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Global sensitivity and uncertainty analysis of a dynamic agroecosystem model under different irrigation treatments

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ABSTRACT

Savings in consumptive use through limited or deficit irrigation in agriculture has become an increasingly viable source of additional water for places with high population growth such as the Colorado Front Range, USA. Crop models provide a mechanism to evaluate various management methods without performing costly and time-consuming experiments, e.g., field studies investigating irrigation scheduling and timing effects on crop growth. Few studies have focused on CERES-Maize crop model parameterization with respect to water-stressed conditions, and the model has previously been shown to overestimate evapotranspiration (ET) for limited irrigation treatments (stress during vegetative stage). It is therefore desirable to quantify the effects of CERES-Maize input parameters on model output responses typically used for calibration and/or important in limited irrigation management, including vegetative growth, crop yield, and ET. A sensitivity analysis (SA) utilizing the Morris one-at-a-time screening and Sobol' variance-based methods was performed on CERES-Maize v4.5 input parameters affecting water balance and crop growth including soil hydraulic properties, phenological growth properties, and radiation use efficiency. CERES-Maize output responses of interest for the SA included anthesis date, maturity date, leaf number per stem, maximum leaf area index, yield, and cumulative ET. The SA study utilized five years of multi-replicate field management data (both full and limited irrigation treatments) for each combination of random input parameters. Results comparing the Morris mean and the Sobol' total sensitivity index showed very high correlation between the two, indicating that in this study the computationally cheaper Morris method could have been used as an effective indicator of input parameter sensitivity. For the full irrigation treatment, CERES-Maize output responses were mostly sensitive to crop cultivar parameters. For the limited irrigation treatment, CERES-Maize leaf area index, yield, and ET output responses were highly influenced by soil lower limit and drained upper limit input parameters, which define water holding capacity. There was also a greater amount of interaction between input parameters for the limited irrigation treatment than for full irrigation. An uncertainty analysis was also conducted using model outputs from the Sobol' SA method. In some cases, cumulative ET had higher values for limited irrigation than for full irrigation, further indicating the need to evaluate model processes governing ET under water stress. A new methodology for systematic calibration of CERES-Maize, based on the Morris and Sobol' sensitivity indices for the two irrigation treatments, is proposed for future model evaluation as sensitivity differences between treatments indicates that existing CERES-Maize calibration procedures (typically based on non-stressed crops) may need to be reconsidered in cases of water stress.

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1. Introduction

Water availability issues, combined with population growth and the uncertainty of climate change have created significant challenges for water resources scientists (Anderson-Wilk, 2008). English et al. (2002) argue that a fundamental paradigm shift in agroecosystem irrigation management is inevitable as water supplies become more limited, as farmers will manage irrigation to maximize net benefits instead of simply the biological objective of maximizing yields. Limited water resources and increasing pumping costs have recently caused farmers in Colorado, USA to consider limited irrigation as an alternative to full irrigation practices. Alternatively, farmers may consider either a reduction in planted area or schedule irrigation events so that plants do not

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encounter stress during sensitive growth stages. Thus, in many irrigated areas such as the Colorado Front Range, studies (e.g., DeJonge et al., 2011) are increasingly exploring benefits of limited or deficit irrigation of water-intensive crops such as corn (*Zea mays* L.). Limited irrigation practices incorporate water management under restricted water application, and minimize water stress during critical crop growth stages in order to maximize yields (Schneekloth et al., 2009).

Crop simulation models can play an important role in assessing the costs and benefits of limited irrigation and the interactions of timing and amount of irrigation water applications. The Decision Support System for Agrotechnology Transfer (DSSAT) Cropping System Model (CSM) includes several sub-models specific to individual crops. For example, the DSSAT CERES-Maize model (Hoogenboom et al., 2004; Jones and Kiniry, 1986; Jones et al., 2003; Ritchie et al., 1998) has been widely used to assess cropping and management strategies for both rainfed and irrigated corn. For example, Xie et al. (2001) found that simulated vegetative growth and kernel weight are extremely sensitive to drought stress. A group of researchers found that CERES-Maize overestimated the effects of water stress on vegetative growth, and subsequently adjusted the stress functions and improved simulation results (Mastrorilli et al., 2003; Nouna et al., 2000). Saseendran et al. (2008b) simulated various water allocations and irrigation amounts in northeastern Colorado using CERES-Maize, and found that split irrigation applications of 20% of the total water applied during vegetative growth stages and 80% of the total water applied during reproductive growth stages obtained the highest yield for a given irrigation allocation (ranging from 100 to 700 mm of total irrigation). López-Cedrón et al. (2008) evaluated CERES-Maize for rainfed and irrigated treatments with the intent to improve the model's ability to predict biomass and yield under water-limited conditions (where the model had previously given good predictions under irrigated conditions). They found that the model adequately predicted irrigated treatments but underpredicted rainfed treatments. Most recently, DeJonge et al. (2011) provided a detailed statistical comparison of CERES-Maize with a field experiment consisting of full and limited irrigation treatments in northern Colorado, finding that the model performed better in the non-stressed (full irrigation) treatment than in the stressed (limited irrigation) treatment. Additionally, they found the model estimated yield adequately but overestimated ET for full irrigation and underestimated ET for limited irrigation.

The CERES-Maize crop model described above is a complex nonlinear dynamic system that simulates outputs such as crop yield as a function of various inputs including plant cultivar, soil hydraulic parameters, and irrigation timing/amount. It contains a large number of input parameters which are commonly estimated based on field experiments or determined through model calibration and/or parameterization. Accurate estimation of values for important CERES-Maize input parameters is imperative as the accuracy of model outputs is a direct outcome. Therefore, it is desirable to conduct a sensitivity analysis (SA) and uncertainty analysis (UA) as components of further CERES-Maize evaluation to determine which model input parameters require the most certainty. Saltelli et al. (2004) defined SA as "the study of how uncertainty in the output of a model (numerical or otherwise) can be apportioned to different sources of uncertainty in the model input." The aim of SA is to determine how sensitive the output of a model is with respect to the elements of the model which are subject to uncertainty or variability. SA methods are typically classified as local (i.e., derivative-based) or global (Saltelli et al., 2008). When the purpose of the SA is to study the effects of several input parameters on the model output responses, local SA (e.g., one-factor-at-a-time or OAT) is less useful than global sensitivity analysis (GSA) where the output variability is evaluated while the input factors vary in their individual uncertainty domains (Monod et al., 2006). GSA methods, such as Morris (1991), Fourier Amplitude Sensitivity Test (FAST, Saltelli et al., 1999), and Sobol' (1993) can determine not only sensitivity to individual factors, but sensitivity to interactions between factors as well. The Morris (1991) method is a OAT "screening method" that is a computationally efficient means of identifying sensitive parameters, but is ultimately considered global because it attempts to explore the majority of the parameter space (Saltelli et al., 2004). Variance-based methods such as FAST and Sobol' are commonly accepted methods of GSA that explore the entire parameter space but are more efficient than complete factorial design (Saltelli et al., 2000a), and outputs from variance-based simulations can be used to derive cumulative distribution functions (CDFs) for UA. Since they can be difficult to determine precisely due to the intrinsic variability in natural processes, costly monitoring, or data measurement error, input data and model parameters are rarely if ever known with certainty for agroecosystem models like CERES-Maize (Wang et al., 2005). Therefore, performing a UA is desirable in order to correctly estimate model parameters and generate accurate model predictions (Makowski et al., 2002).

