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Comparison of evapotranspiration methods in the DSSAT Cropping System Model: II. Algorithm performance

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ABSTRACT

Accurate calculations of evapotranspiration (ET) are highly important for agroecosystem model simulations, and improvement of ET algorithms is an on-going model development goal. The objective of this study was to evaluate and compare six ET methods in the Decision Support System for Agrotechnology Transfer (DSSAT) Cropping System Model (CSM) using agronomic and weighing lysimetry data from cotton field studies at Bushland, Texas. Three options were tested for estimating potential ET as required by the DSSAT-CSM: 1) a Priestley-Taylor method, 2) a Penman-Monteith combination equation estimate of grass reference ET with a DSSAT-specific single crop coefficient equation, and 3) the ASCE Standardized Reference ET Equation combined with a dual crop coefficient method for non-stressed conditions. The latter two reference ET methods were adapted to provide reasonable estimates for DSSAT-required potential ET. Additionally, two methods for calculation of soil water evaporation were tested, including both the original and updated formulations of Ritchie approaches for DSSAT-CSM. The combinations of the three potential ET and two soil water evaporation approaches led to six possible ET simulation options in the model. A computationally-intensive multiobjective optimization method was used to select among model parameterization options and ensure that modeler bias did not influence ET method comparisons. Among 23 agroecosystem metrics that included lysimeter-based ET, various cotton growth variables, and soil water content in multiple soil layers, the original Ritchie soil water evaporation approach performed statistically equivalent to or better than the more recent Ritchie method ($p \leqslant 0.05$). The default ET method in the model, which involved Priestley-Taylor potential ET with the more recent Ritchie soil water evaporation method, was outperformed by other ET methods for 14 of 23 agroecosystem metrics ($p \leqslant 0.05$). When the original Ritchie soil water evaporation method was combined with potential ET from the ASCE reference ET and dual crop coefficient method, the model performed statistically equivalent to or better than the other five ET options for all but 1 of 23 agroecosystem metrics ($p \leqslant 0.05$). Based on three years of cotton data from the Bushland lysimetry fields, a DSSAT-CSM ET approach based on the standardized ET methodologies described by ASCE and FAO-56 combined with the original Ritchie soil water evaporation method provided holistic improvements to model simulations among multiple agroecosystem metrics.

1. Introduction

A recent landmark effort to compare evapotranspiration (ET) simulations among diverse maize (*Zea mays* L.) models revealed twofold or greater variation in ET estimates for rainfed conditions in central Iowa (Kimball et al., 2019), which suggested that the models require improvements to provide consistent and accurate ET simulations. Among the 29 models intercompared by Kimball et al. (2019), six models involved different ET simulation options with the Decision Support System for Agrotechnology Transfer (DSSAT) Cropping System Model (CSM) (Jones et al., 2003). The DSSAT-CSM ET methods included six combinations of three methods for computing potential ET and two methods for computing soil water evaporation, as discussed below in detail. The results were surprising, revealing that an older soil water evaporation algorithm (Ritchie, 1972) outperformed the newer, default evaporation method in the model (Ritchie et al., 2009). Also, a reduced-input potential ET method based on Priestley and Taylor (1972) outperformed two more modern methods based on formulations

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of the Penman-Monteith equation (Allen et al., 1998) with associated crop coefficient adjustments. Although the study will remain a distinguished contribution toward evaluation of ET simulation methods, major issues impacting the simulations were that 1) no data were available to quantify amounts of water loss to artificial subsurface drainage systems (which are ubiquitous across the Iowa landscape) and 2) only limited data were available on the status of soil water content profiles. Therefore, further comparisons of the six DSSAT-CSM ET methods are needed for other environments, where water balances are more fully characterized and where artificial subsurface drainage is not a confounding factor.

Although the results of Kimball et al. (2019) provided great insights on the state of ET simulation methodologies, they noted that model parameterization choices made by modelers with different levels of skill and experience may have introduced biases in the model comparisons. Indeed, potential bias issues were readily apparent in the effort to calibrate the six DSSAT-CSM ET methods for the Kimball et al. (2019) study, a task that was conducted solely by the lead author of the present article. When the goal is to make meaningful comparisons among ET algorithms and state definitively that one method is better than another, how does one make model parameterization choices while eliminating subjectivity and bias due to 1) personal opinions on favored simulation approaches, 2) failure to fully consider or even comprehend the appropriate parameter adjustments to be made, 3) the complexities introduced by interacting parameters, 4) the conflicting scenarios where parameter adjustments lead to improved results for one metric (e.g., ET) but worsened results for another metric (e.g., yield) and vice versa, and 5) the lack of protocols for basing model comparisons on statistical inference? These questions led Thorp et al. (2019) to develop a methodology for comparing ET simulation algorithms while reducing the subjectivity of parameterization choices; however, these procedures were only partially developed and implemented for the DSSAT-CSM simulations reported in the Kimball et al. (2019) study.

Thorp et al. (2019) described a computationally-intensive methodology for guiding parameterization decisions and making unbiased comparisons of ET methods in an agroecosystem model, and the approach was demonstrated by comparing three ET methods in the Cotton2K model. The study used agronomic and ET data from weighing lysimetry fields at a cotton (*Gossypium hirsutum* L.) field site near Bushland, Texas (Howell et al., 2004; Evett et al., 2012a). In the first of two analysis phases, a Sobol global sensitivity analysis (GSA) (Cariboni et al., 2007; Pianosi et al., 2016; Saltelli et al., 2000; Sobol, 2001) was conducted to identify influential model input parameters, understand model output sensitivities, and provide guidance on appropriate parameters for adjustment. Results of the GSA guided decisions for the second phase of analysis, in which a multiobjective optimization approach (Taboada et al., 2007) was used to make parameterization choices and evaluate simulation results against multiple agronomic measurements, while considering large numbers of input parameterization options. Results of the simulation analysis were evaluated using inferential statistics to determine the ET algorithms that performed statistically better than others, while collectively considering various types of agronomic measurements. The methodology was useful for comparing ET methods in the Cotton2K model while minimizing, if not eliminating, the subjective parameterization decisions that could make such comparisons less meaningful. The Thorp et al. (2019) methodology is generally applicable for other simulation models and can provide further comparisons of the six ET methods in the DSSAT-CSM, as discussed herein.

The overall goal of the present study was to apply the second phase of the Thorp et al. (2019) methodology to evaluate the performance of six ET methods in the DSSAT-CSM using agronomic data from cotton field studies at Bushland, Texas. Field data for the analysis included ET measurements from four weighing lysimeters at the field site and other agronomic measurements from co-located field experiments that compared fully-irrigated, deficit-irrigated, and dryland cotton production. Specific objectives were to use multiobjective optimization methods with high-performance computing to 1) evaluate the percent root mean squared error (%RMSE) between measured and simulated data for 23 agroecosystem metrics in response to adjustments in 38 influential model input parameters (determined from a prior Sobol GSA) and 2) conduct statistical inference tests among %RMSE results to identify ET simulation options that performed significantly better than others. As reported in a companion paper (Thorp et al., 2020), the influential model input parameters were identified from the first phase of the Thorp et al. (2019) methodology, which involved a Sobol GSA with the DSSAT-CSM using data from the same field site. As compared to the Kimball et al. (2019) study, the present study was unique by conducting DSSAT-CSM ET method comparisons with 1) a different crop (cotton as opposed to maize), 2) a different environment (semi-arid west Texas as opposed to humid central Iowa), 3) more carefully controlled water management conditions (scheduled irrigation management as opposed to rainfed agriculture), 4) a different ET measurement system (weighing lysimetry as opposed to eddy covariance), and 5) a more comprehensive computational effort to minimize modeler bias.

2. Materials and methods

2.1. Field experiments

Cotton field experiments to quantify evapotranspiration (ET) of fully-irrigated, deficit-irrigated, and dryland cotton production were conducted in four weighing lysimetry fields at the USDA-ARS Conservation and Production Research Laboratory (CPRL) near Bushland, Texas (35.187°N; 102.097°W; 1170 m above mean sea level) during the 2000 and 2001 growing seasons (Howell et al., 2004). Also, the Bushland Evapotranspiration and Agricultural Remote sensing EXperiment (BEAREX08) quantified ET for fully-irrigated and dryland cotton production at the same site during 2008 (Evett et al., 2012a). The soil texture at the site was predominantly clay loam and silty clay loam, as determined from textural analysis of soil samples (Tolk et al., 1998). Growing season precipitation and short crop reference ET from April through September amounted to 153 and 1324 mm in 2000, 182 and 1244 mm in 2001, and 333 and 1269 mm in 2008, respectively. Strong regional advection from the south and southwest typically led to relatively large reference ET values at the site, and precipitation levels much smaller than reference ET led to water limitation and need for irrigation. In all three seasons, irrigation was applied using a 10-span lateral-move overhead sprinkler irrigation system (Lindsay Manufacturing, Omaha, Nebraska) equipped with mid-elevation spray application (MESA) nozzles at a height of approximately 1.5 m above the ground surface. The machine was oriented from north to south, traveled in an east or west direction, and irrigated two lysimetry fields simultaneously.

Four large weighing lysimeters were installed at the Bushland field site in the 1980's (Marek et al., 1988) and have been used to monitor ET for a variety of crops for three decades (Evett et al., 2012a, 2016; Howell et al., 1995, 2004). Evett et al. (2012b) described the weighing lysimeters and their relative positions with >110 m fetch among four fields, which were designated using the intercardinal directions (NE, SE, NW, and SW) of each field location. During the 2000 and 2001 cotton studies, the SE and NE lysimetry fields were managed using full and limited irrigation, respectively. Full irrigation was defined as weekly irrigation to replenish root zone soil water content to field capacity, and limited irrigation was half of the full rate. In the 2008 season, both the NE and SE lysimetry fields were fully irrigated. The NW and SW lysimetry fields were not irrigated (dryland production) in 2001 or 2002, and less than 130 mm was applied in the 2008 early season to encourage germination and emergence. Soil water content was periodically measured (i.e., one or two weeks between measurements) at two access tube locations in each lysimeter using a calibrated neutron scattering probe (model 503DR1.5 Hydroprobe, CPN

Table 1
Summary of the 12 cotton management scenarios evaluated with DSSAT-CSM CROPGRO-Cotton. Field experiments were conducted within the four weighing lysimetry fields at Bushland, Texas, USA in 2000, 2001, and 2008.[1]

Year	Lysimetry Field	Planting Date (DOY)	Row Spacing	Plant Density	Irrigation Depth	Rainfall[2] Depth	Harvest Date (DOY)
			(cm)	(p m^{-2})	(mm)	(mm)	
2000	NE	16 May (137)	76	17.6	292	249	6 Dec (341)
2000	NW	15 May (136)	76	11.1	0	249	6 Dec (341)
2000	SE	16 May (137)	76	18.6	534	249	6 Dec (341)
2000	SW	15 May (136)	25	8.8	0	249	6 Dec (341)
2001	NE	16 May (136)	76	14.9	213	368	3 Nov (307)
2001	NW	16 May (136)	76	12.3	0	368	20 Oct (293)
2001	SE	16 May (136)	76	15.3	403	368	16 Nov (320)
2001	SW	16 May (136)	38	7.1	0	368	20 Oct (293)
2008	NE	21 May (142)	76	12.6	409	362	24 Nov (329)
2008	NW	5 Jun (157)	76	10.1	129	362	29 Nov (334)
2008	SE	21 May (142)	76	11.5	410	362	25 Nov (330)
2008	SW	5 Jun (157)	76	13.5	129	362	24 Nov (329)

[1] day of year, DOY; northeast, NE; northwest, NW; southeast, SE; southwest, SW.
[2] 1 January to 30 September.

