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Comparison of evapotranspiration methods in the DSSAT Cropping System Model: I. Global sensitivity analysis

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ABSTRACT

Global sensitivity analysis (GSA) is useful for evaluating the responsiveness of agroecosystem models to input parameter adjustments. Evaluations of model sensitivity for diverse water status conditions and evapotranspiration (ET) algorithms will facilitate better use of models to provide water management recommendations. The objective of this study was to conduct a GSA to identify influential parameters in the Decision Support System for Agrotechnology Transfer (DSSAT) Cropping System Model (CSM), specifically using the CROPGRO-Cotton module with data from cotton field studies conducted in 2000, 2001, and 2008 at Bushland, Texas. The field studies tested fully-irrigated, deficit-irrigated, and dryland cotton production in a semi-arid environment. Using high performance computing resources, a GSA was conducted to evaluate the sensitivity of 24 model outputs with respect to 37 model input parameters. The GSA was conducted for six different ET methodologies available in the model. With first-order sensitivity indices <0.05, nearly half of the tested input parameters did not influence any model output for any of the tested simulation scenarios. Among the parameters with first-order sensitivity indices >0.05, eleven were cultivar parameters that controlled crop development and growth, and five were soil parameters that specified initial soil water conditions, soil water limits, drainage rate, and root growth characteristics. The influences of another soil parameter and one ET parameter were relevant only for the ET methods that required them. Large differences in sensitivity indices were found based on the choice between two soil water evaporation methods. In addition to providing insights for other applications of this model, the results specifically informed further efforts to evaluate the model using measured data from the Bushland cotton studies to compare performance among the six ET methods, as reported in a companion paper.

1. Introduction

Agroecosystem models can simulate the complex, dynamic, and often nonlinear processes that occur in crop production systems. However, prior to conducting model simulations, many parameters (i.e., tens to hundreds) must be specified to describe the soil properties and crop cultivar characteristics, and weather and management data must be input for the conditions under investigation. The models also contain many internal state variables, which are temporally manipulated over a specific time interval by iteratively evaluating the biophysical equations incorporated into the model code. The output data from agroecosystem models have many potential uses, including synthesizing research results, guiding management practices, and informing policy decisions (Boote et al., 1996). However, the sensibility of the simulation results is often dependent on the modeler's knowledge of model output sensitivities as related to model input specifications. Global sensitivity analysis (GSA) techniques have been developed as a primary means for agroecosystem modelers to quantify the relationships between model input and output data and increase understanding of model functionality (Cariboni et al., 2007; Pianosi et al., 2016; Saltelli et al., 2000). However, GSA studies with agroecosystem models are not routine, and additional efforts are necessary to improve understanding of model sensitivity.

A GSA can quantify the variability in model output data with respect to contributions from individual model input parameters as well as their interactions. Use of GSA to evaluate agroecosystem models has increased in recent years. For example, Pathak et al. (2007) used GSA to evaluate the CROPGRO-Cotton module within the Decision Support System for Agrotechnology Transfer (DSSAT) Cropping System Model (CSM) (Jones et al., 2003). They reported that GSA improved their

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understanding of model sensitivities as compared to local sensitivity analysis alone, mainly because GSA better considered parameter interactions, uncertainty ranges, and nonlinear model responses. They identified two CROPGRO-Cotton parameters, the specific leaf area under standard growth conditions (SLAVR) and the duration between first seed and physiological maturity (SD-PM), which were most influential on outputs of crop yield and season length, respectively. DeJonge et al. (2012a) used GSA to evaluate the sensitivity of the CERES-Maize model for both full and limited irrigation. Results indicated that model outputs were mostly influenced by crop cultivar parameters with full irrigation, but soil parameters became more influential with limited irrigation. The study also demonstrated unrealistic evapotranspiration (ET) simulations with higher ET for limited irrigation as compared to full irrigation in some cases, which supported the conclusions of DeJonge et al. (2012b) that CERES-Maize tended to overestimate ET for water-stressed conditions. Vazquez-Cruz et al. (2014) used GSA to evaluate the TOMGRO model, determining that 1) the maximum leaf area expansion parameter was most influential on the number of nodes and leaf area index (LAI) and 2) the coefficient of biomass partitioning was most influential on plant and fruit weights. Liang et al. (2017) used GSA to evaluate the Water Heat Carbon Nitrogen Simulator (WHCNS), finding that nitrate leaching was more sensitive to soil hydraulic and crop parameters than to nitrogen transformation parameters. Finally, Stella et al. (2014) demonstrated the use of GSA to reduce complexity of the WOrld FOod STudies (WOFOST) model. These studies demonstrate the use of GSA to evaluate many aspects of agroecosystem models, including impacts of crop, water, and nutrient parameters on simulated crop development, growth, and yield and on water and nitrogen balances. Continued efforts are needed to use GSA for understanding the sensitivity of agroecosystem models with diverse environmental data, management practices, and algorithm specifications.

Due to the importance of ET simulations for accurate modeling results, many recent studies have focused on the evaluation, intercomparison, and improvement of ET algorithms in agroecosystem models (Anapalli et al., 2016; DeJonge et al., 2012b; DeJonge and Thorp, 2017; Kimball et al., 2019; Marek et al., 2016; Marek et al., 2017; Sau et al., 2004; Thorp et al., 2014b). Related to this effort, Thorp et al. (2019) described several barriers to making unbiased comparisons of ET simulation approaches, including human subjectivity in manual parameter calibration, the complex effects of parameter interactions, and the lack of statistical comparison approaches. They developed a methodology for unbiased comparison of ET algorithms and demonstrated the approach to compare three ET methods in the Cotton2K agroecosystem model. The simulation workflow involved two main phases. The first phase involved GSA to identify influential model input parameters and understand model sensitivities. In a second phase of simulations, results of the GSA were used to inform a multiobjective optimization for model calibration, leading to simulation results for ET algorithm comparison via inferential statistics. Within the Thorp et al. (2019) methodology, GSA is necessary to eliminate non-influential parameters from consideration, which simplifies and focuses the multiobjective optimization only on parameters that have the greatest influence on model output. Application of this methodology to compare ET simulations for other agroecosystem models is needed.

The overall goal of the present study was to conduct the first phase of the Thorp et al. (2019) methodology, which involved GSA to identify influential model input parameters, identify non-influential parameters, and understand sensitivities of the DSSAT-CSM CROPGRO-Cotton model. Six options for ET simulations were considered. Specific objectives were to 1) use GSA techniques to evaluate the sensitivity of 24 model outputs to 37 model input parameters, 2) identify differences in model sensitivity among six ET simulation options in the model, and 3) identify differences in model sensitivity for conditions of fully-irrigated, deficit-irrigated, and dryland cotton (*Gossypium hirsutum* L.) production at a field site near Bushland, Texas. The results of the present study informed a second study that implemented the second phase of the Thorp et al. (2019) methodology to evaluate ET algorithm performance against field measurements, which is described in a companion paper (Thorp et al., 2020).

2. Materials and methods

2.1. Field site

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). Evett et al. (2012b) described the weighing lysimeters for ET measurements at Bushland and their relative positions with >110 m fetch among four fields, which were designated using the intercardinal direction (NE, SE, NW, or SW) of each field location. In 2000 and 2001, the SE and NE lysimeter 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 lysimeter fields were fully irrigated. The NW and SW lysimeter fields were not irrigated (dryland production) in 2001 and 2002, and less than 130 mm was applied in the 2008 early season to encourage germination and emergence. 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. Differences in irrigation management among the lysimetry fields provided unique environmental conditions for evaluating sensitivities of the DSSAT-CSM CROPGRO-Cotton model in the present study.

Meteorological information, including solar irradiance (MJ m^{-2}), air temperature (°C), dew point temperature (°C), and wind speed (km d^{-1}), was obtained from a Texas High Plains ET Network weather station, which was positioned over a well-watered, clipped grass surface adjacent to the field site. Precipitation data (mm) were obtained from a tipping bucket rain gauge managed by the experimentalists at the field site. 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 deficient precipitation levels led to water limitation and need for irrigation. Weather and crop management data from these field studies were used to parameterize the model for the present study, whereas the initial conditions and soil and cultivar parameters were iteratively adjusted to conduct a GSA, as discussed later.