Very little SA literature exists for crop models that concentrates specifically on the methodology, particularly sensitivity differences between treatments and/or GSA methods. Ma et al. (2000) performed a SA on the RZWQM for a manured corn field in eastern Colorado. Four groups of model input parameters (saturated hydraulic conductivity, organic matter/nitrogen (N) cycling, plant growth, and irrigation water/manure application rates) were selected with plant N uptake, silage yield, and nitrate leaching as outputs evaluated. Latin Hypercube Sampling (LHS) was used to randomly choose parameters from various probability distributions and the resulting model parameter sets were analyzed using linear regression analysis. Crop yield output response was found to be most sensitive to plant growth input parameters and manure application rates. Makowski et al. (2005) explored using SA methods to reduce the number of field experiments performed for estimating genetic parameters by determining key cultivar parameters whose uncertainty most affects AZODYN winter wheat model outputs. They used a winding stairs method and an extended FAST (eFAST) method, finding that only five genetic parameters out of 13 explored have a significant influence on simulated yield and grain protein content. Pathak et al. (2007) evaluated the DSSAT-CROPGRO cotton model in terms of the most sensitive crop growth parameters for predicting development and yield under irrigated and rainfed conditions. They used both local and global SA methods to evaluate the model and found that the factorial design GSA method was beneficial with regard to defining interactions among parameters, but suggested the method was more computationally expensive than desired. Varella et al. (2010) used the eFAST GSA method to evaluate the ability of the STICS model to accurately evaluate outputs based on varying soil input factors. The results showed that a few soil parameters (e.g., clay content, organic N content, and soil water content at field capacity) were accessible by inverse parameter estimation using observations of yield at harvest, leaf area index, and N absorbed by the plant at various dates. However, the quality of parameter estimation largely depended on several factors, in particular the climate of the observed year and the type of soil at depth (Varella et al., 2010). Campolongo et al. (2007) suggested that the Morris screening method is underutilized in the context of SA and can be used to simplify more robust methods such as Sobol' (1993). The rice model WARM (Water Accounting Rice Model) was recently evaluated to determine the effect of site and climate on model sensitivity in Europe using the Morris and Sobol' SA methods, finding that radiation use efficiency, optimum temperature, and leaf area index at emergence were the most sensitive model input parameters (Confalonieri et al., 2010a) and the Morris SA method produced results comparable to the more computationally expensive Sobol' method (Confalonieri et al., 2010b). These studies are included in a limited number of direct comparisons between the Morris and Sobol' or other variance-based methods in recent literature (i.e., Chu-Agor et al., 2011; Fox et al., 2010; Muñoz-Carpena et al., 2010, 2007). Assessment of these approaches in the context of this study should provide new insight to crop modelers in regard to computational expense and results for each approach.

Very few examples in the literature focus directly on SA for CERES-Maize input parameters, especially in regard to irrigation management in semi-arid regions. St'astná and Zalud (1999) performed a local SA on the CERES-Maize and MACROS (Modules for an Annual CROp Simulation) models, adjusting wilting point, saturated soil water content, and field capacity from −6 to 6% of their nominal values to evaluate changes in yield and LAI. They found a linear dependence of LAI on all three parameters, and negligible influence on yield. Bert et al. (2007) studied the sensitivity of maize yield predictions in Argentina to uncertainty in several soil-related parameters (e.g., soil N and water content at sowing, soil organic matter content, and soil infiltration curve number) as well as solar radiation using a combination of mathematical (local) and graphical SA approaches. They found that CERES-Maize showed more sensitivity to solar radiation than for soil parameters, and that some parameters (e.g., soil curve number and soil water content at sowing) exhibited non-linear responses. He (2008) performed a Morris SA on CERES-Maize cultivar and soil input parameters, evaluating corn yield and N leaching output responses. It was determined that thermal time from emergence to end of juvenile phase, thermal time from silking to physiological maturity, phyllochron interval, soil lower limit, soil drained upper limit, and soil fertility factor model input parameters all have a strong influence on crop yield, and the soil lower limit, soil drained upper limit, soil drainage rate, and runoff curve number have a strong influence on N leaching. Although He (2008) evaluated sensitive soil and cultivar parameters for the CERES-Maize model, the study was conducted in Florida, USA with very sandy soils and high rainfall (average 1320 mm annual).

The above CERES-Maize SA studies do not quantify higher-order interactions between variables, a likely issue in such a robust model. Additionally, most studies in any context of SA explore overall sensitivity of the model in general, without quantifying sensitivity differences between treatments as we would expect in this case. Therefore, a detailed SA in regard to potential CERES-Maize input parameter sensitivity differences between irrigation treatments would be extremely beneficial to modelers who wish to use the model in dryland, semi-arid, or other similar management regimes with limited water resources. Improved knowledge of model sensitivity to various inputs will assist new users of the model with calibration based on these parameters, similar to methods described in Ma et al. (2011). Increased understanding in regard to CERES-Maize input parameter sensitivity and response to water-stressed treatments may also be valuable to users of the new RZWQM2, which has been coupled with the DSSAT plant growth modules (Ma et al., 2007, 2006).