International, Inc., Martinez, California), which provided data from 0.1 to 1.9 m in 0.2 m incremental depths. Specific protocols for weighing lysimetry measurements during the three cotton growing seasons were given by Howell et al. (2004) and Evett et al. (2012a). Howell et al. (1995) discussed the calibration technique for mass measurement within the lysimeter, which can provide ET estimates at time scales less than one hour. More recently, Marek et al. (2014) presented techniques for quality assurance and quality control of data collected from the lysimeters. Based on this post-processing protocol, lysimeter-based ET data (ETC) for the present study was aggregated on a daily basis from 1 January through 31 December in 2000, 2001, and 2008. Furthermore, lysimetry data from 1 January through 31 May was designated as soil water evaporation-dominated ET data (ETS), and lysimetry data from 1 June through 30 September was designated as plant transpiration-dominated ET data (ETP). Note that ETC, ETS, and ETP all represent ET measurements from both crop and soil, and the only difference is the timeframe over which the ET data were collected and accumulated.

Cotton planting dates ranged from mid-May to early June in the three growing seasons (Table 1). After establishment, cotton plants were destructively sampled on a two-week basis from small areas (1.0 to 2.0 m^2) more than 10 m away from the lysimeter. The samples were processed in the laboratory to estimate leaf area index (LAI), leaf dry matter (LDM), stem dry matter (SDM), boll dry matter (BDM), and canopy dry matter (CDM). Plants were dissected into component parts, placed into paper bags, and weighed after drying in a commercial oven at 60°C until mass stabilized (requiring 24 h or longer), indicating all water had been removed from the sample. Prior to drying, leaf area was measured using a digital scanning leaf area meter (LI-3100, LI-COR, Lincoln, Nebraska) and used for computation of LAI. Prior to field sampling, cotton canopy height (CHT) was measured in all three growing seasons, and canopy width (CDW) was measured in 2008 only. Observations of emergence date (EDAT) and anthesis date (ADAT) were available for a subset of the cotton plantings. Cotton harvest dates ranged from late October to early December in the three growing seasons. Yield measurements were obtained by sampling mature bolls from five 10.0-m^2 areas in each lysimetry field. Turnout percentages were measured using a small research gin, which provided data for fiber and cottonseed yield for each lysimeter in each growing season. Seed cotton yield (SCY) was computed as the sum of fiber and cottonseed yield.

2.2. DSSAT-CSM CROPGRO-Cotton

The DSSAT-CSM CROPGRO-Cotton model (ver. 4.7.1.003) was used to simulate the conditions of the four lysimetry fields for the three cotton growing seasons at Bushland, Texas. Because the companion paper reports a comprehensive evaluation of model sensitivities via a Sobol GSA, more specific details on the formulation of crop development and growth algorithms and water and nitrogen balance computations are described there (Thorp et al., 2020). Additional details about DSSAT-CSM CROPGRO-Cotton can be found in Jones et al. (2003) and Thorp et al. (2014a,b, 2017).

The present paper focuses specifically on comparisons of six ET simulation options in the DSSAT-CSM, which involve the six possible combinations of three approaches to estimate potential ET and two approaches to simulate soil water evaporation (Table 2). Like many other agroecosystem models, calculations of potential ET form the basis of water use estimation in the DSSAT-CSM, and they establish the feedback mechanism to limit crop growth for water-stressed conditions. Although most applied ET scientists now explicitly use reference ET methods, the DSSAT-CSM was originally conceived prior to development of reference ET approaches and continues to incorporate potential ET concepts for ET estimation. Among the three potential ET methods, one method, based on Priestley and Taylor (1972), can be classified as a true potential ET method and is therefore appropriate for the modeling framework. The other two approaches adapt reference ET methods to provide DSSAT-required estimates of potential ET. The approaches involve different formulations of the Penman-Monteith equation combined with different crop coefficient strategies for non-stressed crop conditions. DeJonge et al. (2020) discussed the important differences between reference ET and potential ET, focusing specifically on implications for ET calculations in agroecosystem models.

The very early developments of the DSSAT-CSM incorporated a Priestley and Taylor (1972) method for potential ET computations and the Ritchie (1972) method for simulating soil water evaporation (RR, Table 2). The combination of these methods is likely the most widely used ET approach in the history of the model. A second soil water evaporation routine was more recently added to the DSSAT-CSM (Suleiman and Ritchie, 2003, 2004; Ritchie et al., 2009), which simulates upflux of water from deeper to shallower soil layers in response to evaporation. The Ritchie et al. (2009) method is currently the default soil water evaporation algorithm in the model, while the Priestley and Taylor (1972) approach remains the default potential ET method (RS, Table 2). Traditionally, the model design requires a daily computation of potential ET, and simulated LAI is used to partition potential ET (PET) to potential soil water evaporation (PE) and potential plant transpiration (PT):

$$PE = PET(\exp[-KEP(LAI)]) \quad (1)$$

Table 2
Summary of six evapotranspiration (ET) options in the Decision Support System for Agrotechnology Transfer (DSSAT) Cropping System Model (CSM). The six ET approaches involve the combinations of three methods to estimate potential ET and two soil water evaporation methods, which are specified by changing settings for the "EVAPO" and "MESEV" parameters, respectively, in the DSSAT-CSM management file.

Short Name	EVAPO Setting	MESEV Setting	Description
RR	R	R	Potential ET is computed via a Priestley and Taylor (1972) method, requiring only daily solar irradiance and maximum and minimum air temperatures. Soil water evaporation is computed using the Ritchie (1972) method. These represent the earliest methods in the model, which have been used most widely.
FR	F	R	"Grass" reference ET is computed using the Penman-Monteith combination equation based on Eqs. (3)–(5) in FAO-56 (Allen et al., 1998) using fixed constants for the "grass" reference surface. Potential ET for cotton is computed by adjusting the reference ET using a DSSAT-specific single crop coefficient as a function of leaf area index. The method requires daily solar irradiance, wind speed, and maximum, minimum, and dew point air temperatures. Partitioning of potential ET to soil and plant surfaces is based on an exponential function of leaf area index. Soil water evaporation is computed using the Ritchie (1972) method.
GR	G	R	Standardized short crop reference ET (ET_{os}) is computed using the FAO Penman-Monteith equation based on Eq. 6 in FAO-56 (Allen et al., 1998) and explicitly following the American Society of Civil Engineers (ASCE) Standardized Reference Evapotranspiration Equation (Walter et al., 2005). Following DeJonge and Thorp (2017), potential T is computed by adjusting ET_{os} using an FAO-56 basal crop coefficient (K_{cb}) calculated from leaf area index, and potential E is computed based on ET_{os} and an FAO-56-based evaporation coefficient. The method requires daily solar irradiance, wind speed, and maximum, minimum, and dew point air temperatures. Soil water evaporation is computed using the Ritchie (1972) method.
RS	R	S	Potential ET is computed identically to the RR method above. Soil water evaporation is computed using the Ritchie et al. (2009) method. These represent the current default methods in the model.
FS	F	S	Potential ET is computed identically to the FR method above. Soil water evaporation is computed using the Ritchie et al. (2009) method.
GS	G	S	Potential E and potential T are computed identically to the GR method above. Soil water evaporation is computed using the Ritchie et al. (2009) method.

$$PT = PET - PE \tag{2}$$

where KEP is an input parameter named the energy extinction coefficient and has a default value of 0.7. Subsequently, the model determines whether soil water content and plant root growth is sufficient to supply PE and PT. The sufficiency of soil water content to supply PE is determined by either the Ritchie (1972) or the Ritchie et al. (2009) algorithm, and actual soil water evaporation is the minimum of PE and the amount determined by the evaporation algorithm. Likewise, the sufficiency of the simulated root system and soil water content to supply PT is determined by a root water uptake algorithm, and actual plant transpiration is the minimum of PT and the amount determined by the uptake calculations. Finally, plant stress coefficients are computed from the ratio of simulated values for actual and potential transpiration. These stress coefficients feedback on the crop simulation to limit calculations of photosynthesis and crop growth.

Since DSSAT version 4.0, a reference ET method based on the Penman-Monteith combination equation has been available to estimate the DSSAT-required potential ET (F, Table 2). The method was developed following Eqs. (3)–(5) in the Food and Agriculture Organization of the United Nations (FAO) Irrigation and Drainage Paper No. 56 (FAO-56) (Allen et al., 1998). Several formulations of this method were previously evaluated by Sau et al. (2004), but only one approach was released with DSSAT. This method assumes a constant reference crop height of 0.12 m, surface resistance of 70 s m^{-1}, LAI of 2.88 m m^{-2}, and surface albedo of 0.23 in the Penman-Monteith combination equation (Eq. 3 as presented on page 19 in FAO-56), giving approximately "grass" reference ET (ET_{pm}). The method uses the following equations to adjust reference ET to potential ET:

$$K_c = 1.0 + (EORATIO - 1.0)\frac{LAI}{6.0} \tag{3}$$

$$PET = K_c(ET_{pm}) \tag{4}$$

where EORATIO is an input parameter similar to a maximum FAO-56 crop coefficient. However, Eq. 3 is specific to DSSAT and does not appear in FAO-56 or any related primary ET reference. Also, the EORATIO parameter is hard-coded to 1.0 for many crops in the DSSAT-CSM (e.g., maize), leading to K_c equal to 1.0 (Eq. 3). Currently, only the CROPGRO models (e.g., soybean, cotton, peanut, and dry bean) fully implement the EORATIO method. This means the DSSAT-CSM incorrectly simulates potential ET as reference ET for crops like maize (DeJonge et al., 2020), although Eq. 3 is fully implemented for the CROPGRO-Cotton model tested herein. DeJonge et al. (2020) discussed how reference ET and potential ET are fundamentally different and stressed that reference ET computations must be paired with appropriate FAO-56 crop coefficients to adjust daily ET estimates from the reference surface to the crop surface. Although the Penman-Monteith formulation in DSSAT-CSM has been known both colloquially and in literature as DSSAT's "FAO-56" method, the approach deviates substantially from FAO-56 as described by Allen et al. (1998) and has therefore misled some model users (DeJonge et al., 2020).