2.2. DSSAT-CSM CROPGRO-Cotton

The DSSAT-CSM CROPGRO-Cotton model (ver 4.6.1.003) was evaluated using GSA techniques with cotton data sets at Bushland, Texas. The model uses mass balance principles and biophysical process equations to simulate carbon, nitrogen, and hydrologic processes and transformations that occur in an agroecosystem. The model operates on a daily time step, with some subprocesses calculated hourly. Simulations of cotton development proceed through a series of stages (e.g., emergence, first leaf, first flower, first seed, first cracked boll, and 90% open boll) based on photothermal unit accumulation from planting to harvest. Light interception is simulated based on an elliptical hedgerow canopy, and potential carbon assimilation is computed from leaf-level biochemistry equations with growth and maintenance respiration deducted. The model calculates stress effects from deficit soil water and nitrogen (N) conditions, which further reduce the carbohydrate available for simulated plant growth. Assimilated carbon is partitioned to various plant parts, including leaves, stems, roots, bolls, and seed cotton (fiber + seed). Leaf senescence is simulated in response to natural aging, N remobilization, water deficits, light stress, and physiological maturity. Both deficit and excess soil water conditions lead to root senescence. Water deficit stress is simulated when the potential demand for water lost through plant transpiration is greater than the amount of water supplied by the soil through the simulated root system. The amount of water supplied by the soil is a function of available water holding capacity, as defined by model inputs for drained upper limit and lower limit. The model simulates a layered, one-dimensional soil profile with a tipping-bucket method for water redistribution and algorithms for calculating soil and plant N balances. Additional details about DSSAT-CSM CROPGRO-Cotton can be found in Jones et al. (2003) and Thorp et al. (2014a,b, 2017).

Six ET simulation methods within the DSSAT-CSM were used in this study, based on the six possible combinations of three approaches to estimate potential ET and two approaches to simulate soil water evaporation (Table 1). The original ET techniques in DSSAT-CSM included a Priestley and Taylor (1972) method for potential ET computations and the Ritchie (1972) method for simulating soil water evaporation. A second soil water evaporation routine, which calculated upward movement of water through soil layers in response to ET, was later added (Suleiman and Ritchie, 2003; Suleiman and Ritchie, 2004; Ritchie et al., 2009). The Ritchie et al. (2009) method is currently the default soil water evaporation algorithm in the model, while the Priestley-Taylor approach remains the default potential ET method. Since DSSAT v4.0, a method using the Penman–Monteith combination equation has been available for potential ET calculations. 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. Following several efforts to improve this potential ET approach (Thorp et al., 2010; DeJonge et al., 2012b; Thorp et al., 2014b), DeJonge and Thorp (2017) added a separate potential ET method to the model, which 1) used the Penman–Monteith combination equation as expressed in Eq. 6 of FAO-56 and as fully documented in the American Society of Civil Engineers (ASCE) Standardized Reference Evapotranspiration Equation (Walter et al., 2005) and 2) implemented an FAO-56 dual crop coefficient method with basal crop coefficients (K_{cb}) computed from DSSAT-simulated LAI data. Further details on the DSSAT-CSM ET methods are provided in the companion paper (Thorp et al., 2020). In the present study, model sensitivity was evaluated among all six ET methods in the DSSAT-CSM, hereafter denoted RR, FR, GR, RS, FS, and GS as described in Table 1.

2.3. Simulation workflow

The simulation workflow for the present study included 1) a Sobol (2001) sampling scheme to choose large numbers of input parameterization options from a high-dimensional parameter space, 2) high-performance computing to efficiently conduct large numbers of DSSAT-CSM CROPGRO-Cotton simulations, 3) a database approach to link input parameter sets with relevant model output data, and 4) a global sensitivity analysis (GSA) to understand model sensitivities and identify influential input parameters (Fig. 1). Further details of the workflow implementation are described in the following sections.

2.4. Sobol sampling

A Sobol (2001) sampling procedure was used to choose high-dimensional parameter sets for input to the model. A Python (www.python.org) script that incorporated the Sensitivity Analysis Library (SALib) was developed to conduct the Sobol sampling and later to compute Sobol sensitivity indices for a Sobol GSA (Saltelli, 2002; Saltelli et al., 2010; Sobol, 2001). As compared to random sampling, Sobol sampling techniques were previously shown to be advantageous and more efficient to develop databases that describe high-dimensional model input and output relationships (Lamsal et al., 2018), because the Sobol algorithm can select parameter sets that are more evenly dispersed across the multidimensional parameter space.

Thirty-seven model input parameters were sampled for inclusion in

Table 1

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.

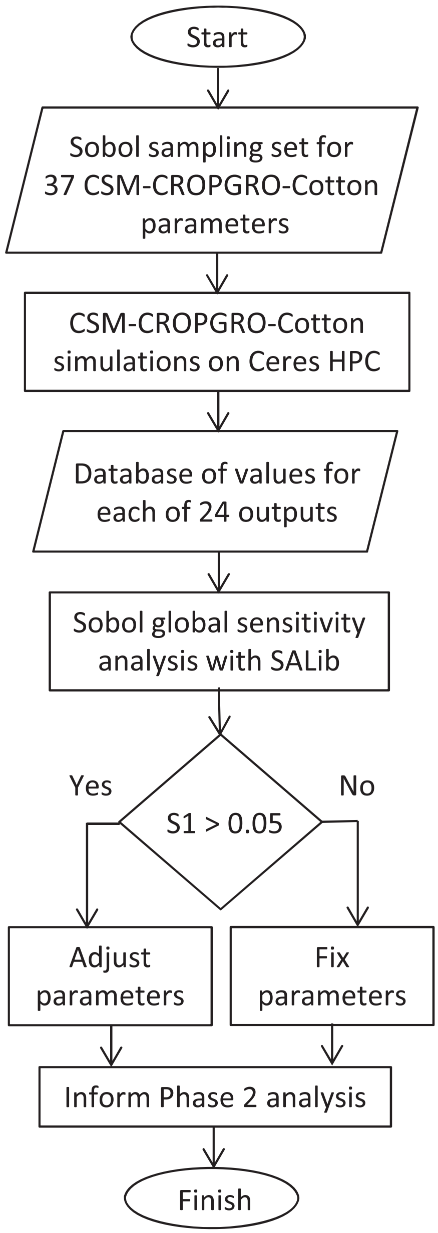

Fig. 1. Workflow for the "Phase 1" analysis to compare evapotranspiration methods in the DSSAT Cropping System Model (CSM), including 1) a Sobol method for sampling 37 input parameters for DSSAT-CSM CROPGRO-Cotton, 2) model simulations on the Ceres high performance computer (HPC), 3) a database approach to link model input parameters from Sobol sampling to 24 model output values, and 4) a Sobol global sensitivity analysis using Python's Sensitivity Analysis (SALib) module. The "Phase 1" simulation results informed the "Phase 2" analysis, as reported in a companion paper (Thorp et al., 2020).

the Sobol GSA (Table 2). Fourteen of these parameters were specified from the CROPGRO-Cotton "cultivar" file (COGRO046.CUL), which relate to photothermal durations for cotton growth stages, photosynthesis rate, and leaf and boll growth characteristics. Seven parameters were specified from the CROPGRO-Cotton "ecotype" file (COGRO046.ECO), which relate to additional photothermal time requirements, leaf appearance rate, and plant height and width. Evapotranspiration parameters were from the CROPGRO-Cotton "species" file (COGRO046.SPE). Two of the potential ET methods (R and F, Table 1) used the KEP parameter, which is an energy extinction coefficient to partition potential ET among plant and soil surfaces. Only one potential ET method (F, Table 1) used the EORATIO parameter, which increased potential ET as a function of LAI. The third potential ET method (G, Table 1) used the SKC parameter to compute basal crop coefficients as a function of LAI and the KMAX parameter to define the maximum basal crop coefficient (DeJonge and Thorp, 2017), but other ET methods did not use these parameters. Although these parameters have unique function among the ET methods, identical parameter values were tested for EORATIO and KMAX and for KEP and SKC. Regarding the soil profile characterization, eleven parameters were specified from the DSSAT-CSM "soil" file (SOIL.SOL), including the soil albedo, depth of first-stage soil drying (applicable only for the Ritchie (1972) soil water evaporation method), soil drainage rate, lower limit (i.e., wilting point), drained upper limit (i.e., field capacity), saturated upper limit (i.e., porosity), root growth factors, saturated hydraulic conductivity, soil bulk density, and initial soil organic carbon. To simplify and reduce the number of parameters tested in the GSA, the soil parameters were evaluated for the entire profile and not at the level of individual soil layers. Thus, for each simulation, identical parameter values were specified among all the layers in the soil profile. One exception was the root growth factors, which define the shape of the rooting profile. Two parameters were created to define the shape: 1) SRGF1 specified the root growth factor for the top soil layer and 2) SRGF2 specified the linear rate of root growth factor decline with soil profile depth. Although SRGF1 and SRGF2 were not specific model inputs, they were created to simplify the specification of the root growth factor profiles, based on a linear decrease from the top soil layer with zero being the lowest possible factor level. Three parameters were specified from the CROPGRO-Cotton management files (.COX), including initial conditions for soil water content and concentrations of ammonium and nitrate. Similar to parameters in the soil file, identical initial conditions were specified among all soil layers in the profile to simplify the GSA.