Similar to SA for CERES-Maize input parameters, very few CERES-Maize UA studies exist in the literature. A notable exception is the work of He et al. (2009, 2010). He et al. (2009) used the generalized likelihood uncertainty estimation (GLUE) method to estimate CERES-Maize genotype and soil parameters for sweet corn production in northern Florida. Genotype coefficients (P1, P5, and PHINT) and soil parameters (SLDR, SLRO, SDUL, SLLL, and SSAT) were generated using a multivariate normal distribution that preserved the parameter correlations (Table 1). The GLUE procedure resulted in different prior and posterior distributions of selected parameters (P1, P5, SLDR, SLRO, SLLL, and SDUL). In the posterior distribution of estimated parameters, the uncertainties in parameters were substantially reduced, with coefficient of variation (CV) values mostly lower than 10%. The average CV value of the parameters was reduced from 27.2% in the prior distribution to 4.6% in the posterior distribution. In addition, the GLUE procedure accurately estimated soil parameters (i.e., SLLL, SDUL, and SSAT) when compared to independent measurements made in the laboratory, with an average absolute relative error of about 8.5%. He et al. (2011) used the He et al. (2009) parameter sets (i.e., sets generated from parameter distributions derived with the GLUE method) to simulate dry matter yields under three N fertilizer levels (185, 247, and 309 kg N ha^{-1}) and two irrigation levels (I1 and I2; I2 = 1.5 × I1, where I1 is the irrigation demand calculated based on a daily soil water balance). Due to the uncertainties in soil and genetic parameters, the prediction standard deviation (SD) of simulated dry yields ranged from 655 kg ha^{-1} at I1 to 960 kg ha^{-1} at I2, while the observation SD ranged from 220 to 463 kg ha^{-1} for measured

Table 1
CERES-Maize sensitivity analysis input parameters and output responses.

Name	Definition	Unit	Lower bound	Upper bound
Input parameters				
P1	Thermal time from emergence to end of juvenile	Degree-day	130	350
P2	Development delay factor	Day	0	0.8
P5	Thermal time from silking to physiological maturity	Degree-day	600	950
G2	Maximum possible kernels per plant	Kernel	450	950
G3	Kernel filling rate under optimum conditions	mg day^{-1}	5.0	10.5
PHINT	Phylochron interval	Degree-day	35	75
RUE	Radiation use efficiency	g MJ^{-1}	2	5
SLPF	Soil fertility factor	–	0.7	1.0
SLU1	Evaporation limit	cm	5	12
SLDR	Drainage rate	day^{-1}	0	1
SLRO	Runoff curve number	–	60	95
SLLL	Soil lower limit, or wilting point	mm^3 mm^{-3}	0.11	0.20
SDUL	Drained upper limit, or field capacity	mm^3 mm^{-3}	0.25	0.42
SSAT	Saturation	mm^3 mm^{-3}	0.43	0.51
SSKS	Saturated hydraulic conductivity, macropore	cm h^{-1}	0.3	2.0
SBDM	Bulk density	g cm^{-3}	1.24	1.50
Output responses				
ADAY	Anthesis day	day		
MDAY	Maturity day after planting	day		
LNS	Total leaf number per stem			
LAIX	Maximum leaf area index			
YIELD	Crop yield	kg ha^{-1}		
ETC	Cumulative evapotranspiration	mm		

dry yields. The uncertainties in simulated dry yield were higher than the uncertainties of measured values due to relatively high variations in estimated genetic coefficients. He et al. (2011) concluded that CERES-Maize model performance could be improved further if the variations in estimated genetic coefficients could be reduced. Previous attempts to simulate the difference in irrigation treatments with the CERES-Maize crop growth model have indicated that the model responds more accurately in regard to yield, ET, and vegetative growth under full irrigation with no water stress, as compared to limited irrigation under water stress during the vegetative growth stage (DeJonge et al., 2011). Therefore, in this study focus is placed on evaluating model input properties that should have a large effect on both water availability and crop response to water under full and limited irrigation (e.g., soil hydraulic and phenological growth properties). The overall objectives of this study were to determine and rank the global sensitivity of CERES-Maize v4.5 physiological timing, growth, yield, and ET output responses to soil hydraulic and phenological growth model inputs using both qualitative (Morris) and quantitative (Sobol') SA approaches, and evaluate irrigation treatment differences in output uncertainty. Specifically, this study aimed to identify and quantify a well-defined group of sensitive CERES-Maize input parameters for full and limited irrigation treatments in regard to output responses including anthesis date, maturity date, leaf number per stem, maximum leaf area index, crop yield, and cumulative evapotranspiration. The Morris screening and Sobol' SA methods were used to compare between the full and limited irrigation treatments, using the DeJonge et al. (2011) parameterized model setup as the baseline. Additionally, model outputs from the Sobol' SA method were used to create CDFs for UA. It is hoped that the resulting SA will lead to a justifiable increased focus on improved estimation of sensitive input parameters for CERES-Maize, as well as guidance to potential model improvements under water-stressed conditions.

2. Materials and methods

2.1. Site and experiment description

In a prior study, the CERES-Maize crop growth model was calibrated and validated based on a multi-replicate field research experiment near Fort Collins, CO (40°39′19″N, 104°59′52″W) from 2006 to 2008; details can be found in DeJonge et al. (2011). The soil at the study site is a Fort Collins Loam (fine-loamy, mixed, superactive, mesic Aridic Haplustalf). Two irrigation treatments of continuous corn (the dominant irrigated crop in northeast Colorado) were studied during the 2006 through 2010 growing seasons: full irrigation (ET requirement supplied throughout the season) and limited irrigation (no irrigation before the V12 reproductive stage unless necessary for emergence, then full irrigation afterwards). In all years, less significant early irrigations were required by all treatments to encourage germination and avoid total loss of crop. There were four replications of each treatment, arranged in a randomized complete block design. Each plot consisted of 12 rows spaced 76 cm apart, with a row length of 26 m. All data were taken from the middle four rows, with the outer eight rows serving as buffers to minimize boundary effects from adjacent treatments. Both treatments were monitored weekly for crop growth (total leaf number, LAI, crop height, and biomass), crop development (phenology stages), soil water content (SWC), ET by water balance, and final grain yield. Irrigation water was applied by a linear move sprinkler system, generally at a weekly interval. Irrigation amounts were determined by water balance using crop ET estimates from the onsite weather station (station FTC03; 40°39′09″N, 105°00′00″W; elevation 1557.5 m) within the Colorado Agricultural Meteorological Network (CoAgMet, http://ccc.atmos.colostate.edu/~coagmet/). Daily precipitation, solar radiation, minimum and maximum temperature, vapor pressure (which was converted to dew point temperature), and wind run were continually recorded, and any missing weather data were replaced by data from the Wellington, CO station (station WLT01; 40°40′34″N, 104°59′49″W; elevation 1567.9 m) approximately two km to the north of the FTC03 station.

It was assumed that CERES-Maize sensitivity responses would differ between the full and limited irrigation treatments. Therefore, for each input parameter set, the model was evaluated for both treatments over the five years (2006–2010) management and weather data were fully available (for a total of ten runs per input set). Additionally, simulated inputs (namely irrigation timing and amount) were set to exactly match field management. This was done to ensure that model output response sensitivity was a result of parameter uncertainty and not necessarily varying irrigation schedule and amounts. In all years and treatments, adequate N was applied to avoid N stress.