While these issues motivated several efforts to make the approach more similar to FAO-56 (Thorp et al., 2010; DeJonge et al., 2012; Thorp et al., 2014b), the efforts of DeJonge and Thorp (2017) provided a DSSAT-CSM ET method that most closely followed current standardized ET methods, as embodied in the American Society of Civil Engineers (ASCE) Standardized Reference Evapotranspiration Equation (Walter et al., 2005) and FAO-56 (Allen et al., 1998). They added a separate reference ET method to estimate DSSAT-required potential ET (G, Table 2), which used the FAO Penman-Monteith equation (Eq. 6 as presented on page 24 in FAO-56) to compute either short crop reference ET (ET_o) or tall crop reference ET (ET_r), following the algorithms specified in the ASCE Standardized Reference Evapotranspiration Equation documentation (Walter et al., 2005). Furthermore, DeJonge and Thorp (2017) implemented the FAO-56 dual crop coefficient method with basal crop coefficients (K_{cb}) computed from DSSAT-simulated LAI and paired with ET_o to compute PT:

$$K_{cb} = K_{cbmin} + (K_{cbmax} - K_{cbmin})(1.0 - \exp[-SK_c(LAI)]) \tag{5}$$

$$PT = K_{cb}ET_o \tag{6}$$

where K_{cbmin} and K_{cbmax} are specified from FAO-56 crop coefficient tables. The evaporation coefficient (K_e) is computed following Eq. 71 in FAO-56, with the stress coefficient (K_r) set to 1.0 to derive non-stressed evaporation potential:

$$PE = K_eET_o \tag{7}$$

Due to differences in the DSSAT-CSM and FAO-56 soil profile definitions, FAO-56 concepts are used only to define the evaporation potential (PE), while the DSSAT algorithms of Ritchie (1972) or Ritchie et al. (2009) are used for computation of actual soil water evaporation.

The DeJonge and Thorp (2017) ET formulation closely adapts standardized ET methods as described in Allen et al. (1998) and Walter et al. (2005) for computation of PT and PE in the DSSAT-CSM. As shown by DeJonge and Thorp (2017), the method also provided simulated ET time series that demonstrated expected ET behavior, while the behavior of other DSSAT-CSM ET methods deviated from theoretical expectations. Because DeJonge and Thorp (2017) did not evaluate or compare the performance of the various DSSAT ET methods against measured ET data, the present study provides further performance assessments and comparisons using the three-year cotton data set from the Bushland weighing lysimetry fields. Hereafter, the six ET methods in DSSAT-CSM are denoted RR, FR, GR, RS, FS, and GS, as described in Table 2.

2.3. Simulation workflow

The simulation workflow for the present study included 1) a Sobol sampling scheme to select large numbers (i.e., over 15 million) of input parameterization options from a high-dimensional parameter space, 2) high-performance computing to efficiently conduct DSSAT-CSM CROPGRO-Cotton simulations, 3) a database approach to link input parameter sets with %RMSE values computed from measured and simulated data for multiple agroecosystem metrics, 4) a multiobjective optimization approach to identify optimal parameterization options that minimize %RMSE among the metrics, and 5) inferential statistics to compare performance of six ET methods in the model (Fig. 1). Further details of the workflow implementation are described in the following sections.

2.4. Sobol sampling

As reported in the companion paper (Thorp et al., 2020), a Python (www.python.org) script that incorporated the Sensitivity Analysis Library (SALib) was used to conduct Sobol sampling for a Sobol GSA. In the present study, the same SALib algorithm was used for Sobol sampling; however, the sampled parameter space was modified based on the results of the previous GSA. Only the influential parameters were included in the present analysis. This ensured that parameter adjustments would have meaningful impact on the model output and therefore lead the analysis toward improved model fit to measured data. Parameters that were deemed non-influential from the previous GSA were fixed, either to default values or based on past experience with the model. The GSA was not repeated for the new Sobol sample. Instead, a subset of the Sobol samples was chosen via multiobjective optimization to identify optimal model parameterizations.

For the previous GSA (Thorp et al., 2020), a first-order sensitivity index threshold of 0.05 was used to identify the influential parameters. As a result, several parameters were influential for only a few but not all of the six ET methods (see Table 2 in the companion paper). For the present study, the data were assessed with a slightly reduced sensitivity index threshold of 0.031, which permitted consistent influential parameters among all six ET methods for all but two parameters: the top-layer root growth factor (SRGF1) and the maximum basal crop coefficient (KMAX). Both of these parameters remained consistently influential for the Ritchie (1972) evaporation method (R, Table 2) but not influential for the Ritchie et al. (2009) method (S, Table 2). The modified sensitivity index threshold permitted more consistent parameter adjustments among ET methods, which was expected to encourage a fairer performance comparison among ET methods. It is a conservative adjustment, allowing flexibility for a few parameters that would otherwise be fixed, all in the interest of greater fairness among ET method comparisons.

Only 12 of 38 influential model input parameters were crop cultivar parameters (Table 3). Six of these parameters controlled photothermal durations for cotton growth stages, including photothermal time from planting to emergence (PL-EM), from emergence to flowering (EM-FL), from flowering to first boll (FL-SH), from flowering to first seed (FL-SD), from first seed to maturity (SD-PM), and for maximum boll load (PODUR). Three parameters controlled leaf growth, including

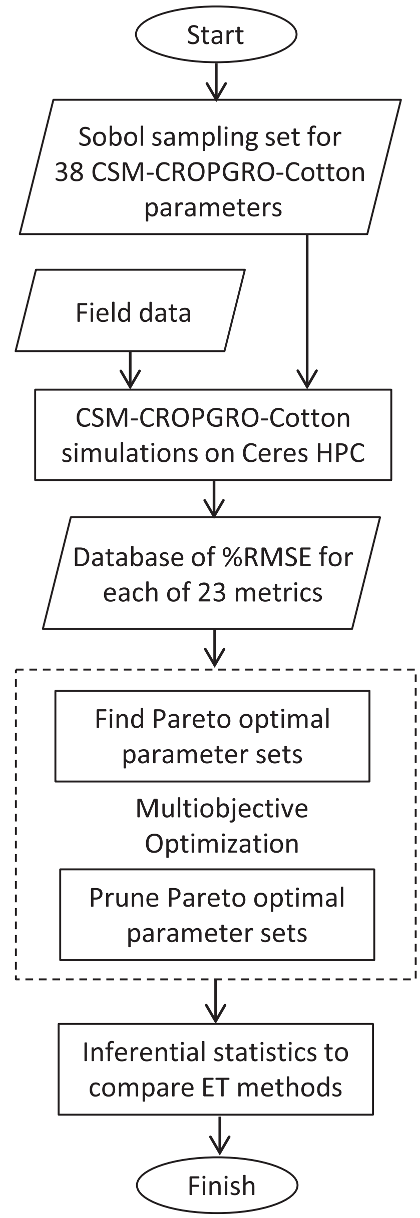

Fig. 1. Workflow for the "Phase 2" analysis to compare evapotranspiration methods in the DSSAT Cropping System Model (CSM), including 1) a Sobol method for sampling 38 input parameters for DSSAT-CSM CROPGRO-Cotton, 2) model simulations on the Ceres high performance computer (HPC), 3) a database approach to link model input parameters from Sobol sampling to 23 percent root mean squared error (%RMSE) computations between measured and simulated data for 23 agroecosystem metrics, 4) a multiobjective optimization approach to identify parameterization options that minimize %RMSE among the 23 metrics, and 5) inferential statistics to compare performance of six ET simulation methodologies among the 23 metrics. This "Phase 2" simulation analysis was informed by the "Phase 1" analysis, as reported in a companion paper (Thorp et al., 2020).

maximum photosynthesis rate (LFMAX), the specific leaf area for standard conditions (SLAVR), and the leaf appearance rate (TRIFL). The remaining three parameters controlled the maximum daily growth fraction partitioned to bolls (XFRT) and the relative cultivar width (RWDTH) and height (RHGHT). Their ranges of flexibility were specified identically to that in the companion study, based on experience with the model and examples from model input files (Table 3).

The previous GSA (Thorp et al., 2020) identified increased model sensitivity to parameters defining the soil profile water limits, including

Table 3
The DSSAT-CSM CROPGRO-Cotton parameters sampled for multiobjective optimization with their lower bounds (LB) and upper bounds (UB).

Parameter	Description	LB	UB
EM-FL	Photothermal time - emergence to flowering (°C d)	30.0	50.0
FL-SH	Photothermal time - flowering to first boll (°C d)	1.0	15.0
FL-SD	Photothermal time - flowering to first seed (°C d)	1.0	20.0
SD-PM	Photothermal time - first seed to maturity (°C d)	25.0	55.0
LFMAX	Maximum photosynthesis rate (mg CO_2 m^{-2} s^{-1})	0.9	3.0
SLAVR	Specific leaf area for standard conditions (cm^2 g^{-1})	110.0	190.0
XFRT	Maximum daily growth fraction partitioned to bolls (%)	0.3	1.0
PODUR	Photothermal time to maximum boll load (°C d)	5.0	20.0
PL-EM	Photothermal time - planting to emergence (°C d)	2.0	12.0
TRIFL	Leaf appearance rate (# $°C^{-1}$ d^{-1})	0.1	0.4
RWDTH	Width of cultivar relative to standard cultivar	0.7	1.30
RHGHT	Height of cultivar relative to standard cultivar	0.7	1.30
KMAX	Maximum basal crop coefficient (unitless)	0.9	1.3
SLU1	Evaporation limit for Ritchie (1972) method (cm)	4.0	20.0
SLDR	Soil drainage rate (fraction d^{-1})	0.05	0.6
SLLL005	Lower limit from 0 to 5 cm (cm^3 cm^{-3})	0.114	0.222
SLLL015	Lower limit from 5 to 15 cm (cm^3 cm^{-3})	0.114	0.222
SLLL030	Lower limit from 15 to 30 cm (cm^3 cm^{-3})	0.125	0.240
SLLL045	Lower limit from 30 to 45 cm (cm^3 cm^{-3})	0.127	0.245
SLLL060	Lower limit from 45 to 60 cm (cm^3 cm^{-3})	0.126	0.243
SLLL090	Lower limit from 60 to 90 cm (cm^3 cm^{-3})	0.126	0.241
SLLL120	Lower limit from 90 to 120 cm (cm^3 cm^{-3})	0.126	0.241
SLLL150	Lower limit from 120 to 150 cm (cm^3 cm^{-3})	0.130	0.249
SLLL180	Lower limit from 150 to 180 cm (cm^3 cm^{-3})	0.134	0.261
SLLL210	Lower limit from 180 to 210 cm (cm^3 cm^{-3})	0.132	0.250
SDUL005	Drained upper limit from 0 to 5 cm (cm^3 cm^{-3})	0.285	0.397
SDUL015	Drained upper limit from 5 to 15 cm (cm^3 cm^{-3})	0.286	0.397
SDUL030	Drained upper limit from 15 to 30 cm (cm^3 cm^{-3})	0.284	0.396
SDUL045	Drained upper limit from 30 to 45 cm (cm^3 cm^{-3})	0.282	0.395
SDUL060	Drained upper limit from 45 to 60 cm (cm^3 cm^{-3})	0.270	0.383
SDUL090	Drained upper limit from 60 to 90 cm (cm^3 cm^{-3})	0.274	0.383
SDUL120	Drained upper limit from 90 to 120 cm (cm^3 cm^{-3})	0.266	0.373
SDUL150	Drained upper limit from 120 to 150 cm (cm^3 cm^{-3})	0.273	0.385
SDUL180	Drained upper limit from 150 to 180 cm (cm^3 cm^{-3})	0.284	0.409
SDUL210	Drained upper limit from 180 to 210 cm (cm^3 cm^{-3})	0.284	0.402
SRGF1	Root growth factor in top soil layer (fraction)	0.3	1.0
SRGF2	Root growth factor decline with soil depth (fraction m^{-1})	0.2	0.8
SH2ONE00	Initial soil water content adjustment for NELYS in 2000 (cm^3 cm^{-3})	−0.09	0.09
SH2OSE00	Initial soil water content adjustment for SELYS in 2000 (cm^3 cm^{-3})	−0.09	0.09
SH2ONW00	Initial soil water content adjustment for NWLYS in 2000 (cm^3 cm^{-3})	−0.09	0.09
SH2OSW00	Initial soil water content adjustment for SWLYS in 2000 (cm^3 cm^{-3})	−0.09	0.09
SH2ONE01	Initial soil water content adjustment for NELYS in 2001 (cm^3 cm^{-3})	−0.09	0.09
SH2OSE01	Initial soil water content adjustment for SELYS in 2001 (cm^3 cm^{-3})	−0.09	0.09
SH2ONW01	Initial soil water content adjustment for NWLYS in 2001 (cm^3 cm^{-3})	−0.09	0.09
SH2OSW01	Initial soil water content adjustment for SWLYS in 2001 (cm^3 cm^{-3})	−0.09	0.09
SH2ONE08	Initial soil water content adjustment for NELYS in 2008 (cm^3 cm^{-3})	−0.09	0.09
SH2OSE08	Initial soil water content adjustment for SELYS in 2008 (cm^3 cm^{-3})	−0.09	0.09
SH2ONW08	Initial soil water content adjustment for NWLYS in 2008 (cm^3 cm^{-3})	−0.09	0.09
SH2OSW08	Initial soil water content adjustment for SWLYS in 2008 (cm^3 cm^{-3})	−0.09	0.09