To sample the parameter space for GSA, the lower and upper bounds for the DSSAT-CSM CROPGRO-Cotton parameters (Table 2) were based on experience with the model and examples from input files provided with the model. The ranges for some soil parameters were based on measured soil properties at the field site (Tolk et al., 1998). The N parameter of the Sobol sampling algorithm was set to 158,224 with specification to prepare for calculation of second-order sensitivity effects. Thus, the number of n-dimensional parameter sets ($n = 37$) chosen for the Sobol GSA was $N(2n + 2) = 12,025,024$, as defined within the Sobol algorithm. The value of N was selected based on preliminary estimates of the rate of simulations via high-performance computing, with plans to contain the simulation timeframe to within a couple weeks. Most importantly, as revealed by later tests, the number of simulations was more than satisfactory to ensure stability of Sobol sensitivity indices (Saltelli, 2002).

2.5. Simulations

The DSSAT-CSM CROPGRO-Cotton model was set up to run 12 simulation scenarios based on the three cotton growing seasons and four uniquely-managed lysimetry fields. Simulations were initiated on 1 January of each year and concluded on the recorded harvest date for each lysimetry field. Additional details on the simulation scenarios are provided in the companion paper (Thorp et al., 2020).

Simulations were conducted using USDA's high-performance computing resource called Ceres, which consisted of 64 compute nodes each having 40 logical cores on Intel Xeon processors with hyper-threading and a shared 2 PB storage system with Lustre design. The operating system on Ceres was a Linux CentOS distribution (ver. 6.7). Ceres uses Simple Linux Utility for Resource Management (SLURM) to submit jobs to compute nodes. Located in Ames, Iowa, access to Ceres occurred via the dedicated high-speed networking resource called SCINet.

A Python script that incorporated Python's "multiprocessing" package was developed to manage the simulation tasks on Ceres. The Python script loaded a list of parameter sets into a processing queue,

Table 2
The DSSAT-CSM CROPGRO-Cotton parameters included in the Sobol global sensitivity analysis (GSA) with their lower bounds (LB) and upper bounds (UB). Maximum first-order Sobol sensitivity indices among model outputs are provided for each of six evapotranspiration (ET) methodologies in the model (RR, FR, GR, RS, FS, and GS) with values >0.05 highlighted in bold, indicating an influential model parameter. Only a subset of the ET parameters were applicable to each ET method.

Parameter	Description	Bounds		First-order Sobol Sensitivity Indices					
		LB	UB	RR	FR	GR	RS	FS	GS
CROPGRO-Cotton crop development and growth									
EM-FL	Photothermal time - emergence to flowering (°C d)	30.0	50.0	**0.91**	**0.91**	**0.91**	**0.90**	**0.90**	**0.91**
FL-SH	Photothermal time - flowering to first boll (°C d)	1.0	15.0	**0.11**	**0.11**	**0.10**	**0.09**	**0.09**	**0.09**
FL-SD	Photothermal time - flowering to first seed (°C d)	1.0	20.0	**0.19**	**0.19**	**0.20**	**0.19**	**0.19**	**0.20**
SD-PM	Photothermal time - first seed to maturity (°C d)	25.0	55.0	**0.44**	**0.44**	**0.44**	**0.43**	**0.43**	**0.43**
FL-LF	Photothermal time - flowering to end leaf (°C d)	55.0	75.0	0.00	0.00	0.00	0.00	0.00	0.00
LFMAX	Maximum photosynthesis rate (mg CO_2 m^{-2} s^{-1})	0.9	3.0	**0.11**	**0.08**	**0.08**	**0.12**	**0.10**	**0.09**
SLAVR	Specific leaf area for standard conditions (cm^2 g^{-1})	110.0	190.0	**0.06**	**0.05**	0.04	**0.08**	**0.06**	**0.05**
SIZLF	Maximum size of full leaf (cm^2)	200.0	400.0	0.02	0.02	0.01	0.02	0.01	0.01
XFRT	Maximum daily growth fraction partitioned to bolls (%)	0.3	1.0	**0.17**	**0.14**	**0.12**	**0.13**	**0.12**	**0.11**
WTPSD	Maximum weight per seed (g)	0.1	0.3	0.00	0.00	0.00	0.00	0.00	0.00
SFDUR	Photothermal time - seed filling duration per boll (°C d)	25.0	45.0	0.00	0.00	0.00	0.00	0.00	0.00
SDPDV	Average number of seeds per boll, standard conditions (#)	20.0	35.0	0.00	0.00	0.00	0.00	0.00	0.00
PODUR	Photothermal time to maximum boll load (°C d)	5.0	20.0	0.04	0.04	0.03	0.04	0.04	0.03
THRSH	Ratio of seed cotton weight to boll weight at maturity	60.0	90.0	0.03	0.03	0.03	0.03	0.03	0.03
PL-EM	Photothermal time - planting to emergence (°C d)	2.0	12.0	**0.99**	**0.99**	**0.99**	**0.98**	**0.98**	**0.97**
EM-V1	Photothermal time - emergence to first leaf (°C d)	2.0	12.0	0.03	0.03	0.02	0.03	0.02	0.02
FL-VS	Photothermal time - flowering to last mainstem leaf (°C d)	20.0	80.0	0.00	0.00	0.00	0.00	0.00	0.00
TRIFL	Leaf appearance rate (# $°C^{-1}$ d^{-1})	0.1	0.4	**0.62**	**0.61**	**0.58**	**0.58**	**0.58**	**0.55**
RWDTH	Width of cultivar relative to standard cultivar	0.7	1.30	**0.09**	**0.10**	**0.10**	**0.08**	**0.09**	**0.09**
RHGHT	Height of cultivar relative to standard cultivar	0.7	1.30	**0.13**	**0.12**	**0.12**	**0.12**	**0.13**	**0.12**
OPTBI	Minimum daily temperature with no effect on flowering date (°C)	10.0	30.0	0.00	0.00	0.00	0.00	0.00	0.00
Evapotranspiration									
KEP	Energy extinction coefficient (fraction)	0.5	0.9	0.01	0.01	N/A	0.01	0.01	N/A
EORATIO	Ratio of increase in potential ET with LAI (fraction)	0.9	1.3	N/A	0.01	N/A	N/A	0.01	N/A
SKC	Shaping factor for basal crop coefficient (unitless)	0.5	0.9	N/A	N/A	0.02	N/A	N/A	0.02
KMAX	Maximum basal crop coefficient (unitless)	0.9	1.3	N/A	N/A	**0.05**	N/A	N/A	0.03
Soil properties									
SALB	Soil albedo (fraction)	0.05	0.4	0.00	0.00	0.00	0.00	0.00	0.00
SLU1	Evaporation limit for Ritchie (1972) method (cm)	4.0	20.0	**0.11**	**0.10**	**0.10**	N/A	N/A	N/A
SLDR	Soil drainage rate (fraction d^{-1})	0.05	0.6	0.04	**0.06**	**0.07**	**0.41**	**0.36**	**0.33**
SLLL	Lower limit (cm^3 cm^{-3})	0.056	0.196	**0.28**	**0.29**	**0.29**	**0.27**	**0.27**	**0.28**
SDUL	Drained upper limit (cm^3 cm^{-3})	0.213	0.353	**0.13**	**0.15**	**0.16**	**0.09**	**0.10**	**0.11**
SSAT	Saturated upper limit (cm^3 cm^{-3})	0.370	0.510	0.00	0.01	0.01	0.02	0.02	0.02
SRGF1	Root growth factor in top soil layer (fraction)	0.3	1.0	**0.06**	**0.06**	**0.06**	0.03	0.02	0.02
SRGF2	Root growth factor decline with soil depth (fraction m^{-1})	0.2	0.8	**0.08**	**0.08**	**0.08**	0.03	0.03	0.03
SSKS	Saturated hydraulic conductivity (cm h^{-1})	0.1	1.2	0.00	0.00	0.00	0.00	0.00	0.00
SBDM	Soil bulk density (g cm^{-3})	1.3	1.6	0.00	0.00	0.00	0.00	0.00	0.00
Initial conditions									
SLOC	Initial soil organic carbon (%)	0.1	2.0	0.00	0.00	0.00	0.00	0.00	0.00
SNO3	Initial soil nitrate (μg N g^{-1})	1.0	30.0	0.01	0.00	0.00	0.01	0.00	0.00
SNH4	Initial soil ammonium (μg N g^{-1})	1.0	12.0	0.00	0.00	0.00	0.00	0.00	0.00
SH2O	Initial soil water content (cm^3 cm^{-3})	0.06	0.35	**0.33**	**0.32**	**0.33**	**0.47**	**0.46**	**0.49**

created working directories for conducting simulations in parallel, and copied pertinent DSSAT-CSM CROPGRO-Cotton files to each directory. It then established independent worker processes, one for each requested processing core. Each worker process iteratively selected an item from the processing queue, adjusted model input files to incorporate the current parameter set, conducted the 12 simulation scenarios, and extracted model output data from model output files.

With 12 simulation scenarios, 6 ET algorithms, and 12,025,024 parameter sets, the Sobol GSA needed a total of 865,801,728 simulations, which required 37,583 CPU hr on Ceres and approximately 188 h of wall-clock time. Roughly 153 model simulations s^{-1} were possible on Ceres, as compared to no more than 8 simulations s^{-1} on a modern desktop machine. Thus, high performance computing increased simulation capability by a factor of 20.