2.2. CERES-Maize model description

Crop simulation models such as those found in the Decision Support System for Agrotechnology Transfer (DSSAT v4.5) can play a role in assessing the costs and benefits of limited irrigation and the interactions of timing and amount of irrigation water applications (Hoogenboom et al., 2010; Jones et al., 2003). The DSSAT Cropping System Model (CSM) CERES-Maize is available as part of the DSSAT suite of crop models designed to estimate production, resource use, and risks associated with crop production practices (Jones and Kiniry, 1986; Ritchie et al., 1998). It has been widely used to assess cropping and management strategies for corn (both rainfed and irrigated) for well over two decades. CERES-Maize is a process-oriented corn growth model that simulates the following: biomass accumulation based on light interception; partitioning of accumulated biomass to leaves, stems, roots, and grain; environmental stresses; and crop growth and development including phenological states, biomass production, and yield. Additionally, the CSM contains modules for soil water balance as well as soil N transformations and uptake, which are used for other crop modules in addition to CERES-Maize. Required model inputs include soil characteristics, daily weather, cultivar parameters, fertilizer applications, irrigations, planting date, plant population, and other management practices. To facilitate use of a minimum data set, the CSM uses a simple water balance algorithm following a layered soil and a "tipping-bucket" approach (Ritchie, 1998). The USDA curve number technique (USDA-SCS, 1972) is used to calculate runoff and infiltration amounts resulting from rain and irrigation. The Priestley–Taylor (1972) and FAO-56 Penman-Monteith method (Allen, 1998) are available as options in DSSAT to calculate reference ET; the latter was used in this study. This method requires daily solar radiation, minimum and maximum temperature, daily average dew point temperature, and wind speed; these inputs are used in combination with energy balance and mass transfer to calculate reference ET, or potential ET. Instead of applying a crop coefficient to determine crop ET, CERES-Maize partitions the potential ET into potential soil evaporation and potential plant transpiration, and actual soil evaporation and plant transpiration rates depend on the soil water availability to meet the potential values (López-Cedrón et al., 2008). Water stress is generally determined as the comparison between potential transpiration (demand) and available root water or plant extractable soil water (supply) (Saseendran et al., 2008a). In well-watered conditions, available root water exceeds daily potential transpiration. As the soil dries, available root water decreases until it cannot meet transpiration demand, thus introducing stress into the simulated crop.

Because it is relevant to the study, it is important to understand how yield and biomass production is determined in CERES-Maize. In CERES-Maize, crop development rates are calculated based only on temperature and photoperiod (Ritchie et al., 1998). Biomass partitioned to grain in CERES-Maize can be affected by daily minimum temperature (Singh, 1985). Four discrete functions of simulated leaf-tip number are used for predicting plant canopy leaf area in CERES-Maize (Jones and Kiniry, 1986). N uptake is simulated based on the crop N demand and available N in the soil. In terms of crop yield, number of grains per plant is a function of the potential number of kernels per plant and the average crop growth rate (g/plant) from silking to the beginning of grain filling. The model assumes one ear of corn per plant, however if the number of kernels per plant is significantly smaller than the potential number of kernels, the model creates some barren plants. Ear growth rate (g/ear/day) is increased by daily thermal time but can be decreased by water or N stress. The effective grain filling period is based on the thermal time from silking to maturity, and during this period leaf senescence increases, whereas ears, stalks, and roots are the only active growing tissues. Daily grain growth rate is a function of temperature, grains per plant, potential kernel growth rate, and soil moisture effect on growth (Ritchie et al., 1998).

2.3. Input parameters and output responses

CERES-Maize input parameters were selected that are relevant in regard to their ability to affect crop growth timing and magnitude, yield, and ET (Table 1). These mainly include crop cultivar parameters typically used in model calibration and soil hydraulic parameters (i.e., DeJonge et al., 2011; Fraisse et al., 2001; He, 2008). Random values for each parameter were determined assuming a uniform distribution between the lower and upper bounds (Table 1). While sensitivity and uncertainty analyses often attempt to define appropriate input distributions, these studies often utilize simplified distributions for most of the parameters. Monod et al. (2006) note that "the range of input values usually has more influence on the output than the distribution shapes" and other studies echo this statement (i.e., Helton, 1993; Haan et al., 1998). Also, the use of uniform distributions characterizes a more conservative assumption since unimportant parameters, as determined by the GSA, will show little influence regardless of distribution (Saltelli et al., 2008). Maize cultivar parameters P1, P2, P5, G2, G3, and PHINT (Table 1) were used as calibration parameters in DeJonge et al. (2011). Many of these same parameters were previously used in the He (2008) Morris SA study, but they were evaluated separately from soil hydraulic parameters because it was assumed that these groups of parameters were independent. However, in this study all parameters are evaluated simultaneously as it is assumed that interactions between soil hydraulic parameters are possible in the context of water-stressed conditions. Additionally, some model growth components are based strictly on thermal time and have no influence from stress, i.e., as indicated by total leaf count in DeJonge et al. (2011) showing no decrease in simulated successive leaf tip appearances. It is therefore important to identify in this context which cultivar parameters have no stress effects to growth and subsequent yield and ET. In addition to the cultivar parameters, the ecotype parameter (i.e., a type of parameter meant to be specific to the species or subspecies at hand) for radiation use efficiency (RUE, g dry matter per MJ photosynthetically active radiation, PAR) was evaluated for sensitivity. In DSSAT versions 4.0 and above, RUE is set to 4.2 g MJ^{-1} PAR (Hoogenboom et al., 2010), but Lindquist et al. (2005) suggest maize simulation models such as CERES-Maize that rely on RUE for biomass accumulation should use RUE of 3.8 g MJ^{-1} absorbed PAR for non-stressed crops. Additionally, Stöckle et al. (2008) indicate that RUE has a dramatic daily fluctuation in response to weather variability. While CERES-Maize model developers do not recommend using RUE as a calibration parameter (Ma et al., 2011; K. Boote, personal communication), there is some discrepancy as to what the baseline value should be. Instead of adjusting RUE, Ma et al. (2011) suggest using the soil fertility factor (SLPF) to adjust the conversion rate from solar radiation to biomass, and this input was evaluated in addition to RUE as an input in this study. Cultivar and ecotype upper and lower bounds were generally determined by the range of values used in prior studies as indicated by the DSSAT v4.5 software (Hoogenboom et al., 2010). CERES-Maize output responses (Table 1) were selected based on potential effects from water stress, and were statistically evaluated in the DeJonge et al. (2011) study. Growth stage timing outputs include anthesis day and maturity day after planting (ADAY and MDAY, respectively), crop growth outputs include total leaf number per stem and maximum leaf area index (LNS and LAIX, respectively), and the most important evaluation outputs for limited irrigation management: crop yield (YIELD) and cumulative evapotranspiration (ETC).