the lower limit (SLLL) and drained upper limit (SDUL). The SLLL and SDUL values for each of 10 soil layers were adjusted individually in the present study, because soil water content data were available for all soil layers. This was different from the previous GSA, in which the SLLL and SDUL data were specified identically among all the layers, because the goal was simply to identify influential parameters rather than optimize SLLL and SDUL uniquely among soil layers. The default layer depths for soil profiles in DSSAT-CSM were used: 0–5 cm, 5–15 cm, 15–30 cm, 30–45 cm, 45–60 cm, 60–90 cm, 90–120 cm, 120–150 cm, 150–180 cm, and 180–210 cm. The upper and lower bounds for SLLL and SDUL were based on soil texture measurements by Tolk et al. (1998) for the Pullman soil at the Bushland field site. The Rosetta pedotransfer functions (Zhang and Schaap, 2017) provided mean Van Genuchten (1980) parameters for the Bushland soil texture data and also provided standard deviation as a measure of parameter uncertainty. The ranges of SLLL and SDUL were calculated based on ranges of plus and minus two standard deviations from the mean Van Genuchten (1980) parameters for the Pullman soil (Table 3). Suction pressures of 1500 and 33 kPa were assumed for SLLL and SDUL, respectively, in the Van Genuchten (1980) model.

The GSA also identified the initial soil water content (SH2O) as a highly influential parameter (Thorp et al., 2020). Measured soil water content data were available only after the start of the growing season. Therefore, the data could not be used to directly specify the initial soil water contents for model simulations, which were initialized on 1 January because lysimeter-based ET measurements were available then. The following strategy was adopted to adjust initial soil water contents uniquely for each lysimeter in each growing season. First, to establish the general shape of the soil water content profile, the average seasonal soil water content in each soil layer was computed from measured data for each lysimeter and growing season. Next, a single parameter was used to initialize the model by adjusting all the soil water contents in the soil profile between ±0.09 cm^3 cm^{-3} relative to the average seasonal soil water content in each layer (Table 3). The parameter range was chosen to ensure that the model would not be initialized with a soil water content value greater than porosity. In this way, the initial soil water content parameters, which were deemed highly influential in the previous GSA, were allowed flexibility while the optimization algorithm, discussed later, ensured that in-season simulated soil water content measurements were fit to measured data.

Table 4
Agroecosystem metrics evaluated for three cotton growing seasons among four lysimetry fields (NELYS, SELYS, NWLYS, and SWLYS) at Bushland, Texas, USA. The 23 metrics are listed in priority order for evaluation of the DSSAT-CSM CROPGRO-Cotton agroecosystem model using multiobjective optimization techniques.

Metric	Description	Unit	NELYS *n*	SELYS *n*	NWLYS *n*	SWLYS *n*
ETC	Evapotranspiration	mm d^{-1}	940	967	927	927
SCY	Seed cotton yield	kg ha^{-1}	3	3	3	3
LAI	Leaf area index	m^2 m^{-2}	19	19	17	17
CHT	Canopy height	m	19	19	17	17
EDAT	Emergence Date	day of year	3	3	1	1
ADAT	Anthesis Date	day of year	1	1	1	1
CDM	Canopy dry matter	kg ha^{-1}	19	19	17	17
LDM	Leaf dry matter	kg ha^{-1}	19	19	17	17
SDM	Stem dry matter	kg ha^{-1}	12	12	10	10
BDM	Boll dry matter	kg ha^{-1}	12	12	10	10
CWD	Canopy width	m	9	9	6	6
ETP	ETC from 1 Jan to 31 May	mm d^{-1}	357	360	359	356
ETS	ETC from 1 Jun to 30 Sep	mm d^{-1}	429	436	425	432
SWC010	Soil water content at 10 cm	cm^3 cm^{-3}	30	29	24	24
SWC030	Soil water content at 30 cm	cm^3 cm^{-3}	30	29	24	24
SWC050	Soil water content at 50 cm	cm^3 cm^{-3}	30	29	24	24
SWC070	Soil water content at 70 cm	cm^3 cm^{-3}	30	29	24	24
SWC090	Soil water content at 90 cm	cm^3 cm^{-3}	30	29	24	24
SWC110	Soil water content at 110 cm	cm^3 cm^{-3}	30	29	24	24
SWC130	Soil water content at 130 cm	cm^3 cm^{-3}	30	29	24	24
SWC150	Soil water content at 150 cm	cm^3 cm^{-3}	30	29	24	24
SWC170	Soil water content at 170 cm	cm^3 cm^{-3}	30	29	24	24
SWC190	Soil water content at 190 cm	cm^3 cm^{-3}	30	27	23	18

Five additional water balance parameters were adjusted, including two soil root growth factors (SRGF1 and SRGF2), the soil drainage rate (SLDR), the evaporation limit (SLU1) which was applicable only for the Ritchie (1972) evaporation approach (R, Table 2), and the maximum basal crop coefficient (KMAX) which was influential only for the DeJonge and Thorp (2017) potential ET method with Ritchie (1972) soil water evaporation (GR, Table 2). The root growth factors define the shape of the rooting profile and were calculated using two variables: 1) SRGF1 specified the root growth factor for the top soil layer and 2) SRGF2 specified the linear rate of decline with soil profile depth. Similar to the companion study, root growth profiles were specified using a linear decrease from the top soil layer with zero being the smallest possible factor level. Because SRGF1 was non-influential for the Ritchie et al. (2009) evaporation method (Thorp et al., 2020), it was fixed to 1.0 for that case, indicating unrestricted root growth in that layer. Other non-influential soil parameters were fixed based on field measurements or experience with the model.

The *N* parameter of SALib's Sobol sampling algorithm was set to 158,224 with specification to prepare for calculation of second-order sensitivity effects (although the resulting parameter sets were not used for a second GSA). Thus, the number of *n*-dimensional parameter sets ($n = 49$) chosen was $N(2n + 2) = 15,822,400$, as defined within the Sobol algorithm. The value of *N* was identical to that used in the companion study based on estimated timeframes for conducting simulations via high-performance computing. The total number of parameters for each lysimeter and growing season combination was 38; however, because initial soil water conditions were permitted to vary uniquely per lysimeter and growing season (as discussed above), the *n* for the Sobol algorithm was 49.

2.5. Simulations

Similar to the companion study, DSSAT-CSM CROPGRO-Cotton was set up to run 12 simulation scenarios based on the three cotton growing seasons and four uniquely-managed lysimetry fields (Table 1). Simulations were initiated on 1 January in each year and concluded on the recorded harvest date for each lysimetry field. Within the SW lysimetry field in 2001, twin rows spaced 25 cm apart were planted on 76 cm centers. Because CROPGRO-Cotton did not consider this planting configuration, a row spacing of 38 cm (i.e., half of 76 cm) was simulated.

Simulations were conducted using USDA's high-performance computing resource called Ceres. A Python script that incorporated the "multiprocessing" package was used to manage simulation tasks among processing cores. With 12 simulation scenarios, 6 ET algorithms, and 15,822,400 parameter sets, the simulation analysis required a total of 1,139,212,800 simulations, which required 327,875 CPU hr on Ceres and approximately 1,639 h of wall-clock time. This study was more computationally expensive than the companion study, which was in part related to the greater number of simulations required. Additional details regarding the simulation set up are presented in the companion paper (Thorp et al., 2020).

2.6. Database method

Field experiments at Bushland provided data for 23 agroecosystem metrics (Table 4), including ET from weighing lysimeters, soil water content from neutron scattering probes, and crop development and growth information. Measured and simulated data for these metrics were aggregated among the three cotton growing seasons for each tested parameter set by calculating the percent root mean squared error (%RMSE) uniquely for each metric:

$$\%\text{RMSE}_i = f_i(\mathbf{m}_i, \mathbf{s}_i) = \frac{100}{\bar{\mathbf{m}}_i}\sqrt{\frac{1}{n_i}\sum_{j=1}^{n_i}(m_{ij} - s_{ij})^2} \tag{8}$$

where $\mathbf{m}_i$, $\mathbf{s}_i$, and n_i are the measured and simulated data vectors and vector length, respectively, among the three cotton growing seasons for the *i*th metric (Table 4). The %RMSE statistics were calculated uniquely for each lysimeter to permit separate evaluation of irrigated versus dryland cotton production conditions. The simulation jobs on Ceres concluded by outputting a separate model response database for each lysimetry field, which included the DSSAT-CSM CROPGRO-Cotton input parameter sets with associated %RMSE statistics for each of the 23 agroecosystem metrics.