2.6. Database method

Model output data were recorded using a database method to link model input parameter sets with model output responses, similar to the approach developed by Lamsal et al. (2018) for use of DSSAT-CSM on a high-performance computer. The approach permitted the simulation analysis to be conducted and recorded in one step, while the GSA was conducted in a separate and subsequent step. Twenty-four model outputs were recorded for each simulation (Table 3), including the dates of crop emergence, anthesis, and maturity. Because the GSA was not able to assess time series responses, crop growth outputs such as LAI, seed cotton dry matter, canopy height, and others were characterized using the maximum value from the simulated time series to represent the overall crop growth response. Regarding the water balance, four ET metrics were obtained from the model output, including cumulative ET, transpiration, and soil water evaporation from planting to harvest and soil water evaporation during the pre-plant fallow period from model initialization (1 January) to planting. Cumulative deep drainage from initialization to harvest was also obtained from the soil water balance output and included in the GSA.

Table 3
The DSSAT-CSM CROPGRO-Cotton outputs included in the Sobol global sensitivity analysis (GSA)

Output	Description	Unit
Crop development		
EDAT	Crop emergence date	day of year
ADAT	Crop anthesis date	day of year
MDAT	Crop maturity date	day of year
LFNX	Maximum leaf number per stem	# stem^{-1}
Crop growth		
LAIX	Maximum leaf area index	m^2 m^{-2}
LDMX	Maximum leaf dry matter	kg ha^{-1}
SDMX	Maximum stem dry matter	kg ha^{-1}
SCDX	Maximum seed cotton dry matter	kg ha^{-1}
RDMX	Maximum root dry matter	kg ha^{-1}
CDMX	Maximum aboveground canopy dry matter	kg ha^{-1}
SDNX	Maximum seed number	# m^{-2}
BDMX	Maximum boll dry matter	kg ha^{-1}
BLNX	Maximum boll number	# m^{-2}
WSPX	Maximum water stress factor on photosynthesis	fraction
WSGX	Maximum water stress factor on growth	fraction
NSTX	Maximum nitrogen stress factor	fraction
CHTX	Maximum canopy height	m
CWDX	Maximum canopy width	m
RDPX	Maximum root depth	m
Evapotranspiration and drainage		
ETPH	Cumulative evapotranspiration from planting to harvest	mm
TRPH	Cumulative crop transpiration from planting to harvest	mm
EVPH	Cumulative soil water evaporation from planting to harvest	mm
EVIP	Cumulative soil water evaporation from initialization to planting	mm
DRNC	Cumulative deep drainage	mm

2.7. Global sensitivity analysis

To gain insights on DSSAT-CSM CROPGRO-Cotton responses to adjustment of model input parameters, a Sobol GSA (Cariboni et al., 2007; Pianosi et al., 2016; Saltelli et al., 2000; Saltelli, 2002; Saltelli et al., 2010; Sobol, 2001) was conducted using algorithms from the SALib package in Python. Although the Sobol method is more computationally intensive than other GSA methods, it was chosen due to the availability of high-performance computing resources, which ensured efficiency of simulations. Less computationally intensive sensitivity analyses are normally conducted first; however, only Sobol GSA was used here, because 1) high-performance computing resources were available and 2) subsequent comparisons of ET algorithm performance, as described in the companion paper (Thorp et al., 2020), also incorporated the Sobol sampling aspect of the Sobol GSA.

First-order, second-order, and total sensitivity indices were calculated for each combination of the 37 input parameters (Table 2) and 24 model outputs (Table 3). Median first-order sensitivity indices among 3 cotton growing seasons and 4 lysimeter fields were computed to summarize indices among different environments. Based on the recommendation of Zhang et al. (2015), any parameter having a median first-order sensitivity index >0.05 for any of the 24 model outputs was considered an influential parameter. Second-order and total order indices were incorporated into discussions of the key results. Because the main purpose of the Sobol GSA was to analyze model output responses to variability in model inputs, the results and discussion focus on comparisons of sensitivity indices among the tested input parameters, ET simulation strategies, and uniquely-managed lysimetry fields. No field measurements were included in the present analysis, but details regarding model comparisons to measured data were provided in the companion paper (Thorp et al., 2020).

3. Results

3.1. Non-influential parameters

Of the 37 evaluated model input parameters, 18 had no substantial influence on any of the model output variables (Table 2). Three of these were related to crop development, including parameters defining photothermal time from flowering to end of leaf growth (FL-LF), from emergence to first leaf (EM-V1), and from flowering to the last mainstem leaf (FL-VS). Additionally, the parameter defining minimum daily temperature with no effect on flowering date (OPTBI) was not influential for the Bushland environment. Regarding leaf growth, the parameter defining the maximum size of full leaves (SIZLF) was also not influential. Five parameters related to seed development and growth were not influential, including the maximum weight per seed (WTPSD), the photothermal time for seed filling (SFDUR), the average number of seeds per boll under standard conditions (SDPDV), the photothermal time to maximum boll load (PODUR), and the ratio of seed cotton weight to boll weight at maturity (THRSH). First-order sensitivities for the PODUR parameter were only slightly less than the 0.05 sensitivity threshold. Regarding ET simulations, neither the KEP, EORATIO, nor SKC parameters were influential for the ET methods that required them. Regarding the soil parameters, the soil albedo (SALB), soil bulk density (SBDM), saturated upper limit (SSAT), and saturated hydraulic conductivity (SSKS) were not influential on any model output. For SSAT and SSKS, the result was likely because the environment was semi-arid and irrigation was properly managed, leaving little opportunity for soils to reach fully saturated conditions. Finally, the initial conditions for soil organic carbon, soil nitrate, and soil ammonium were not influential on the model outputs, likely because the field site was fertilized to avoid nitrogen limitations. The results suggested that nearly half of the model parameters under investigation (Table 2) require no further discussion, because none of the 24 model outputs (Table 3) were sensitive to adjustment of these parameters. Other GSA studies for different environments or management practices may reach different conclusions regarding these parameters, although the GSA results for DSSAT-CSM CROPGRO-Cotton by Pathak et al. (2007) for a humid environment in Georgia were similar to results of the present analysis.

3.2. Influential parameters

The linkages between model outputs and influential input parameters provided insights on model functionality (Table 4). Influential photothermal time parameters functioned as expected, with the photothermal time from planting to emergence (PL-EM) influencing both emergence date (EDAT) and anthesis date (ADAT), and the photothermal time from emergence to flowering (EM-FL) influencing ADAT and physiological maturity date (MDAT). The photothermal time from flowering to first boll (FL-SH) mainly influenced seed cotton dry matter (SCDX) and seed numbers (SDNX), while the photothermal time from flowering to first seed (FL-SD) influenced SDNX and MDAT. Finally the photothermal time from first seed to physiological maturity (SD-PM) only affected MDAT. With maximum first-order sensitivity indices above 0.4 (Table 2), the primary model parameters influencing crop development were PL-EM, EM-FL, and SD-PM.

Six cultivar parameters related to crop growth were influential on the simulations (Table 4). The maximum photosynthesis rate (LFMAX) was influential on leaf dry matter (LDMX), root dry matter (RDMX), canopy dry matter (CDMX), and the nitrogen stress factor (NSTX) for all six ET methods; LFMAX was also influential on leaf area index (LAIX), stem dry matter (SDMX), and soil water evaporation during the growing season (EVPH) for four or five of the ET methods. The specific leaf area for standard conditions (SLAVR) was influential only on LAIX for three of the ET methods (RR, RS, and FS). The maximum daily growth fraction partitioned to bolls (XFRT) influenced seed number (SDNX), boll number (BLNX), and boll dry matter (BDMX) among all ET

Table 4
The DSSAT-CSM CROPGRO-Cotton outputs with corresponding influential model inputs, based on Sobol global sensitivity analysis (GSA) with median first-order Sobol sensitivity indices >0.05 among four lysimeter fields and three cotton growing seasons at Bushland, Texas. Parameters that were influential among all six evapotranspiration methodologies (RR, FR, GR, RS, FS, and GS) are specified separately from those that were influential for one or more, but not all, methods.