The soil was assumed to be the same texture as used in DeJonge et al. (2011), determined as a Fort Collins loam (fine-loamy, mixed, superactive, mesic Aridic Haplustalf) by the NRCS Web Soil Survey (http://websoilsurvey.nrcs.usda.gov/app/WebSoilSurvey.aspx), with a typical profile of loam from 0 to 18 cm, loam or clay loam from 18 to 56 cm, and loam, silt loam, or fine sandy loam from 56 to 152 cm. In order to test parameter uncertainty (and avoid error from input uncertainty), the soil was assumed to exhibit properties of a loam or clay loam throughout the profile (Table 1). To simplify analysis, the nine separate soil layers were determined simultaneously and assumed to be homogeneous throughout all layers. From the soil surface, these layers are at depths of 0–5, 5–15, 30–45, 45–60, 60–90, 90–120, 120–150, and 150–178 cm. Upper and lower bounds for soil lower limit (SLLL), soil drained upper limit (SDUL), saturation (SSAT), and saturated hydraulic conductivity (SSKS) were taken from Schwab et al. (1993) as typical values for loam or clay loam (Table 1). By limiting the analysis to loam and clay loam soil types, the upper and lower bounds applied ensure that SLLL < SDUL < SSAT, as would be expected mathematically. Upper and lower bounds for bulk density (SBDM) were found in the DSSAT input files for recommendations based on soil classification (Hoogenboom et al., 2010).

2.4. Sensitivity and uncertainty analysis methods

In general, SA is the study of how the variation of the output of a model can be apportioned to different sources of variation or input (Saltelli et al., 2000a). Sensitivity analyses are typically classified as either local sensitivity analysis or global sensitivity analysis (Saltelli et al., 2000a). Local SA examines the local response of model output responses by varying input parameters one at a time while holding other parameters at fixed values. GSA characterizes methods that possess two basic properties (Saltelli et al., 2000a): (i) multiple parameters are varied simultaneously, and (ii) sensitivity is measured over the entire range of each input factor. When dealing with a nonlinear model and input factors that are affected by uncertainties of varying magnitude, a GSA approach is the more robust option. Thus, more studies currently are using GSA techniques instead of local SA. Most of the global SA methods are variance-based, for example the global sensitivity index is presented by the contribution of each input factor to the total variance of the model output. Methods for GSA are typically decomposed into four steps: (1) definition of the inputs and their distribution; (2) generation of a sample of input values; (3) evaluation of the model output for each sample set of inputs; and (4) estimation of the effect of each input on the model output (Tong, 2010). To perform the last step, two main approaches are used: a model approximation (e.g., linear regression) or a direct decomposition of the output variance;

the latter is typically considered more advantageous in nonlinear models. The following paragraphs briefly describe two common GSA methods which are used in this study, the Morris screening method and the method of Sobol'.

Morris (1991) proposed an experimental plan to determine which input factors have important effects on an output using individually randomized one-factor-at-a-time (OAT) designs, also referred to as "elementary effects." The method is well-suited for cases with a large number of input factors and/or expensive computation, and is often considered a good compromise between accuracy and efficiency (Campolongo et al., 2007). The main idea behind the Morris screening method is to discriminate, at low sample size, among effects which are (a) non-influential or negligible, (b) linearly influential and additive, and (c) non-linearly influential or influential by interactions with other factors (Campolongo et al., 2007; Saltelli et al., 2004, 1999). For each input, two sensitivity measures are computed: μ^*, which assesses the overall influence of the factor on the output, and σ, which estimates the ensemble of the factor's higher order effects, i.e. non-linear and/or due to interactions with other factors (Campolongo et al., 2007). While considered a GSA method because it covers the entire space over which the factors may vary, the experimental part of the method is composed of individually randomized OAT experiments (Saltelli et al., 2004). Morris suggests evaluating a graphical representation of σ vs. μ^* to determine the most important factors. One of the main advantages of the Morris method is the low computational cost, especially in comparison with other screening methods such as fractional factorial designs. However, the sensitivity measures are typically considered qualitative (i.e., ranking significant input factors) but not necessarily quantitative in regard to the degree of significance. Quantitative methods, such as the variance-based method of Sobol' discussed next, give precise calculations of output variance but are also more computationally expensive (Saltelli et al., 2004).

The Sobol' (1993) GSA method computes an ANOVA-based decomposition of the output variance, where both main effects and interaction terms can be computed (Saltelli et al., 2000a). The Sobol' sensitivity index represents the fraction of the total variance that is due to any individual factor or combination of factors. Additionally, the method of Sobol' is able to estimate the total sensitivity index ST_i, defined as the sum of all effects (including first-order and higher-order) involving the input factor of interest (Saltelli et al., 2000b). With k quantitative input factors, the decomposition of the variance var($\hat{Y}$) generalizes to:

$$var(\hat{Y}) = \sum_{i=1}^{k} D_i + \sum_{1\le i<j\le k} D_{ij} + \cdots + D_{1,2,\ldots,k} \quad (1)$$

where D_1 is the variability associated with the main effect of input factor x_1, D_2 is the variability associated with the main effect of x_2, and D_{12} is the variability associated with the interaction between x_1 and x_2, and so on. This technique is very similar to the analysis of variance (ANOVA), except that var($\hat{Y}$) represents the variability of $\hat{Y}$ in terms of the overall uncertainty of the input factors, including irregular and non-linear effects (Monod et al., 2006). The sensitivity indices are derived from the above equation by dividing individual importance measures by the total variability var($\hat{Y}$):

$$S_i = \frac{D_i}{var(\hat{Y})} \quad (2)$$

$$S_{ij} = \frac{D_{ij}}{var(\hat{Y})} \quad (3)$$

and so on, where S_i is called the first order sensitivity index for factor x_i, measuring the main effect of x_i on the output [or the fractional contribution of x_i to the variance of $f(x)$]. S_{ij} is called the second-order sensitivity index which measures the interaction effect of the two inputs x_i and x_j, without considering the sum of the individual effects (Saltelli et al., 2000b). A useful property of these sensitivity indices is that all of the possible first-order sensitivity index terms sum to one:

$$\sum_{i=1}^{k} S_i + \sum_{1\le i<j\le k} S_{ij} + \cdots + S_{1,2,\ldots,k} = 1 \quad (4)$$

The total sensitivity index (ST_i) can be defined as the sum of all the sensitivity indices involving the factor in question. For example, in a three-factor model, the three total effect terms for ST_i are:

$$\begin{aligned} ST_1 &= S_1 + S_{12} + S_{13} + S_{123} \\ ST_2 &= S_2 + S_{12} + S_{23} + S_{123} \\ ST_3 &= S_3 + S_{13} + S_{23} + S_{123} \end{aligned} \quad (5)$$

where each S_i is simply the fraction of the variance of that value to the total variance of the model, as previously defined. Although the sum of the individual effect terms will add to one, the sum of all the ST_i values is typically larger than one because interactions are counted multiple times.