Table 5
Analysis of variance results (*F* statistics and *p* values) and Tukey's multiple comparisons tests among the pruned Pareto optimal solutions from DSSAT-CSM CROPGRO-Cotton simulations using three potential evapotranspiration methodologies (R, F, and G). The group means for percent root mean squared errors (% RMSE) are given for each method and agroecosystem metric, and statistically better performing methods for each metric are highlighted in bold with gray background. [1]

Metric	F	p value	R %RMSE	F %RMSE	G %RMSE
ETC	5.20	0.0059**	60.8 a	**57.6 b**	**59.0 ab**
SCY	0.72	0.4880	**42.7 a**	**44.9 a**	**42.5 a**
LAI	32.73	0.0000***	92.6 a	79.7 b	**66.9 c**
CHT	25.34	0.0000***	25.6 a	**21.0 b**	**19.8 b**
EDAT	7.55	0.0006***	**0.5 b**	**0.5 ab**	0.6 a
ADAT	4.20	0.0156*	**0.6 b**	1.0 a	**0.9 ab**
CDM	14.67	0.0000***	34.1 a	**30.0 b**	**29.6 b**
LDM	13.03	0.0000***	70.5 a	**63.6 b**	**58.7 b**
SDM	8.44	0.0003***	44.2 a	42.2 a	**37.8 b**
BDM	2.39	0.0926	**68.8 a**	**62.8 a**	**65.1 a**
CWD	1.49	0.2260	**25.5 a**	**25.3 a**	**23.8 a**
ETP	8.27	0.0000***	44.2 a	**40.8 b**	**40.8 b**
ETS	22.34	0.0000***	**92.1 b**	**92.7 b**	99.2 a
SWC010	49.93	0.0000***	36.9 a	30.8 b	**28.4 c**
SWC030	10.69	0.0000***	15.0 a	**13.9 b**	**13.5 b**
SWC050	6.46	0.0017**	14.2 a	**12.5 b**	**13.0 b**
SWC070	7.07	0.0010***	15.4 a	**13.3 b**	**14.3 ab**
SWC090	15.61	0.0000***	13.2 a	**10.8 b**	**11.3 b**
SWC110	0.52	0.5960	**15.2 a**	**14.8 a**	**15.3 a**
SWC130	0.27	0.7650	**16.0 a**	**15.8 a**	**15.5 a**
SWC150	0.04	0.9630	**15.9 a**	**15.8 a**	**15.7 a**
SWC170	0.50	0.6060	**17.9 a**	**17.6 a**	**16.9 a**
SWC190	0.44	0.6420	**17.6 a**	**18.3 a**	**17.4 a**
# of Best Fits			11 of 23	19 of 23	21 of 23

[1]anthesis date, ADAT; boll dry matter, BDM; canopy dry matter, CDM; canopy height, CHT; canopy width, CWD; emergence date, EDAT; evapotranspiration (1 Jan to harvest), ETC; evapotranspiration (1 Jun to 30 Sep), ETP; evapotranspiration (1 Jan to 31 May), ETS; leaf area index, LAI; leaf dry matter, LDM; seed cotton yield, SCY; stem dry matter, SDM; soil water content; SWC.

2.7. Multiobjective optimization

Because there were 23 agroecosystem metrics to consider (Table 4), identifying the best parameterization options for DSSAT-CSM CROPGRO-Cotton required multiobjective optimization (MOO) techniques (Taboada et al., 2007). The objective function to be optimized incorporated k unique %RMSE calculations, one for each agroecosystem metric ($k = 23$), expressed as

$$f_{MOO}(\mathbf{m}, \mathbf{s}) = (f_1(\mathbf{m}_1, \mathbf{s}_1), f_2(\mathbf{m}_2, \mathbf{s}_2), \ldots, f_k(\mathbf{m}_k, \mathbf{s}_k)) \quad (9)$$

where the terms are as described for Eq. 8. Eq. 9 represents the set of % RMSE calculations (Eq. 8) for each of k agroecosystem metrics, based on the results of simulations for a given parameter set among nearly 16 million sets tested. The first step toward reduction of plausible parameter sets was to calculate the subset of Pareto optimal solutions (Cheikh et al., 2010), which were the solutions that were not dominated (or non-dominated) by any other solution. In mathematical terms, a solution x_1 dominates another solution x_2 if the following two conditions are met:

- $f_i(x_1) \leq f_i(x_2)$ for all $i \in \{1, 2, \ldots, k\}$
- $f_j(x_1) < f_j(x_2)$ for at least one $j \in \{1, 2, \ldots, k\}$

In words, a solution dominates another if the %RMSE calculations for k agroecosystem metrics are all less than or equal to that for the other solution, and at least one %RMSE calculation is less than that for the other solution. The goal was to find the parameter sets with %RMSE calculations that were not dominated by the RMSE calculations for any other parameter set. Following the methodology of Thorp et al. (2019), a Python script was developed to calculate the Pareto optimal solution set among the evaluated parameterization options for each DSSAT-CSM ET method and lysimetry field.

A known problem with Pareto optimal sets is that they often remain large and cumbersome, and they do not adequately ease the burden of selecting one or several practical solutions. Following Taboada et al. (2007) and as implemented by Thorp et al. (2019), a "pruning" algorithm was developed to reevaluate each Pareto optimal solution and combine the k objective function outcomes (Eq. 9) to a single evaluation criterion by assigning k weightings following a predetermined objective function priority. Because ET and crop yield were the most

Table 6
Analysis of variance results (F statistics and p values) and Tukey's multiple comparisons tests among the pruned Pareto optimal solutions from DSSAT-CSM CROPGRO-Cotton simulations using two soil water evaporation methodologies (R and S). The group means for percent root mean squared errors (%RMSE) are given for each method and agroecosystem metric, and statistically better performing methods for each metric are highlighted in bold with gray background. [1]

Metric	F	p value	R %RMSE	S %RMSE
ETC	5.43	0.0203*	**58.5 b**	60.5 a
SCY	1.42	0.2340	**42.4 a**	**44.6 a**
LAI	0.74	0.3910	**80.1 a**	**82.5 a**
CHT	2.69	0.1020	**21.9 a**	**23.2 a**
EDAT	2.20	0.1390	**0.5 a**	**0.6 a**
ADAT	1.64	0.2020	**0.9 a**	**0.7 a**
CDM	0.04	0.8480	**31.6 a**	**31.4 a**
LDM	1.28	0.2590	**65.9 a**	**63.6 a**
SDM	0.48	0.4900	**41.3 a**	**42.3 a**
BDM	0.12	0.7290	**66.2 a**	**65.4 a**
CWD	3.58	0.0591	**25.6 a**	**24.0 a**
ETP	0.03	0.8690	**42.1 a**	**42.2 a**
ETS	245.70	0.0000***	**89.2 b**	101.6 a
SWC010	26.06	0.0000***	**30.8 b**	34.9 a
SWC030	1.83	0.1770	**14.4 a**	**14.0 a**
SWC050	0.47	0.4920	**13.2 a**	**13.5 a**
SWC070	6.44	0.0155*	**13.9 b**	15.1 a
SWC090	16.09	0.0001***	**11.2 b**	12.8 a
SWC110	47.23	0.0000***	**13.9 b**	16.8 a
SWC130	3.21	0.0738	**15.4 a**	**16.4 a**
SWC150	14.04	0.0002***	**14.9 b**	17.0 a
SWC170	1.55	0.2140	**18.0 a**	**16.9 a**
SWC190	0.54	0.4620	**18.0 a**	**17.4 a**
# of Best Fits			23 of 23	16 of 23

[1] anthesis date, ADAT; boll dry matter, BDM; canopy dry matter, CDM; canopy height, CHT; canopy width, CWD; emergence date, EDAT; evapotranspiration (1 Jan to harvest), ETC; evapotranspiration (1 Jun to 30 Sep), ETP; evapotranspiration (1 Jan to 31 May), ETS; leaf area index, LAI; leaf dry matter, LDM; seed cotton yield, SCY; stem dry matter, SDM; soil water content; SWC

important of agroecosystem metrics in this study, the priority of objective functions were specified in the following order: ETC, SCY, LAI, CHT, EDAT, ADAT, CDM, LDM, SDM, BDM, CWD, ETP, and ETS, followed by the ten soil water content measurements from top to bottom in the profile (Table 4). The weightings were used to calculate the weighted average among the groups of 23 %RMSE results among all solutions in the Pareto optimal set, and the parameter set with the smallest weighted average was identified. The process was iterated until 1,000 iterations passed without identification of a new pruned solution. The set of pruned Pareto optimal solutions determined from this process was used for all further analysis. For model evaluation purposes, simulated data were estimated based on the median simulation result among the pruned Pareto optimal solutions. Additional details on the multiobjective optimization strategy are presented by Thorp et al. (2019).

2.8. ET method comparison

The performance of the six DSSAT-CSM ET methods (Table 2) was compared by conducting an analysis of variance (ANOVA) on %RMSE results for each of the 23 agroecosystem metrics (Table 4) among the pruned Pareto optimal solutions. Tukey's multiple comparisons tests were also conducted to identify which ET methods resulted in statistically different %RMSE values for each agroecosystem metric ($p \leq 0.05$), and the smallest of these identified the better ET method for a given metric. Statistical analysis was conducted using the R Project for Statistical Computing software (www.r-project.org).

3. Results

3.1. Inferential statistics

Among the three methods for simulating potential ET, the DeJonge

Table 7
Analysis of variance results (*F* statistics and *p* values) and Tukey's multiple comparisons tests among the pruned Pareto optimal solutions from DSSAT-CSM CROPGRO-Cotton simulations using six combinations of three potential evapotranspiration methods two soil water evaporation methods (RR, FR, GR, RS, FS, and GS). The group means for percent root mean squared errors (%RMSE) are given for each method and agroecosystem metric, and statistically better performing methods for each metric are highlighted in bold with gray background.[1]

Metric	*F*	*p* value	RR %RMSE	FR %RMSE	GR %RMSE	RS %RMSE	FS %RMSE	GS %RMSE
ETC	3.40	0.0051**	**60.1 ab**	**57.7 ab**	**57.7 ab**	61.5 a	**57.2 ab**	61.5 a
SCY	3.67	0.0029**	**36.8 b**	45.9 a	**43.8 ab**	47.6 a	**42.7 ab**	**40.1 ab**
LAI	20.12	0.0000***	84.1 b	84.0 b	**71.7 c**	99.8 a	**70.4 c**	**57.9 c**
CHT	10.11	0.0000***	25.5 ab	**20.9 c**	**19.8 c**	25.8 a	**21.3 bc**	**19.7 c**
EDAT	4.63	0.0004***	**0.5 b**	**0.5 b**	**0.6 ab**	**0.5 b**	**0.7 ab**	0.7 a
ADAT	1.89	0.0948	**0.7 a**	**0.9 a**	**0.9 a**	**0.6 a**	**1.0 a**	**0.8 a**
CDM	6.47	0.0000***	34.1 a	**30.6 ab**	**30.2 b**	34.1 a	**28.7 b**	**28.4 b**
LDM	8.50	0.0000***	68.7 ab	66.9 ab	**61.9 bc**	72.0 a	**56.3 c**	**53.0 c**
SDM	3.53	0.0039**	44.2 a	**42.6 ab**	**37.1 b**	44.2 a	**41.3 ab**	**39.0 ab**
BDM	2.95	0.0124*	**65.5 ab**	**66.3 ab**	**66.8 ab**	71.6 a	**55.3 b**	**62.1 ab**
CWD	1.67	0.1410	**26.0 a**	**26.2 a**	**24.6 a**	**25.0 a**	**23.3 a**	**22.3 a**
ETP	3.94	0.0017**	44.3 a	**41.6 ab**	**40.5 ab**	44.1 a	**39.1 b**	**41.4 ab**
ETS	96.53	0.0000***	**85.7 e**	88.9 d	92.9 c	97.5 b	101.0 b	111.0 a
SWC010	24.50	0.0000***	35.9 a	**29.1 b**	**27.9 b**	37.7 a	34.5 a	**29.2 b**
SWC030	6.62	0.0000***	15.8 a	**13.8 b**	**13.7 b**	**14.3 b**	**14.0 b**	**13.2 b**
SWC050	2.58	0.0257*	**14.3 a**	**12.4 a**	**12.9 a**	**14.1 a**	**12.5 a**	**13.0 a**
SWC070	6.52	0.0000***	15.9 a	**12.9 c**	**13.1 bc**	15.0 ab	**14.1 abc**	16.6 a
SWC090	13.21	0.0000***	13.8 a	**10.1 b**	**10.1 b**	12.8 a	12.3 a	13.5 a
SWC110	10.48	0.0000***	**14.0 b**	**13.8 b**	**13.8 b**	16.2 a	16.9 a	18.0 a
SWC130	0.81	0.5460	**15.7 a**	**15.5 a**	**15.0 a**	**16.3 a**	**16.4 a**	**16.6 a**
SWC150	4.30	0.0008***	**15.4 b**	**15.2 b**	**14.1 b**	**16.3 ab**	**17.0 ab**	18.7 a
SWC170	0.67	0.6430	**18.3 a**	**18.3 a**	**17.3 a**	**17.6 a**	**16.3 a**	**16.2 a**
SWC190	0.59	0.7090	**18.3 a**	**18.6 a**	**17.0 a**	**17.0 a**	**17.6 a**	**18.1 a**
# of Best Fits			13 of 23	19 of 23	22 of 23	9 of 23	19 of 23	16 of 23

