, 7 b, 8 b, and 9 b), respectively. As discussed above, the uncertainties in quantifying $ET_{EC,}$ expressed as EBR, for these crops during these crop seasons, varied between 2 and 12%. Considering these inherent uncertainties in ET quantified using the EC method, the accuracies in ET_S simulations obtained in this study are within an acceptable range for irrigation applications in the humid climate of this location.

The seasonal cumulative ET_O, in general, were comparable in amount with ET_{EB} or ET_{EC} estimates of corn, soybean, and cotton ET across corn, soybean, and cotton crops and their cropping seasons in 2016, 2017, and 2018 (Figs. 3c, 4 c, 5 c, 6 c, 7 c, 8 c, and 9 c). Across the three crops and cropping seasons, ET_S were, in general, lower than ET_O but closer in magnitude to ET_{EB} or ET_{EC}. Simulations were with PD (percentage difference between cumulative seasonal ET_S and ET_{EC} or ET_{EB}) of 8 and -8% in soybean in 2016 and 2017, respectively (Figs. 5c, 6 c), 3% in corn in 2017 (Fig. 7c), and -9 and -8% in cotton in 2017 and 2018 (Figs. 8c and 9 c). The higher level of accuracy in simulations of seasonal cumulative ET requirements of the three crops renders the RZWQM2 model an excellent tool for strategic irrigation planning in the region. In the absence of measured data, ET_O is generally used as a surrogative of ET for crop irrigation demand applications. For this reason, the simulated ET_S is a better candidate for irrigation water management applications in the event measured data are lacking.

Estimated seasonal total ET_{EB} was higher than ET_O and ET_S in both corn and soybean in 2016 (Figs. 3c and 4 c). This can probably be due to the fact that in the residual EB approach, all the energy inputs, excepting what was used in ground heat flux, in sensible heat, and in canopy photosynthesis, were assumed to fully contribute to latent heat energy flux or ET (Anapalli et al., 2018). It is possible that this

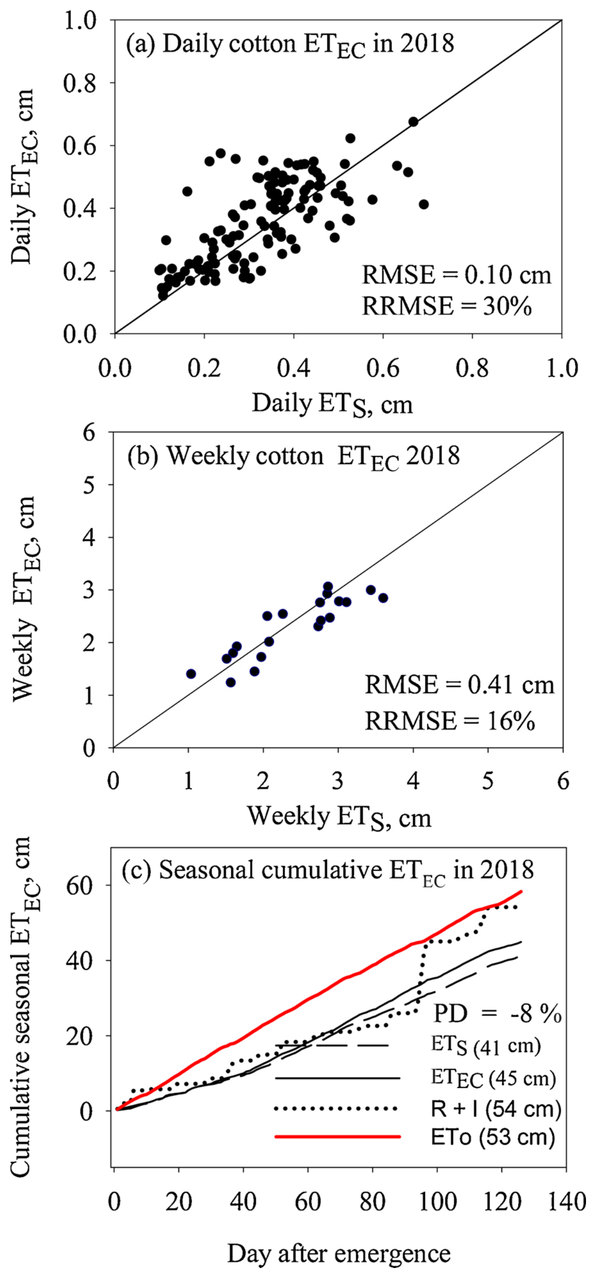

Fig. 9. Comparison between simulated (ET_S) and eddy covariance-measured (ET_{EC}): total (a) daily and (b) weekly ET, and (c)seasonal cumulative ET_{EC}, grass reference-crop ET (ET_O), and rainfall in cotton in 2018. R + I is total water input from rainfall and irrigation.

assumption has led to some overestimation in ET_{EB} estimations. In the case of ET_{EC} estimations, except in soybean in 2016 where ET_{EC} was higher than ET_{EB} (Fig. 5c), all the ET_{EC} estimates were higher than ET_S (Figs. 6c, 7 c, 8 c, and 9 c).

4. Conclusions

Adequate supply of water for meeting the ET demand is critical to crop production. The RZWQM2, an agricultural system model, can simulate ET at a location of interest from commonly measured weather and crop management data. We simulated the corn, soybean, and cotton ET across 2016, 2017, and 2018 crop seasons using RZWQM2 and assessed accuracies of these simulations by comparing them with ET quantified from EB and EC methods. Weekly ET simulations in corn, soybean, and cotton cropping systems were accurate enough for their use in irrigation water management decision support in the climate of the Lower MS Delta region. Seasonally, deviations of simulated ET from those estimated from EC and EB methods across the three crops and crop seasons were within 11%. This level of accuracy renders the RZWQM2 model an excellent tool for strategic irrigation planning in the region. In the absence of measured data, ET_O (potential ET for a grass reference crop) was generally used as a surrogative of ET, without verifications of its accuracies in quantifying ET in climates and soils, for crop irrigation water management. In this context, the simulated ET is suitable for generating crop irrigation water requirement information for water resources planning, allocation, and management applications in the event measured data are lacking.

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