GSA input samples were generated with SimLab (2010), and evaluation of CERES-Maize model input sets was automated with SimLab and MATLAB (Mathworks, 2010). The Morris SA was executed by sampling $r = 10$ elementary effects (i.e., individualized comparisons per factor) and $k = 16$ input factors for a total experiment cost (as suggested by Morris, 1990) of $r(k + 1) = 170$ model input sets. The Sobol' SA was executed by using $k = 11$ input factors after eliminating five insensitive inputs from the Morris analysis, and a sample size of $n(k + 2)$ model input sets (Saltelli, 2002; Campolongo and Saltelli, 1997), where n is defined having a range of 100 or higher (Saltelli, 1999). This study used $n = 160$ for a total of 2080 input sets, consistent with other examples with similar number of input parameters (Campolongo and Saltelli, 1997; Saltelli et al., 2000a), and verified as having results similar to over 15,000 input sets. Each input set was run for both full and limited irrigation treatments, using observed management data from five years (2006–2010). CERES-Maize output response uncertainty was assessed using statistics and CDFs created from the Sobol' simulation outputs.

3. Results

3.1. Morris screening method

Results for the Morris SA are shown in both graphical (Fig. 1) and tabular (Table 2) form. Morris (1991) suggested that only factors with relatively high values of μ^* and σ are considered important. As mentioned in the previous section, high values for μ^* indicate large overall sensitivity to the input parameter, whereas a high value for σ indicates interaction or non-linear effects associated with the input parameter. ADAY was most sensitive to P1, a trend that was typical for every output response except YIELD and ETC (Table 2). In order of decreasing μ^* (i.e., decreasing sensitivity), PHINT was the next highest, with slightly higher σ than P1 indicating more interaction. ADAY was less sensitive to P2 than PHINT, but σ for these inputs was nearly the same as P1. For these three input parameters, there was little difference between treatments (Fig. 1). There was minor sensitivity to the soil parameters SLLL and SDUL (due to higher standard deviations) for the limited irrigation treatment, but very low μ^* values (indicating low overall influence). Another phenological timing output, MDAY was similar to ADAY in that it was most sensitive to P1, with the full irrigation treatment having a slightly higher μ^* (Fig. 1). This trend is logical, as changes to ADAY will naturally cause changes to MDAY, although their sensitivity to inputs was not identical because of thermal growth accumulations

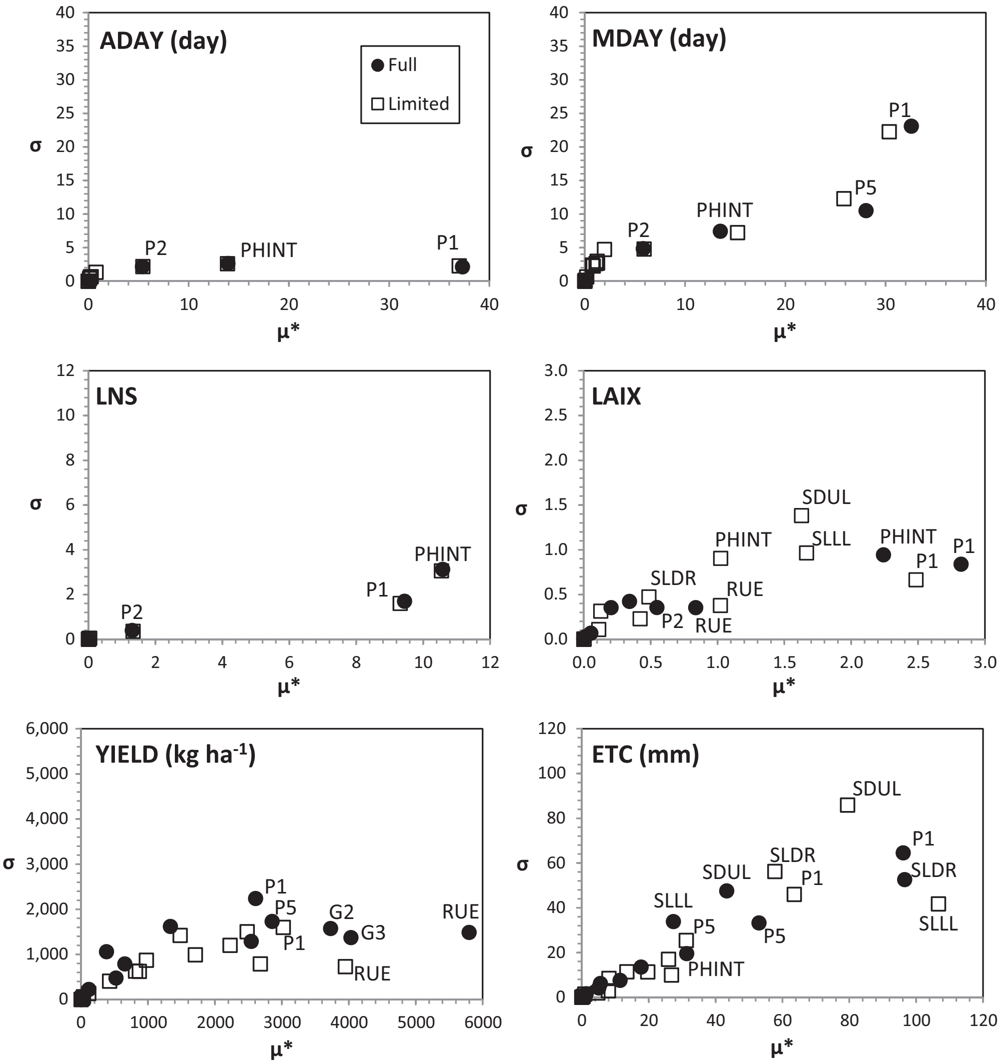

Fig. 1. Morris sensitivity analysis results shown in graphical form for all CERES-Maize output responses of interest. Filled circles indicate full irrigation treatment, open squares indicate limited irrigation treatment. Labels of the most important factors are shown.

after ADAY. P5 and PHINT were the next most influential inputs with sensitivity to P2 very low.