[1] anthesis date, ADAT; boll dry matter, BDM; canopy dry matter, CDM; canopy height, CHT; canopy width, CWD; emergence date, EDAT; evapotranspiration (1 Jan to harvest), ETC; evapotranspiration (1 Jun to 30 Sep), ETP; evapotranspiration (1 Jan to 31 May), ETS; leaf area index, LAI; leaf dry matter, LDM; seed cotton yield, SCY; stem dry matter, SDM; soil water content; SWC

and Thorp (2017) approach (G, Table 2) performed either statistically better than or similarly to the other two potential ET methods for all but two of the agroecosystem metrics (Table 5). Only for emergence date (EDAT) and soil water evaporation from 1 January through 31 May (ETS) did the Priestley-Taylor approach (R, Table 2) and Penman-Monteith combination equation approach (F, Table 2) perform statistically better than the DeJonge and Thorp (2017) implementation of the ASCE Standardized Reference ET equation with FAO-56 dual crop coefficients. Likewise, with the exception of anthesis date (ADAT), the F method performed statistically better than or similarly to the R method among all metrics. Regarding differences for EDAT and ADAT, the mean %RMSE differences among metrics were not more than 0.1% and 0.4%, respectively. Thus, although the results were significantly different for EDAT and ADAT, the magnitudes of the error differences did not indicate large performance differences. Specifically, EDAT and ADAT were not simulated more than ±2 and ±6 days different from available observations for 95% of simulations among pruned Pareto optimal solutions. As compared to the G potential ET method, the F and R methods provided statistically worse simulations for several of the plant-based metrics, including LAI and SDM, while the R method additionally simulated CHT, CDM, LDM, ETC, ETP and soil water contents from the surface to 90 cm with statistically greater error. The results demonstrated model performance advantages when using the DeJonge and Thorp (2017) approach for potential ET simulations in the DSSAT-CSM.

The poorer performance of the DeJonge and Thorp (2017) approach for ETS (Table 5) may not be of great concern. First, ETS was a lower priority metric. All other ET and plant growth metrics were specified with greater priority in the multiobjective optimization, and only the soil water content metrics were specified with lower priority (Table 4). Second, ETS was specified as ET from 1 January through 31 May, mostly a fallow period prior to crop planting and emergence (Table 1) with secondary importance to ET during the crop growing season. Furthermore, the total amount of ET for ETS (i.e., 145–179 mm) was 2–3 times less than the amount of ET for ETP (i.e., 331–723 mm). The ET for ETP is much more relevant for water use during the cotton growing season, although ETS was included in the analysis due to availability of ET measurements during that time. Finally, as discussed further later, poorer ETS performance was attributed to the combination of the G potential ET method with the Ritchie et al. (2009) soil water evaporation method (GS, Table 2), while the combination of G potential ET with the Ritchie (1972) soil water evaporation method (GR, Table 2) performed similarly to other ET options.

With the Ritchie (1972) soil water evaporation methodology, simulations of all 23 agroecosystem metrics were statistically equivalent to or better than that for the Ritchie et al. (2009) method (Table 6). The results clearly showed that simulations of ETC, ETS, and soil water contents at 5 of 10 soil profile depths were statistically better with the Ritchie (1972) method, and none of the metrics were better simulated with the Ritchie et al. (2009) method. The result corroborated findings

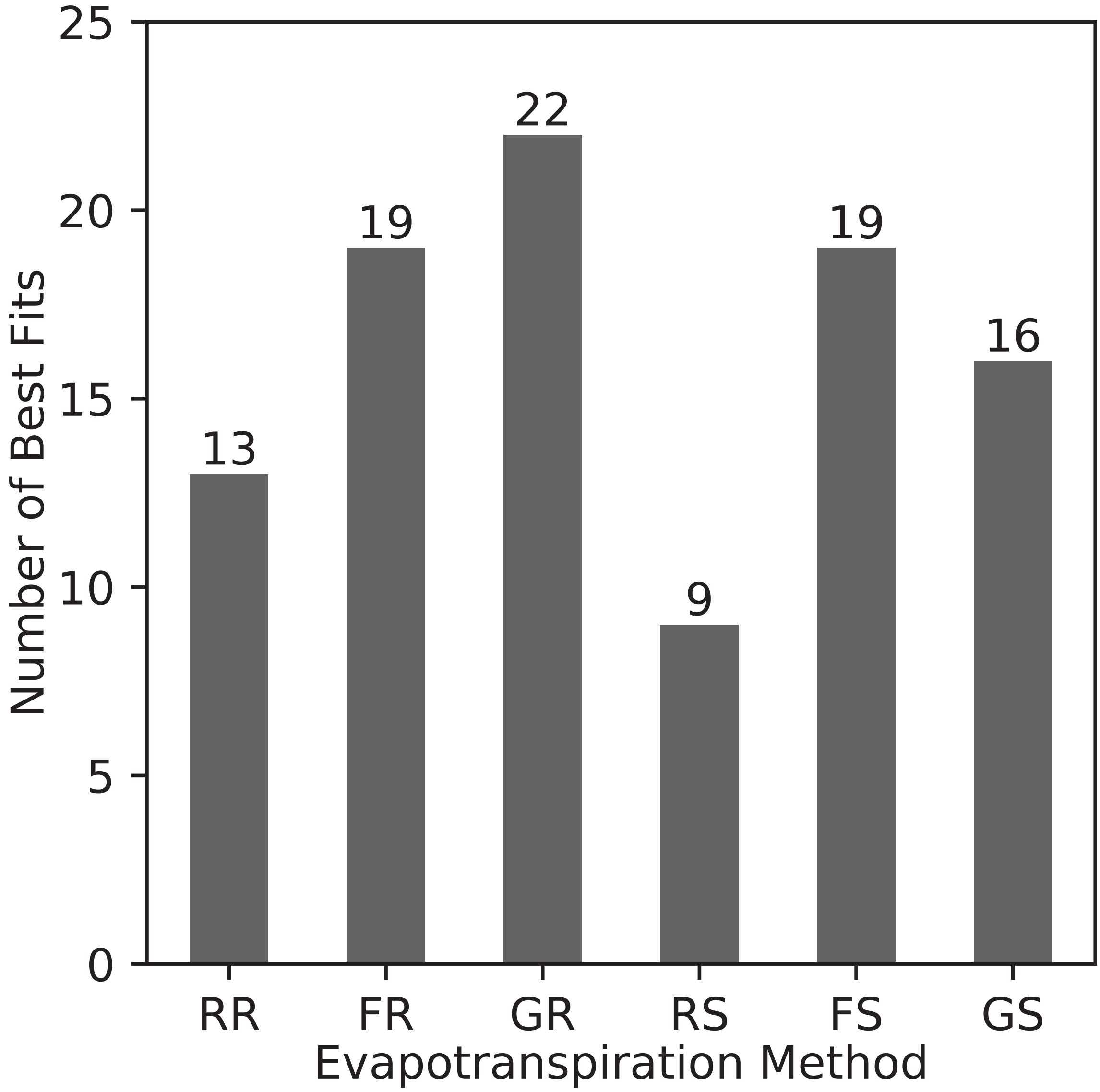

Fig. 2. Number of agroecosystem metrics (out of 23 total metrics) for which each of six DSSAT-CSM evapotranspiration methods (RR, FR, GR, RS, FS, and GS) provided a best fit, as assessed through statistical inference.

reported by Kimball et al. (2019), suggesting that the Ritchie et al. (2009) soil water evaporation method requires further development prior to regular use in the DSSAT-CSM.

By assessing the six combinations of potential ET and soil water evaporation options in the DSSAT-CSM, the results showed that the ASCE reference ET and dual crop coefficient method of DeJonge and Thorp (2017) combined with the Ritchie (1972) soil water evaporation method (GR, Table 2) performed statistically equivalent to or better than the other ET options for all but one agroecosystem metric, that is ETS (Table 7). The performance of ET methods using the Ritchie et al. (2009) soil water evaporation method was statistically poorer, particularly for ETC, ETS, and soil water content metrics. Also, simulations based on Priestley and Taylor (1972) potential ET demonstrated poorer performance for many plant growth metrics (LAI, CHT, CDM, LDM, and SDM), transpiration-dominated ET (ETP), and soil water content at several depths. The combination of Priestley and Taylor (1972) potential ET with Ritchie et al. (2009) soil water evaporation, which is considered the default ET method in the model, performed most poorly with 14 of 23 agroecosystem metrics simulated statistically better by another method. While the Penman-Monteith combination equation with Ritchie (1972) soil water evaporation (FR, Table 2) performed relatively well, its performance lagged the GR method for several plant growth variables (SCY, LAI, and LDM). Taken together, the results suggested that the GR method offered holistic simulation improvements among multiple agroecosystem metrics, as compared to other ET options in the DSSAT-CSM (Fig. 2).

Considering the simulation results per lysimetry field, model performance generally declined with water-limited environmental conditions (Table 8). Seasonal evapotranspiration (ETC) was simulated significantly better for the fully-irrigated conditions of the SE lysimetry field, as compared to the limited-irrigation conditions of the NE lysimetry field and the dryland conditions of the NW and SW lysimetry fields. Also, many of the plant growth metrics (LAI, CDM, SDM, BDM, and CWD) were simulated more poorly under dryland conditions with enhanced water stress. Future efforts should identify reasons for poorer model performance under water stress and develop improved ET methodologies to better simulate water-limited crop production. With expectations for a more water-limited future, models must be able to achieve accurate ET simulations under the full range of water management scenarios, including fully-irrigated, deficit-irrigated, and dryland crop production.