		Additionally for individual ET methods					
Output	All ET methods	RR	FR	GR	RS	FS	GS
EDAT	PL-EM						
ADAT	EM-FL, PL-EM						
MDAT	EM-FL, FL-SD, SD-PM						
LFNX	TRIFL				SLLL	SLLL	SLLL
LAIX	SLLL, SH2O	LFMAX, SLAVR			LFMAX, SLAVR	LFMAX, SLAVR, SDUL	LFMAX, SDUL
LDMX	LFMAX, SLLL, SH2O	SRGF1, SRGF2	SRGF2	SRGF2	SDUL	SDUL	SDUL
SDMX	TRIFL, SLLL, SH2O	LFMAX	LFMAX	LFMAX	LFMAX, SDUL	LFMAX, SDUL	SDUL
SCDX	FL-SH	FL-SD, XFRT	XFRT	XFRT			
RDMX	LFMAX, SH2O	FL-SH, XFRT, TRIFL	FL-SH, XFRT, TRIFL	TRIFL	XFRT, SLLL	SLLL	SLLL
CDMX	LFMAX, TRIFL, SLLL, SH2O	SRGF1, SRGF2	SRGF1, SRGF2	SRGF1, SRGF2	SDUL	SDUL	SDUL
SDNX	FL-SH, FL-SD, XFRT						
BDMX	XFRT, SH2O		EM-FL	EM-FL, SLLL	EM-FL, SLLL	EM-FL, SLLL	EM-FL, SLLL
BLNX	XFRT, WTPSD, PODUR		SH2O	SH2O			
WSPX	SH2O	SLLL, SRGF1, SRGF2	SLLL, SRGF2	SLLL, SRGF2	SLLL, SRGF2	SRGF2	
WSGX	SH2O	SLLL, SRGF1, SRGF2	SLLL, SRGF2		SLLL, SRGF2		
NSTX	LFMAX, SH2O	SRGF1, SRGF2	SLLL, SDUL, SRGF1, SRGF2	SLLL, SDUL, SRGF1, SRGF2		SLLL, SDUL	SLLL, SDUL
CHTX	TRIFL, RHGHT, SLLL	SH2O	SH2O	SH2O			
CWDX	TRIFL, RWDTH				SLLL	SLLL	SLLL
RDPX	SRGF1, SRGF2, SH2O						SLDR
ETPH	SLLL, SH2O	SDUL, SRGF1, SRGF2	SDUL, SRGF1, SRGF2	SDUL, SRGF1, SRGF2			
TRPH	SLLL, SH2O	SRGF1, SRGF2	SRGF1, SRGF2	SRGF1, SRGF2	SLDR, SDUL	SLDR, SDUL	SLDR, SDUL
EVPH	TRIFL, SDUL	LFMAX, SH2O	LFMAX, SLDR, SH2O	LFMAX, KMAX, SLDR	LFMAX, SLDR, SLLL, SH2O	SLDR, SLLL, SH2O	SLDR, SLLL, SH2O
EVIP	SDUL, SH2O	SLU1, SLLL	SLU1, SLLL	SLU1, SLLL	SLDR	SLDR	SLDR
DRNC	SDUL, SH2O						

methods, and SCDX and RDMX were additionally sensitive to XFRT for three of the six ET methods. The leaf appearance rate (TRIFL) influenced many model outputs among all ET methods, including SDMX, CDMX, leaf number per stem (LFNX), canopy height (CHTX), and canopy width (CWDX). Finally, RWDTH and RHGHT influenced only canopy width and height, respectively. Among cultivar parameters related to crop growth, LFMAX, TRIFL, and XFRT were most influential on the simulations, with maximum first-order sensitivity indices ranging from 0.08 to 0.62 (Table 2).

The GSA was informative on the influence of soil water balance parameters (Table 4). Related to ET, the maximum basal crop coefficient (KMAX) was required only for the DeJonge and Thorp (2017) approach for potential ET (G, Table 1) and was influential only on soil water evaporation (EVPH) and also only when combining this potential ET method with the Ritchie (1972) approach for soil water evaporation (GR, Table 1). A similar parameter (EORATIO) required only for the Penman–Monteith approach for potential ET (F, Table 1) remained non-influential among the simulations. Also, the evaporation limit parameter (SLU1), required only for the Ritchie (1972) evaporation approach, was influential on soil water evaporation but only during the period prior to planting (EVIP). The soil drainage rate (SLDR) influenced EVIP and plant transpiration (TRPH), but only when using the Ritchie et al. (2009) soil water evaporation method (S, Table 1). During the growing season, SLDR influenced soil water evaporation (EVPH) for five of six ET methods, excluding RR. Parameters used to compute root growth factors (SRGF1 and SRGF2) were influential on rooting depth (RDPX) among all ET methods. Additionally, when the Ritchie (1972) soil water evaporation method was used, SRGF1 and SRGF2 were commonly influential on crop growth (LDMX and CDMX); water and nitrogen stress factors (WSPX, WSGX, and NSTX); and ET calculations (ETPH and TRPH). Overall, the model was less sensitive to SRGF parameters when the Ritchie et al. (2009) soil water evaporation method was used.

The GSA demonstrated high model sensitivity to three water balance parameters (Table 4). Among all ET methods, the lower limit (SLLL) influenced LAIX, LDMX, SDMX, CDMX, CHTX, ETPH, and TRPH, but the drained upper limit (SDUL) influenced only soil water evaporation (EVPH and EVIP) and deep drainage (DRNC). When using the Ritchie (1972) evaporation method (R, Table 1), SLLL was additionally influential on stress factors (WSPX, WSGX, and NSTX), and SDUL was additionally influential on ETPH. When using the Ritchie et al. (2009) evaporation method, SLLL was additionally influential on leaf number (LFNX), RDMX, BDMX, CWDX, and EVPH, while SDUL was additionally influential on LDMX, SDMX, CDMX, and TRPH. Importantly, among all ET methods the initial soil water content (SH2O) influenced 14 of the 24 evaluated model outputs: LAIX, LDMX, SDMX, RDMX, CDMX, BDMX, WSPX, WSGX, NSTX, RDPX, ETPH, TRPH, EVIP, and DRNC. With maximum first-order sensitivity indices ranging from 0.09 to 0.49 (Table 2), model inputs for SLLL, SDUL, and SH2O were highly influential on the model simulations.

4. ET method impacts

Among the four ET metrics (ETPH, TRPH, EVPH, and EVIP), differences in model sensitivity among the six ET methods were generally greater between the two soil water evaporation methods than among the three potential ET methods (Fig. 2). During the growing season, the root growth factors (SRGF1 and SRGF2) influenced ET (ETPH) and transpiration (TRPH) (Figs. 2a and 2b), while leaf growth and development parameters (LFMAX and TRIFL) influenced evaporation (EVPH) (Fig. 2c). In all three of these cases, the first-order and total sensitivity indices were slightly greater among ET methods based on Ritchie