Both LNS and LAIX are vegetative growth outputs which should be sensitive to phenological inputs but also to water stress. LNS was mostly sensitive to PHINT and P1, with little difference between irrigation treatments (Fig. 1). There was a limited amount of sensitivity to P2 as well for LNS. On the other hand, for the two treatments there was a large difference between sensitive input

Table 2
Morris sensitivity analysis rankings for both full and limited irrigation treatments and all CERES-Maize output responses evaluated, in decreasing order of importance based on Morris μ^* (1 = most important input for the given output).

Irrigation treatment	Output response	Input parameters[a]										
		P1	P2	P5	G2	G3	PHINT	RUE	SLDR	SLRO	SLLL	SDUL
Full	ADAY	1	3	–[b]	–	–	2	–	–	–	–	–
	MDAY	1	4	2	–	–	3	–	–	–	–	–
	LNS	2	3	–	–	–	1	–	–	–	–	–
	LAIX	1	4	–	–	–	2	3	–	–	–	5
	YIELD	5	–	4	3	2	6	1	–	–	8	7
	ETC	2	7	3	–	–	5	8	1	–	6	4
Limited	ADAY	1	3	–	–	–	2	–	–	–	–	–
	MDAY	1	4	2	–	–	3	–	–	–	–	–
	LNS	2	3	–	–	–	1	–	–	–	–	–
	LAIX	1	7	–	–	–	4	5	6	–	2	3
	YIELD	2	11	7	5	4	10	1	9	8	3	6
	ETC	3	9	5	–	–	6	8	4	7	1	2

[a] Input parameters SLPF, SLU1, SSAT, SSKS, and SBDM had no significant influence on any output responses and were omitted from the rankings.
[b] "–" = no significant influence based on Morris μ^* less than 10% of the maximum μ^* for the output response in question).

parameters for LAIX. For both treatments, P1 was the most influential input considering μ^* but the sensitivity was higher for full irrigation than for limited irrigation. PHINT was also a highly influential input for both treatments, again with much higher sensitivity for full irrigation than for limited irrigation. However, the soil input parameters SLLL and SDUL were highly influential for limited irrigation with μ^* values greater than the value for PHINT. RUE also had some effect on LAIX for both treatments (Fig. 1).

YIELD was most sensitive to RUE for both treatments (Table 2), although it had a higher μ^* and σ for full irrigation (mainly because fully irrigated yield naturally has higher values with more variance expected than for limited irrigation yield). For full irrigation, the next five highest influential parameters were all cultivar coefficients (G3, G2, P5, P1, PHINT). Although these cultivar parameters were also sensitive for limited irrigation, sensitivity to the soil parameter SLLL was much higher for the limited irrigation treatment and should be considered equally influential. In addition, YIELD was also sensitive to the soil parameter SDUL for both treatments. ETC was most sensitive to SLDR and P1 for full irrigation, followed by P5, SDUL, PHINT, and SLLL (Table 2). Several of these parameters were sensitive for limited irrigation; however, the order of sensitivity was much different: SLLL was the most influential input parameter, followed by SDUL, P1, SLDR, and P5. This indicates that when water is limited the cumulative ET is very responsive to the water holding capacity and the drainage from the deepest layer.

As suggested by prior literature (i.e., DeJonge et al., 2011), phenological timing and total leaf count are not responsive to lack of available water, as shown by little treatment difference between sensitivity of any input parameter in ADAY, MDAY, and LNS (Fig. 1). Conversely, there was a large contrast in sensitive inputs between treatments for the LAIX, YIELD, and ETC output responses, with much greater sensitivity to soil hydraulic parameters in limited irrigation, whereas in full irrigation the LAIX, YIELD, and ETC output responses are mainly sensitive to cultivar-specific inputs (Fig. 1).

3.2. Sobol' variance-based method

Because Morris is often used as a "screening" method to eliminate insensitive parameters, the Sobol' analysis used default values for input parameters SLPF, SLU1, SSAT, SSKS, and SBDM, as they indicated no influence on CERES-Maize output responses of interest for the Morris method. The Sobol' total sensitivity index (ST_i) results (Fig. 2) were very similar to the Morris μ^* ranking results (Fig. 1 and Table 2). First-order sensitivities were typically very close to the ST_i for output responses typically sensitive to two or three input parameters (i.e., ADAY, LNS, and LAIX for full irrigation), but yielded many more interactions when the output response was sensitive to three or more parameters (i.e., LAIX for limited irrigation, YIELD, and ETC). Interactions can easily be identified by a large difference between ST_i and S_i in Fig. 2. A ranking of sensitive parameters in decreasing order of ST_i is also displayed (Table 3).

The CERES-Maize output response ADAY was highly sensitive to P1 and slightly sensitive to PHINT (Fig. 2) with minimal interactions between the input parameters. MDAY was also very sensitive to P1 (followed by P5 and PHINT, respectively), with slight interactions between input parameters P1 and P5. LNS was primarily sensitive to P1 and PHINT, again with small interactions between the two inputs. There were minimal differences between full and limited irrigation treatments for the ADAY, MDAY, and LNS output responses, considering both ST_i and S_i values. LAIX was the most sensitive to P1 and PHINT for full irrigation, but for limited irrigation exhibited significant sensitivity to soil parameters SLLL and SDUL as well as RUE. For full irrigation, there were very small interactions between the two sensitive input parameters for LAIX; however, there were larger interactions between P1, SLLL, and PHINT (Fig. 2).

Table 3
Sensitive CERES-Maize input parameters, in order of decreasing total Sobol' sensitivity (ST_i), for both full and limited irrigation treatments and all CERES-Maize output responses evaluated.

Output response	Irrigation treatment	Sensitive input parameters[a]
ADAY	Full	P1, PHINT
	Limited	P1, PHINT
MDAY	Full	P1, P5, PHINT
	Limited	P1, P5, PHINT
LNS	Full	P1, PHINT
	Limited	PHINT, P1
LAIX	Full	P1, PHINT, RUE
	Limited	P1, SLLL, SDUL, PHINT, RUE
YIELD	Full	RUE, G3, G2, PHINT, P5, P1
	Limited	RUE, P1, G3, SLLL, G2, SDUL, P5
ETC	Full	SLDR, P1, P5, SDUL, SLLL, PHINT
	Limited	SLLL, P1, SLDR, SDUL, P5

[a] All sensitive input parameters have ST_i greater than 0.05.

Table 4
Correlation (r) comparisons between the Sobol' method total sensitivity index (ST_i) and the Morris method μ^* for both full and limited irrigation treatments.