Table 8
Analysis of variance results (*F* statistics and *p* values) and Tukey's multiple comparisons tests among the pruned Pareto optimal solutions from DSSAT-CSM CROPGRO-Cotton simulations for four lysimetry fields (NELYS, SELYS, NWLYS, and SWLYS) with differing irrigation management (full, limited, and dryland) using the GR evapotranspiration method. The group means for percent root mean squared errors (%RMSE) are given for each method and agroecosystem metric, and statistically better performing methods for each metric are highlighted in bold with gray background. [1]

Metric	*F*	*p* value	NELYS Limited %RMSE	SELYS Full %RMSE	NWLYS Dryland %RMSE	SWLYS Dryland %RMSE
ETC	429.60	0.0000***	53.1 b	**45.7 c**	71.2 a	70.5 a
SCY	2.25	0.0893	**49.0 a**	**36.7 a**	**44.6 a**	**40.9 a**
LAI	8.09	0.0001***	82.9 ab	**58.3 c**	**67.8 bc**	125.5 a
CHT	0.70	0.5530	**21.1 a**	**19.7 a**	**19.0 a**	**15.3 a**
EDAT	13.90	0.0000***	0.8 a	0.8 a	**0.3 b**	**0.0 b**
ADAT	9.57	0.0000***	0.9 b	**0.2 c**	1.6 a	**0.5 bc**
CDM	11.54	0.0000***	**26.1 c**	**28.9 c**	34.1 b	47.7 a
LDM	5.69	0.0014**	**64.7 b**	**63.2 b**	**55.1 b**	102.5 a
SDM	23.83	0.0000***	**32.7 b**	**26.8 b**	48.7 a	54.0 a
BDM	21.89	0.0000***	67.9 b	**40.6 c**	88.4 a	**49.6 bc**
CWD	14.55	0.0000***	**20.5 b**	**18.7 b**	32.2 a	41.3 a
ETP	435.80	0.0000***	36.8 b	**28.9 c**	52.7 a	53.7 a
ETS	50.20	0.0000***	**87.4 b**	**89.2 b**	101.3 a	**93.8 ab**
SWC010	17.23	0.0000***	**22.6 b**	30.3 a	31.2 a	**26.2 ab**
SWC030	4.10	0.0094**	**12.7 b**	**13.3 b**	14.9 a	15.6 a
SWC050	6.86	0.0004***	**12.4 b**	16.1 a	**10.9 b**	**12.0 b**
SWC070	0.67	0.5760	**12.4 a**	**13.9 a**	**13.1 a**	**13.3 a**
SWC090	1.82	0.1510	**9.7 a**	**11.1 a**	**9.7 a**	**9.7 a**
SWC110	1.10	0.3550	**13.4 a**	**15.0 a**	**13.6 a**	**10.9 a**
SWC130	6.32	0.0007***	**14.4 b**	**12.2 b**	17.6 a	18.2 a
SWC150	4.40	0.0065**	15.1 a	**11.7 b**	15.4 a	**10.7 b**
SWC170	3.12	0.0306*	**19.3 a**	**12.5 a**	**20.0 a**	**9.4 a**
SWC190	1.20	0.3170	**18.7 a**	**15.4 a**	**17.0 a**	**12.1 a**
# of Best Fits			16 of 23	20 of 23	11 of 23	14 of 23

[1] anthesis date, ADAT; boll dry matter, BDM; canopy dry matter, CDM; canopy height, CHT; canopy width, CWD; emergence date, EDAT; evapotranspiration (1 Jan to harvest), ETC; evapotranspiration (1 Jun to 30 Sep), ETP; evapotranspiration (1 Jan to 31 May), ETS; leaf area index, LAI; leaf dry matter, LDM; seed cotton yield, SCY; stem dry matter, SDM; soil water content; SWC

4. Model evaluation

With the Ritchie et al. (2009) soil water evaporation method (S, Table 2), poorer ET simulations during the evaporation-dominated simulation period (1 January to 31 May) were primarily due to overestimation of soil water evaporation (Fig. 3b), whereas the Ritchie (1972) method tended to underestimate soil water evaporation (Fig. 3a). By design, the Ritchie (1972) method limited soil water evaporation to the water available in the top 5 cm of the soil profile, whereas the Ritchie et al. (2009) provided additional water supplies through simulations of upflux from deeper soil profile layers. Thus, the difference in algorithm design clearly drove the tendency for underestimation or overestimation of soil water evaporation with these methods. In particular, the combination of DeJonge and Thorp (2017) potential ET with Ritchie et al. (2009) soil water evaporation (GS, Table 2) simulated ET most poorly during the evaporation-dominated period (Fig. 3b) with the largest %RMSE (23.5%). Likely, increased potential ET from the G method combined with enhanced water supplies for evaporation with the S approach led to greater overestimation. On the other hand, combining DeJonge and Thorp (2017) potential ET with Ritchie (1972) soil water evaporation (GR, Table 2) provided ET simulations similar to other methods during this period (Fig. 3a).

Inspection of the simulated data revealed trends leading to data groupings visible in Figs. 3a and 3b. Specifically, pre-season ET from all lysimeters in 2001 and from the NE and SE lysimeters in 2008 were in the group with largest ET amounts, while data from the NW and SW lysimeters in 2000 were in the group with smallest ET amounts. Thus, the groupings were a function of lysimeter and year. Simulated ET during the evaporation-dominated period ranged from 87–184 mm for the Ritchie (1972) method and 110–236 mm for the Ritchie et al. (2009) method, while lysimeter measurements ranged only between 145–179 mm. Thus, both soil water evaporation methods simulated a much wider range of ET variability as compared with measurements. Although the Ritchie (1972) method led to improved model simulations overall (Table 6), both soil water evaporation approaches require

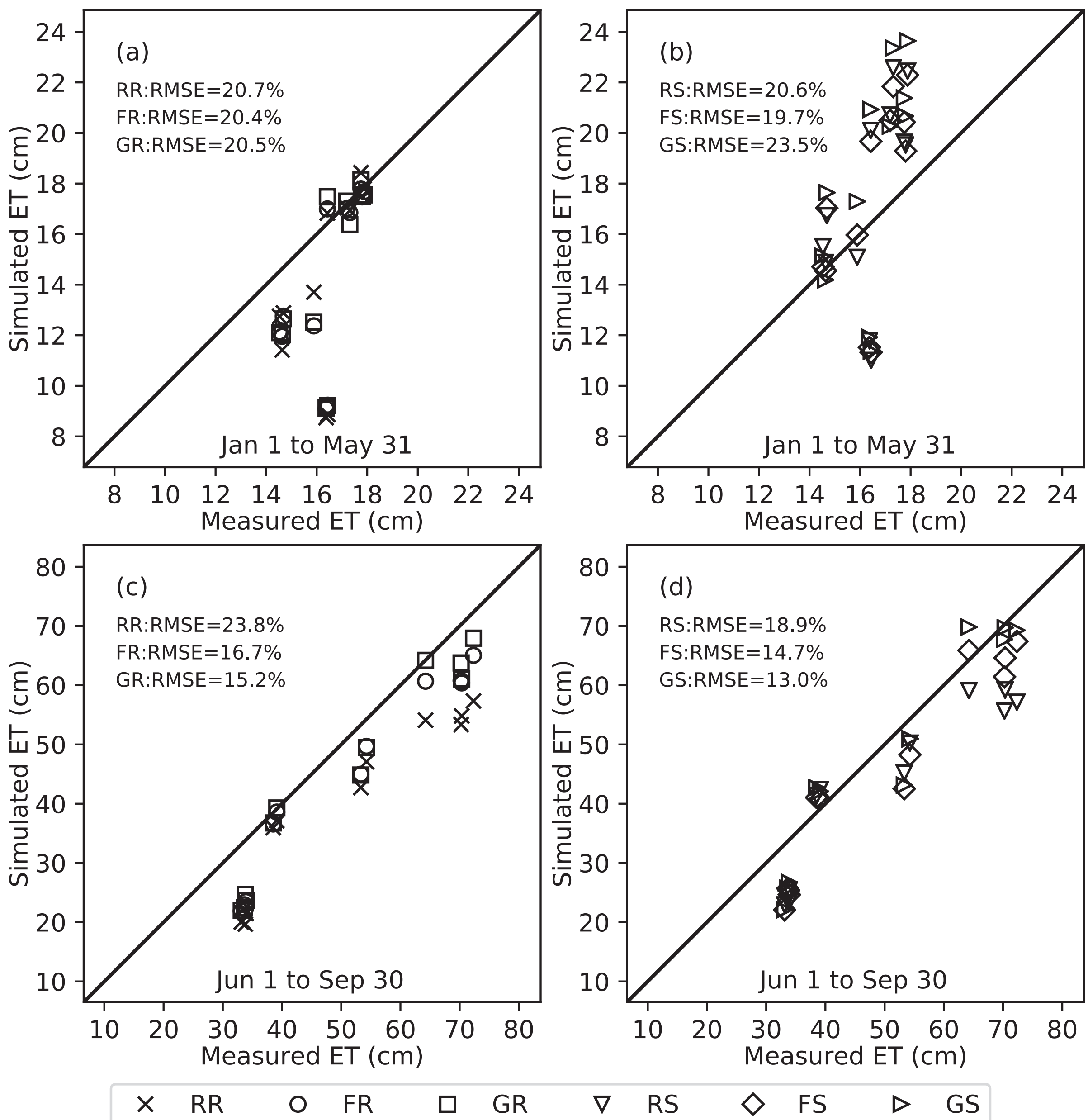

Fig. 3. DSSAT-simulated versus measured evapotranspiration for the evaporation-dominated period (1 January through 31 May) with a) the RR, FR, and GR evapotranspiration simulation methods and b) the RS, FS, and GS methods and for the transpiration-dominated period (1 June through 30 September) with c) the RR, FR, and GR methods and d) the RS, FS, and GS methods. Simulated data are plotted as the median simulation result among parameterization options within pruned Pareto optimal sets. The percent root mean squared error (RMSE) for each case is provided.

improvements to better align simulations with measured data during evaporation-dominated periods.

Regardless of the year, lysimeter, or ET methodology, the model tended to underestimate ET during the transpiration-dominated period from 1 June to 30 September (Figs. 3c and 3d). Notably, the DeJonge and Thorp (2017) potential ET approach (G, Table 2) often provided ET simulations nearer to the one-to-one line, as compared to ET simulations from the other two potential ET methods. The Priestley-Taylor ET method performed poorest for simulations of transpiration-dominated ET, while the Penman-Monteith combination equation performed more similarly to the DeJonge and Thorp (2017) method. However, the DeJonge and Thorp (2017) method provided slightly better simulations of transpiration-dominated ET with the smallest %RMSE, assessed via median simulation results among pruned Pareto optimal solutions (Figs. 3c and 3d).

Generally, the DSSAT-CSM simulations of LAI were overestimated for measured LAI < 2.5 $m^2\ m^{-2}$ (Figs. 4a and 4b). However, reasonable simulations were attained for LAI > 2.5 $m^2\ m^{-2}$. Regardless of the soil water evaporation method used, the DeJonge and Thorp (2017) potential ET method provided LAI simulations with smaller %RMSE, assessed via the median simulation results among pruned Pareto optimal solutions. Accurate LAI simulation is important due its feedbacks on calculations with all three potential ET methods (Eqs. 1, 3, and 5). Simulation results for seed cotton yield (SCY) were reasonable with %RMSE ranging from 28.3% to 43.8% among the six ET methods (Figs. 4c and 4d), while the RR, GR, FS and GS methods all provided statistically equivalent SCY simulations (Table 7).