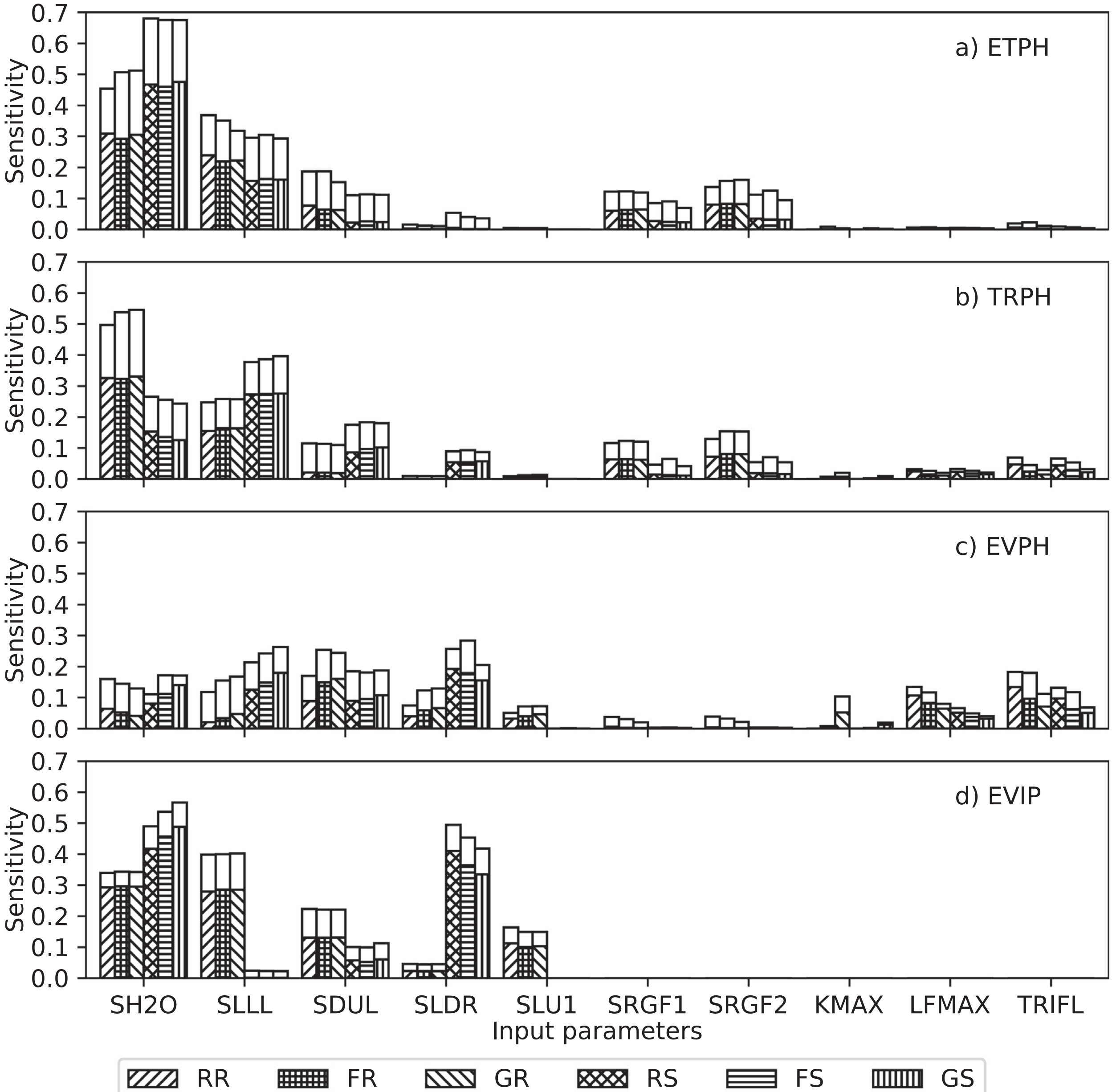

Fig. 2. First-order Sobol sensitivity indices (hashed areas) and total Sobol sensitivity indices (non-hashed areas) among six DSSAT-CSM evapotranspiration methods (RR, FR, GR, RS, FS and GS), which relate 10 model input parameters to a) cumulative evapotranspiration from planting to harvest (ETPH), b) cumulative plant transpiration from planting to harvest (TRPH), c) cumulative soil water evaporation from planting to harvest (EVPH), and d) cumulative soil water evaporation from model initialization (1 January) to planting (EVIP). Median sensitivity indices are shown among three cotton growing seasons and four lysimetry fields.

(1972) soil water evaporation (R, Table 1), as compared to the Ritchie et al. (2009) method (S, Table 1). Median first-order sensitivity of ETPH and TRPH to initial soil water content (SH2O) were similar (approximately 0.3) among approaches using the Ritchie (1972) method (Figs. 2a and 2b). However, for Ritchie et al. (2009), first-order sensitivities of ETPH to SH2O were >0.45 while first-order sensitivities of TRPH to SH2O were <0.15. The result is likely due to greater ET estimation (i.e., overestimation) by the Ritchie et al. (2009) method, as described in the companion paper (Thorp et al., 2020). Higher estimation of ET with the Ritchie et al. (2009) method could have made ETPH more sensitive to SH2O (Fig. 2a), as compared to the Ritchie (1972) method. Furthermore, greater simulated ET may have led to increased TRPH sensitivity to SLLL, which was demonstrated with the Ritchie et al. (2009) method (Fig. 2b).

For soil water evaporation prior to planting (EVIP), differences in model sensitivity can be explained by the differences in functionality between the two soil water evaporation algorithms. The EVIP for the Ritchie et al. (2009) method was generally most sensitive to SH2O and the soil drainage rate (SLDR), while the soil water limits (SLLL and SDUL) were less influential on EVIP (Fig. 2d). Due to simulations of water upflux from the bottom soil layers with the Ritchie et al. (2009) method, SLDR was more influential on EVIP by counteracting the effect of upward flux, while the influence of SLLL and SDUL on EVIP was reduced. In comparison, the Ritchie (1972) method, which simulated no upflux and restricted evaporation to water content in the top 5-cm soil layer, demonstrated greater influence of the SLLL and SDUL parameters on the EVIP simulation, while the influence of SLDR was much smaller. As expected, when no upflux was simulated, the impact of drainage through soil layers was less important for evaporation simulations.

First-order and total sensitivities of leaf area index (LAIX) and canopy dry matter (CDMX) to SH2O were greater for the Ritchie (1972)

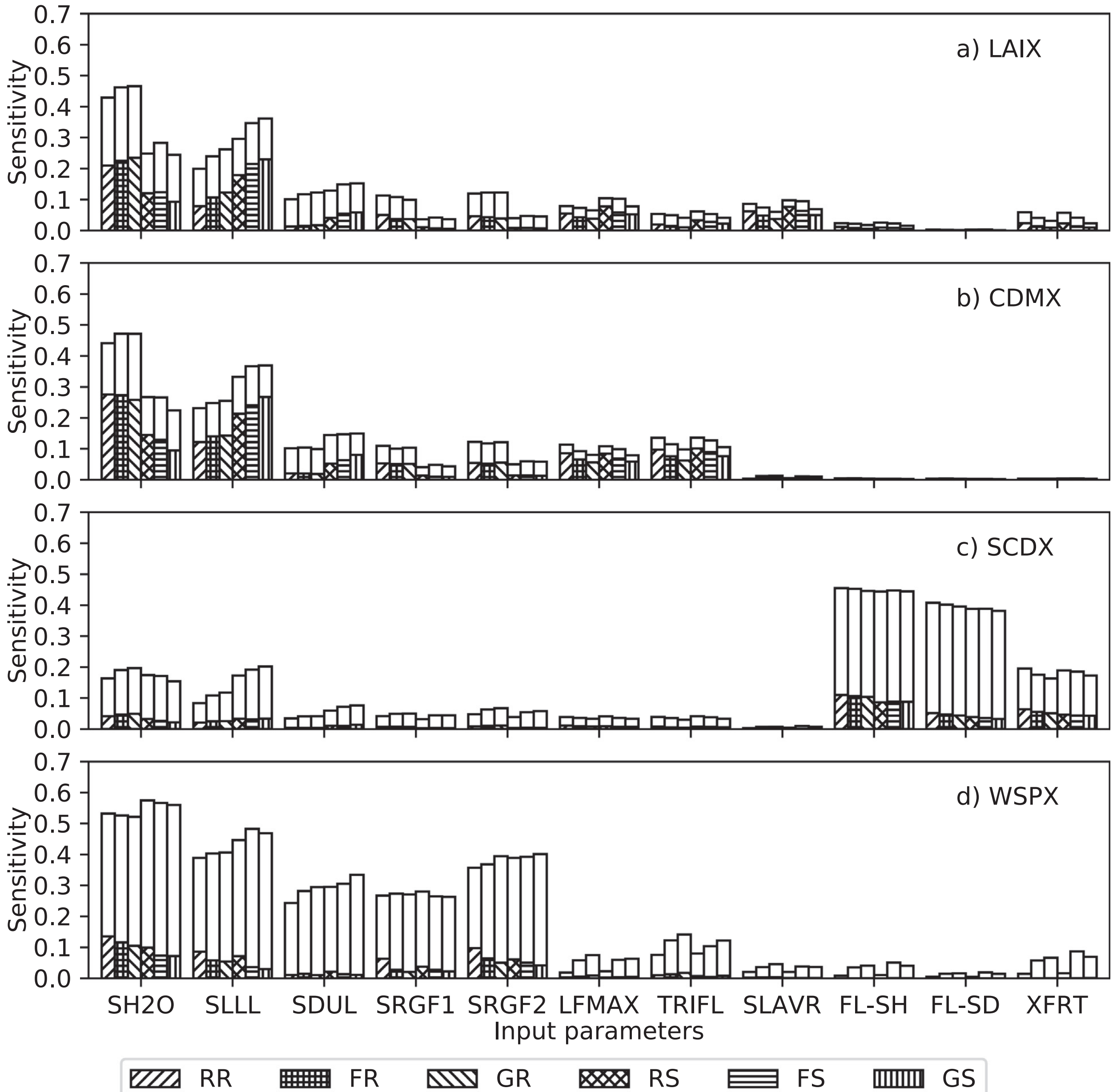

Fig. 3. First-order Sobol sensitivity indices (hashed areas) and total Sobol sensitivity indices (non-hashed areas) among six DSSAT-CSM evapotranspiration methods (RR, FR, GR, RS, FS and GS), which relate 11 model input parameters to a) maximum leaf area index (LAIX), b) maximum canopy dry matter (CDMX), c) maximum seed cotton dry matter (SCDX), and d) maximum water stress factor affecting photosynthesis (WSPX). Median sensitivity indices are shown among three cotton growing seasons and four lysimetry fields.

evaporation method than for the Ritchie et al. (2009) method. On the other hand, the opposite trend was found for sensitivities of LAIX and CDMX to SLLL (Fig. 3a and 3b). This means SLLL was more influential on plant growth with the Ritchie et al. (2009) method, while SH2O was more influential on plant growth with the Ritchie (1972) method. By simulating upflux, the Ritchie et al. (2009) method made LAIX and CDMX simulations more sensitive to SLLL and reduced the influence of SH2O. Unexpectedly, seed cotton dry matter (SCDX) was relatively insensitive to many of the soil water balance parameters (Fig. 3c). The FL-SH and XFRT parameters were most influential on SCDX, and total sensitivity indices were >0.4 for FL-SH and FL-SD, which more than doubled the first-order indices and indicated high interaction with other parameters. The water stress factor on photosynthesis (WSPX) also demonstrated high total sensitivity indices for SH2O, SLLL, SDUL, SRGF1, and SRGF2 (Fig. 3d).

5. Management impacts

Among the four lysimeters, patterns of model sensitivity with respect to irrigation management were observed (Fig. 4). During the growing season, ETPH and TRPH were sensitive to the root growth factors (SRGF1 and SRGF2), and the total sensitivity was slightly reduced for the fully-irrigated lysimeter (SELYS). This means the effects of root growth on ETPH and TRPH were less interactive with other parameters for full irrigation. Furthermore, first-order and total sensitivities of ETPH and TRPH to SH2O both increased with increasing water deficit due to reduced irrigation. The dryland production systems exhibited greatest sensitivity of ETPH and TRPH to SH2O, followed by deficit irrigation and full irrigation (Fig. 4a and 4b). As expected, water limitations made the model more sensitive to initial soil water conditions. Because the analysis among lysimeters considered only the DeJonge and Thorp (2017) potential ET method with Ritchie (1972)

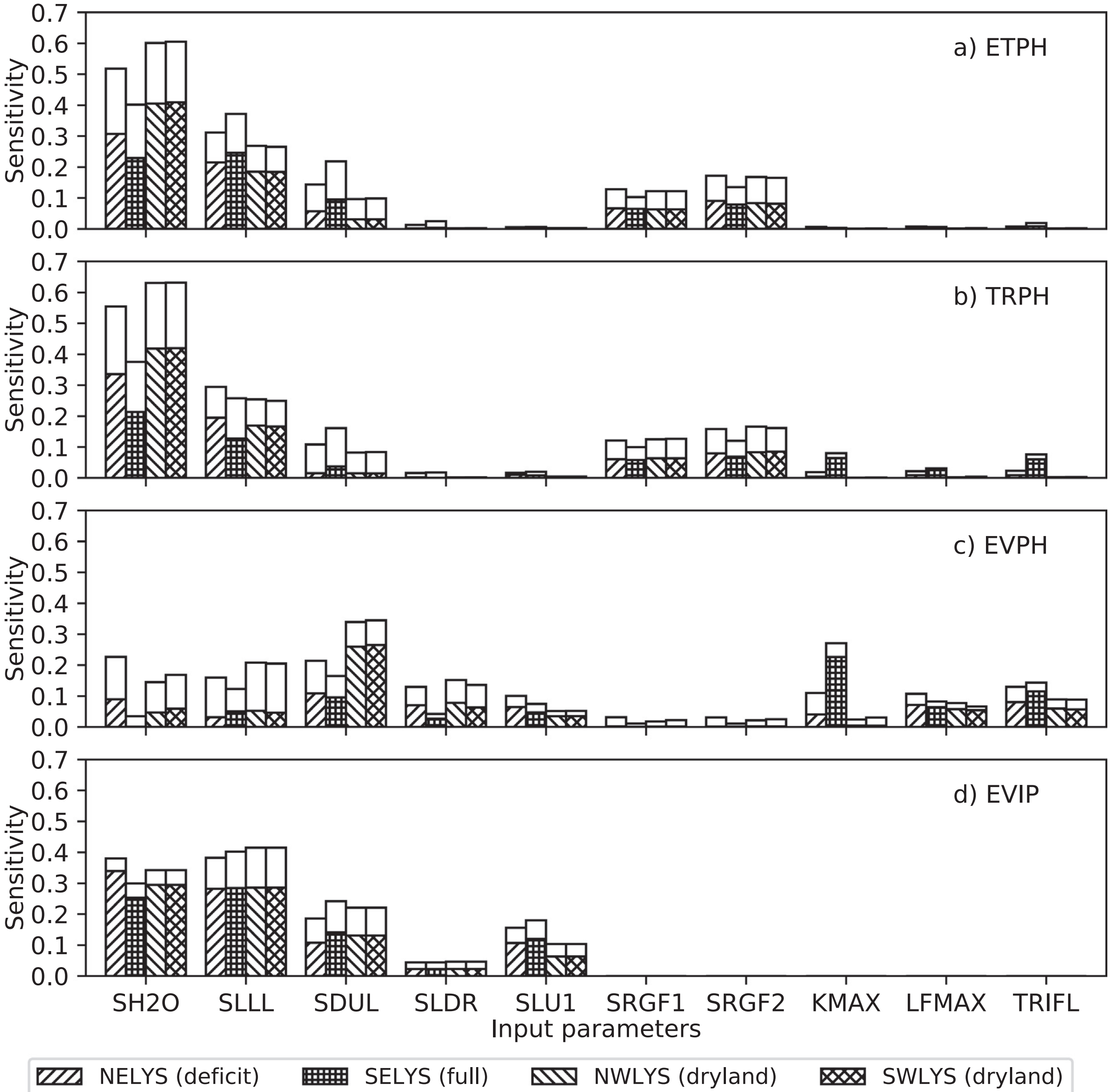

Fig. 4. First-order Sobol sensitivity indices (hashed areas) and total Sobol sensitivity indices (non-hashed areas) among four lysimetry fields (NELYS, SELYS, NWLYS, and SWLYS) with fully-irrigated, deficit-irrigated, and dryland cotton production, which relate 10 model input parameters to a) cumulative evapotranspiration from planting to harvest (ETPH), b) cumulative plant transpiration from planting to harvest (TRPH), c) cumulative soil water evaporation from planting to harvest (EVPH), and d) cumulative soil water evaporation from model initialization (1 January) to planting (EVIP). Median sensitivity indices are shown among three cotton growing seasons for the GR evapotranspiration method alone.

soil water evaporation (GR, Table 1), sensitivity of TRPH and EVPH to the maximum crop coefficient parameter (KMAX) demonstrated the only influence of an ET parameter in this study (Fig. 4b and 4c). Furthermore, because KMAX was used to estimate potential ET, its influence was greater for the fully-irrigated case with ET nearer to potential. For deficit irrigation and dryland production, other parameters had greater influence than KMAX, particularly on EVPH.

Irrigation management also led to different model sensitivities among several crop growth outputs (Fig. 5). Full irrigation reduced the influence of SH2O on LAIX, CDMX, and SCDX, while deficit irrigation and dryland production increased the sensitivity of these outputs to SH2O. Likewise, the influence of SLLL on LAIX, CDMX, and SCDX was greater for treatments with water limitation. Similar to the result of DeJonge et al. (2012a), reduced water inputs from irrigation made the crop growth outputs more sensitive to initial soil water conditions and the lower limit. The LFMAX and TRIFL parameters had greater influence on CDMX with full irrigation as compared to deficit irrigation and dryland, because these parameters establish potential for leaf growth under non-stressed conditions. Likewise, XFRT was more influential on SCDX with full irrigation. The input parameters that set crop growth potentials, such as LFMAX and XFRT, had greater influence on crop growth outputs with full irrigation, because soil water contents were large enough to minimize effects of water stress factors and permit crop growth calculations at potential rates of growth. However, when water stress increased due to irrigation restrictions, soil water balance parameters became more influential on the crop growth simulation.