Many simulation trends were similar to previous efforts using the same Bushland data set to evaluate the Cotton2K model (Thorp et al., 2019), which by comparison is a much more complex and detailed cotton simulation model than DSSAT-CSM. For example, both Cotton2K and DSSAT-CSM tended to underestimate transpiration-dominated ET,

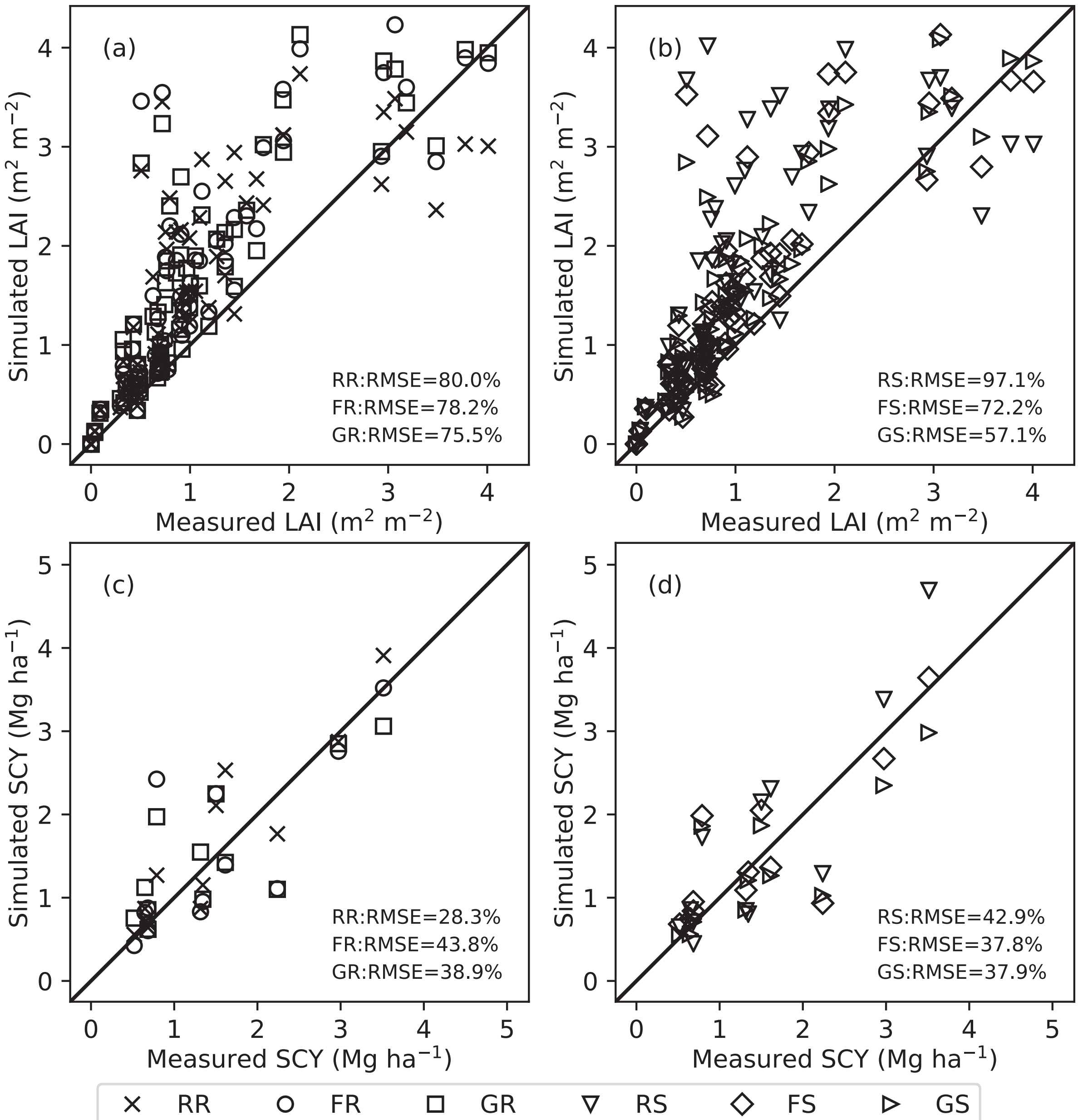

Fig. 4. DSSAT-simulated versus measured leaf area index (LAI) with a) the RR, FR, and GR evapotranspiration simulation methods and b) the RS, FS, and GS methods and seed cotton yield (SCY) with c) the RR, FR, and GR methods and d) the RS, FS, and GS methods. Simulated data are plotted as the median simulation result among parameterization options within pruned Pareto optimal sets. The percent root mean squared error (RMSE) for each case is provided.

regardless of the ET simulation methodology used. However, DSSAT-CSM simulated the evaporation-dominated ET much better than Cotton2K. Furthermore, Cotton2K simulated similar LAI trends with overestimated values for measured LAI < 2.5 m^2 m^{-2}; however, the LAI overestimation was worse with DSSAT-CSM. Simulations of SCY were similar among Cotton2K and DSSAT-CSM models, although DSSAT-CSM resulted in smaller %RMSE for SCY with some ET methods. Overall, the greater complexity of the Cotton2K model did not necessarily demonstrate improved simulation performance for the Bushland data set as compared with the simpler DSSAT-CSM model.

5. Discussion

Based on three years of cotton data from the Bushland, Texas site, the Ritchie (1972) soil water evaporation method (R, Table 2) outperformed the Ritchie et al. (2009) method (S, Table 2). This result agreed with the report by Kimball et al. (2019), who tested the same DSSAT-CSM ET methods using a maize data set from central Iowa. While the Ritchie et al. (2009) method underperformed in these studies, the overall design of the Ritchie et al. (2009) methodology is not poor. Rather, the developers need to reassess the calibration of the algorithm and evaluate the method using data sets that span multiple soil types. The Ritchie et al. (2009) method incorporates several hard-coded coefficients, and adjusting these coefficients was beyond the scope of the present study. Rather, the ET methods were evaluated and compared as presently designed and coded in the model. Future studies must reassess the Ritchie et al. (2009) code and associated coefficients using high-quality ET data sets, such as the Bushland lysimetry data used herein. With further detailed assessment and development, the Ritchie et al. (2009) soil water evaporation method may offer enhanced model performance. In the meantime, users should consider reverting to the Ritchie (1972) soil water evaporation method in DSSAT-CSM until improvements to the Ritchie et al. (2009) method can be finalized.

Regarding the three potential ET methods, the DeJonge and Thorp (2017) approach that incorporated ASCE Standardized Reference ET with an FAO-56 dual crop coefficient procedure (G, Table 2) outperformed a methodology based on the Penman-Monteith combination equation with a DSSAT-specific crop coefficient procedure (F, Table 2), which in turn outperformed the Priestley-Taylor method (R, Table 2). In the study of Kimball et al. (2019), the exact opposite result was reported, although they noted that their result was unexpected and that the differences among the potential ET approaches were generally small relative to differences due to soil water evaporation methods. The opposite result of Kimball et al. (2019) may be related to the humid environment at the Iowa field site and the limitations of the Iowa field data set to quantify soil water content profiles and water losses to artificial subsurface drainage. Furthermore, the simulations results reported by Kimball et al. (2019) were not subjected to the computationally-intensive methodology for guiding parameterization decisions and making unbiased intercomparisons of the ET method performance, as was done herein. As expected, the ET approach based on current standardized methods reported by ASCE (Walter et al., 2005) and in FAO-56 (Allen et al., 1998) led to many statistically significant improvements of cotton growth and water balance simulations based on data from the Bushland, Texas weighing lysimetry fields.

DeJonge et al. (2020) recently published a letter describing tendencies toward improper communication and specification of ET methods in agroecosystem models. The main point was to encourage proper use of standardized ET methods and highlight common confusion regarding differences between potential and reference ET methods. The DSSAT-CSM bases ET calculations on the concept of potential ET, likely because the model was originally conceived at a time prior to development of reference ET concepts. As such, the Priestley and Taylor (1972) methodology (R, Table 2) is appropriate for DSSAT-CSM, because Priestley-Taylor is a potential ET method. However, the Penman-Monteith combination equation as currently implemented in DSSAT-CSM (F, Table 2) and the FAO Penman-Monteith equation (G, Table 2) are both reference ET methods. Therefore, their computations of reference ET require adjustment using appropriate FAO-56 crop coefficients for non-stressed conditions to provide reasonable estimates of DSSAT-required potential ET. The original formulation of the Penman-Monteith combination equation in DSSAT-CSM (F, Table 2) has received past criticism (DeJonge and Thorp, 2017; DeJonge et al., 2020), mainly because the method is misnamed as the “FAO-56” method in DSSAT-related communications. However, this method implements neither 1) the FAO formulation of the Penman-Monteith equation nor 2) proper adjustments of Penman-Monteith reference ET using FAO-56 crop coefficients. As such, naming this DSSAT ET method after FAO-56 is misleading to model users who are familiar with FAO-56 as described by Allen et al. (1998). The DeJonge and Thorp (2017) ET methodology (G, Table 2) was programmed to more closely follow the ET method described in FAO-56, but it is not the same as the methodology often described as the “FAO-56” method in the DSSAT-CSM interfaces and literature. Using high-quality ET data sets from the Bushland, Texas lysimetry field, the present study identified the DeJonge and Thorp (2017) ET methodology as a top-performing potential ET method for DSSAT-CSM, while its formulation is also more firmly rooted in current standardized ET methodologies as described by ASCE (Walter et al., 2005) and FAO-56 (Allen et al., 1998). Future efforts will aim to make the DeJonge and Thorp (2017) methodology more readily available to model users and to provide further intercomparisons of DSSAT ET methods for additional crops and environmental conditions.

6. Conclusions

A computationally-intensive simulation methodology (Thorp et al., 2019) was successfully applied to provide statistical comparisons of six ET methods in the DSSAT Cropping System Model. While the simulation methodology was complex, it enabled statistical comparisons of model performance that were free from subjective choices for model parameterization. Results suggested that the DeJonge and Thorp (2017) method for potential ET combined with the Ritchie (1972) approach for soil water evaporation provided holistic simulation improvements among multiple agroecosystem metrics measured during three cotton growing seasons with fully-irrigated, deficit-irrigated, and dryland cultivation at Bushland, Texas, and this combination of ET approaches performed statistically better than the other five options. Because the DeJonge and Thorp (2017) method applies the standardized ET concepts described in the ASCE Standardized Reference ET Equation (Walter et al., 2005) and in FAO-56 (Allen et al., 1998) to compute DSSAT-required potential ET, the study demonstrated advantages for incorporation of standardized ET methods as an option to improve ET simulations in agroecosystem models. Future work should further evaluate the soil water evaporation methods in the model, with particular focus on improvement of the Ritchie et al. (2009) method.

CRediT authorship contribution statement

K.R. Thorp: Conceptualization, Methodology, Software, Formal analysis, Investigation, Resources, Data curation, Writing - original draft, Writing - review & editing, Visualization, Supervision, Project administration, Funding acquisition. **G.W. Marek:** Conceptualization, Investigation, Resources, Data curation, Writing - review & editing. **K.C. DeJonge:** Conceptualization, Methodology, Writing - review & editing, Visualization. **S.R. Evett:** Investigation, Resources, Writing - review & editing, Supervision, Project administration.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix A. Supplementary material

Supplementary data associated with this article can be found, in the online version, at https://doi.org/10.1016/j.compag.2020.105679.

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