6. Second-order indices

Total indices provided insights on the overall impact of parameter

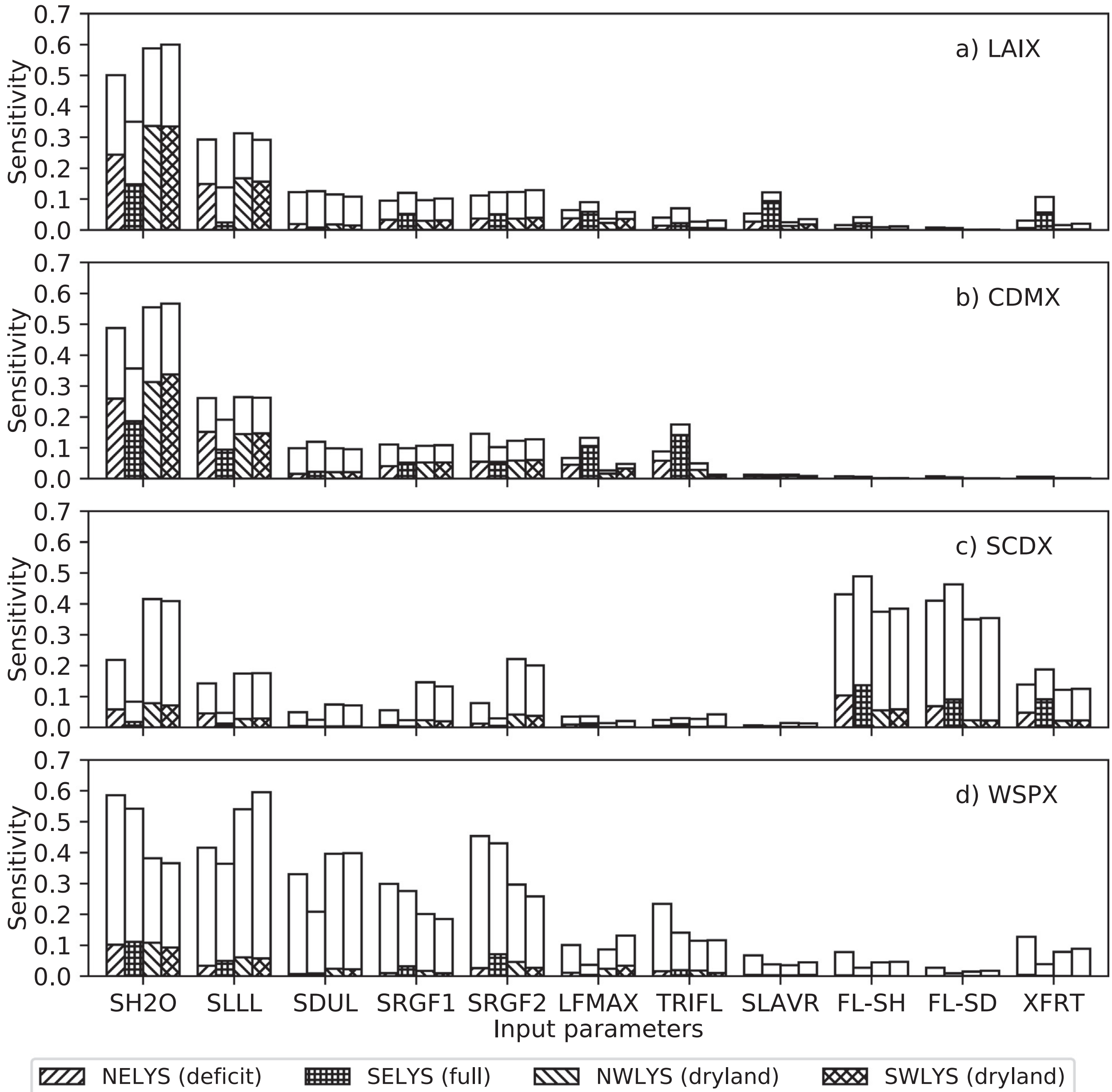

Fig. 5. First-order Sobol sensitivity indices (hashed areas) and total Sobol sensitivity indices (non-hashed areas) among four lysimetry fields (NELYS, SELYS, NWLYS, and SWLYS) with fully-irrigated, deficit-irrigated, and dryland cotton production, which relate 11 model input parameters to a) maximum leaf area index (LAIX), b) maximum canopy dry matter (CDMX), c) maximum seed cotton dry matter (SCDX), and d) maximum water stress factor affecting photosynthesis (WSPX). Median sensitivity indices are shown among three cotton growing seasons for the GR evapotranspiration method alone.

interactions on model sensitivity for a given output (Figs. 2–5), while second-order indices permitted identification of the most influential parameter pairings. Among the four ET outputs (ETPH, TRPH, EVPH, and EVIP), second-order indices describing the interaction between SLLL and SDUL were often >0.05 (not shown), an important result considering that the relationship between these two parameters determined the plant-available water holding capacity of the soil. Other common parameter pairings with larger second-order indices for ET outputs included SLLL with SH2O, SDUL with SH2O, and SLDR with SH2O (influential only for EVIP with the Ritchie et al. (2009) evaporation method), but the indices were rarely >0.08. Water stress factors (WSPX and WSGX), which demonstrated large total indices relative to first-order indices (Figs. 3d and 5d), were sensitive to several second-order parameter interactions, including SLLL with SDUL, SLLL with SH2O, and SRGF2 with SH2O. The interaction of SDUL with SH2O was often influential on deep drainage (DRNC) with second-order sensitivity indices up to 0.34. These were the largest second-order indices in the study. Among four crop growth outputs (LAIX, CDMX, LDMX, and SDMX), the pairings of SLLL with SH2O and SDUL with SH2O commonly led to second-order indices greater than 0.05 but not exceeding 0.08 (not shown). Finally, the interaction of FL-SH with FL-SD was the only parameter pairing with a large influence on SCDX, with second-order indices up to 0.23. Primarily, interactions between the soil water limits (SLLL and SDUL), initial soil water content (SH2O), and root growth factors (SRGF2) led to the largest second-order sensitivities among water balance and crop growth outputs.

7. Discussion

The GSA results demonstrated the sensitivity of the DSSAT-CSM CROPGRO-Cotton model to a variety of input parameters among six ET methods for different irrigation management practices during three cotton growing seasons at Bushland, Texas. Nearly half of the tested input parameters did not provide first-order sensitivity indices that exceeded the 0.05 threshold for any of the tested scenarios. For model users, the information is highly useful to guide efforts toward model calibration, because the sensitivity indices provide knowledge of the relative influence of model input parameters on model output responses. As a result, the guesswork on which parameters to adjust is minimized, and model calibration can occur with greater intentionality and focus. As demonstrated in the companion study (Thorp et al., 2020), the results of this GSA were directly used to reduce the number of parameters adjusted during model calibration. For model developers, the GSA results lead to considerations for model design and development. Specifically, if a given parameter routinely has little influence on model outputs, it could potentially be hard-coded and eliminated as an input parameterization option. Basing these decisions on sensitivity indices from GSA would provide a quantitative method for simplifying the interface between models and model users and for ensuring that model parameterization requirements were not more complicated than necessary (Stella et al., 2014). Alternatively, model developers may want to assess the reasons for reduced or enhanced influence among parameters and consider redesigning model algorithms to ensure parameter influences follow expectations. Naturally, some system parameters should be more influential on system outcomes than others, and GSA can help quantify the influence among parameters and identify whether their relative influence is sensible. As an initial step, GSA should be used to simplify model parameterization decisions by identifying input parameters that have little influence on model outputs.

For the conditions tested in this study, the GSA results identified less than 20 influential parameters for DSSAT-CSM CROPGRO-Cotton (Tables 2 and 4). Users should first focus on appropriately simulating dates of emergence, anthesis, and maturity by adjusting PL-EM, EM-FL, and SD-PM. The FL-SH and FL-SD parameters were also influential on crop development, but less so, and data for adjusting these parameters are usually limited. Using data from well-watered scenarios, leaf development and growth can then be fit with adjustments to TRIFL, LFMAX, and SLAVR, and seed cotton yield can be fit by adjusting XFRT. Also, crop width and height can be adjusted with the RWDTH and RHGHT parameters, respectively. Finally, for water limited scenarios, several parameters affecting the water balance, including SH2O, SLLL, SDUL, SLDR (for Ritchie et al. (2009) evaporation), and SRGF (for Ritchie (1972) evaporation) become more important for model calibration efforts. By focusing model calibration efforts on parameters with greatest influence, these guidelines will improve the applicability of the model for use in operational agricultural management decisions, particularly for applications in irrigation management and crop yield forecasting.

Use of GSA to compare effects of different ET algorithms on model sensitivity is a novel aspect of this work, and important differences in model sensitivity were identified among the two soil water evaporation methods (Ritchie, 1972; Ritchie et al., 2009). Switching between these two methods radically changed the model sensitivity among both ET and crop growth outputs (Figs. 2 and 3). In particular, the influences of several water balance parameters (SH2O, SLLL, SDUL, SLDR, and SRGF) were substantially affected. As compared to the soil water evaporation algorithms, the three potential ET methods did not demonstrate much change to model sensitivity, perhaps because the latter methods establish only the potential for occurrence of ET whereas the former methods directly determine model outputs for soil water evaporation. While the differences in model sensitivity due to potential ET method appear small, the companion paper demonstrated differences among the methods with regard to accuracy of ET simulations (Thorp et al., 2020). When introducing new algorithms, model developers can use GSA to better understand how model sensitivity and parameter influences are affected, which can contribute to assessing the sensibility of model improvements.

8. Conclusions

Global sensitivity analysis (GSA) revealed important relationships between input and output data with the DSSAT-CSM CROPGRO-Cotton model. The most influential parameters included five that controlled crop development (PL-EM, EM-FL, FL-SH, FL-SD, SD-PM), three that controlled leaf growth or development (LFMAX, SLAVR, and TRIFL), one that controlled seed cotton yield (XFRT), two parameters that control canopy height and width (RWDTH and RHGHT), four soil parameters (SLDR, SLLL, SDUL, and SRGF), and initial soil water content (SH2O). When using the Ritchie (1972) evaporation method, the evaporation limit (SLU1) was also influential. When using the DeJonge and Thorp (2017) ET method with the Ritchie (1972) evaporation method, the maximum basal crop coefficient (KMAX) was influential. The GSA was very useful for identifying influential model parameters, which can lead to simplified model parameterization decisions during calibration efforts. The results should be informative to others using the DSSAT models, particularly for crops based on the CROPGRO module. Additionally, as reported in a companion paper (Thorp et al., 2020), the GSA results have informed a second stage of analysis, which involved fitting the model to measurements via multiobjective optimization and comparing the performance of the six ET methods among various measured and simulated agroecosystem variables.

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. **K.C. DeJonge:** Conceptualization, Methodology, Writing - review & editing, Visualization. **G.W. Marek:** Conceptualization, Investigation, Resources, Data curation, Writing - review & editing. **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.2020.105658.

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