Output response	Irrigation treatment	
	Full	Limited
ADAY	0.969	0.970
MDAY	0.943	0.950
LNS	0.960	0.928
LAIX	0.995	0.995
YIELD	0.980	0.969
ETC	0.962	0.954

YIELD was the most sensitive to RUE for both treatments, followed by cultivar parameters typically used in calibration, although for limited irrigation YIELD was much more sensitive to soil parameters SLLL and SDUL. First-order sensitivity was highest in full irrigation to RUE, G2, then G3; however for limited irrigation this was RUE, P1, SLLL, and G2. For YIELD, G3 had the largest amount of interaction, for both treatments. For full irrigation, ETC was primarily sensitive to P1 and SLDR, and slightly sensitive to P5, with interactions involved in all three inputs. For limited irrigation, ETC was the most sensitive to SLLL followed by P1, SLDR, and SDUL, with larger interactions for SLDR and P1 as well. Furthermore, ETC sensitivity to SLDR showed the highest interaction of all the CERES-Maize input parameters across both treatments.

3.3. Comparison between Morris and Sobol' GSA methods

Because the Sobol' ST_i results so closely replicated the order and magnitude of the Morris μ^* results (taking into account the entire sensitivity of the output to each input parameter), a direct comparison was made for each output response and treatment by calculating the correlation (r) between Sobol' ST_i and Morris μ^* (Table 4). Comparisons were made using only inputs evaluated in both GSA methods, so inputs with negligible sensitivity as found by the Morris screening method were eliminated from this comparison. All comparisons yielded r values greater than 0.928, indicating a very high correlation between the two GSA methods used.

3.4. Uncertainty analysis

Statistics and CDFs for all outputs of interest and both irrigation treatments were created from the 2080 Sobol' simulation outputs (Table 5 and Fig. 3, respectively). Although GSA indicated little sensitivity difference in treatments for ADAY, the UA revealed that the reproductive growth stage was delayed for limited irrigation

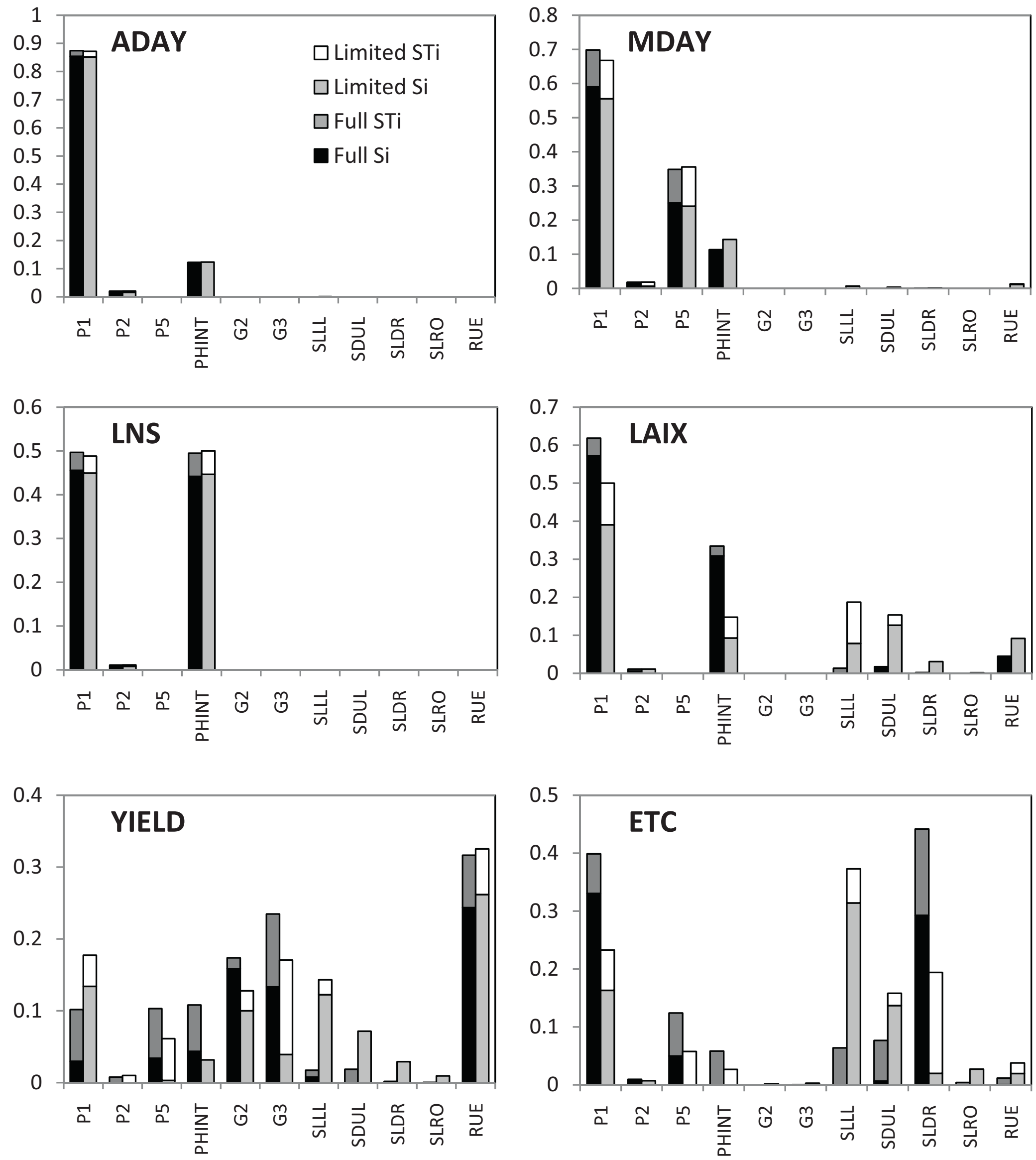

Fig. 2. Sobol' total sensitivity (ST_i), and 1st order sensitivity (S_i) indices for CERES-Maize output responses of interest. Model input parameters are those found sensitive by the Morris screening method.

Table 5
Uncertainty analysis statistics for full and limited irrigation treatments and all output responses, as determined from Sobol' global sensitivity analysis simulations.

Output response (unit)	Irrigation treatment	Minimum	5% CI[a]	Median	95% CI	Maximum
ADAY (day)	Full	57	66	82	103	123
	Limited	65	74	92	114	125
MDAY (day)	Full	101	119	160	174	174
	Limited	118	131	145	174	175
LNS	Full	10.6	12.7	17.9	25.2	30.6
	Limited	10.6	12.5	17.5	24.8	30.0
LAIX	Full	0.20	1.23	3.21	5.39	6.43
	Limited	0.45	2.04	3.82	5.56	6.45
YIELD (kg ha^{-1})	Full	608	2791	6751	14,190	23,696
	Limited	0	1004	6176	13,649	20,926
ETC (mm)	Full	203	346	533	656	747
	Limited	233	439	519	645	731

[a] Confidence interval.

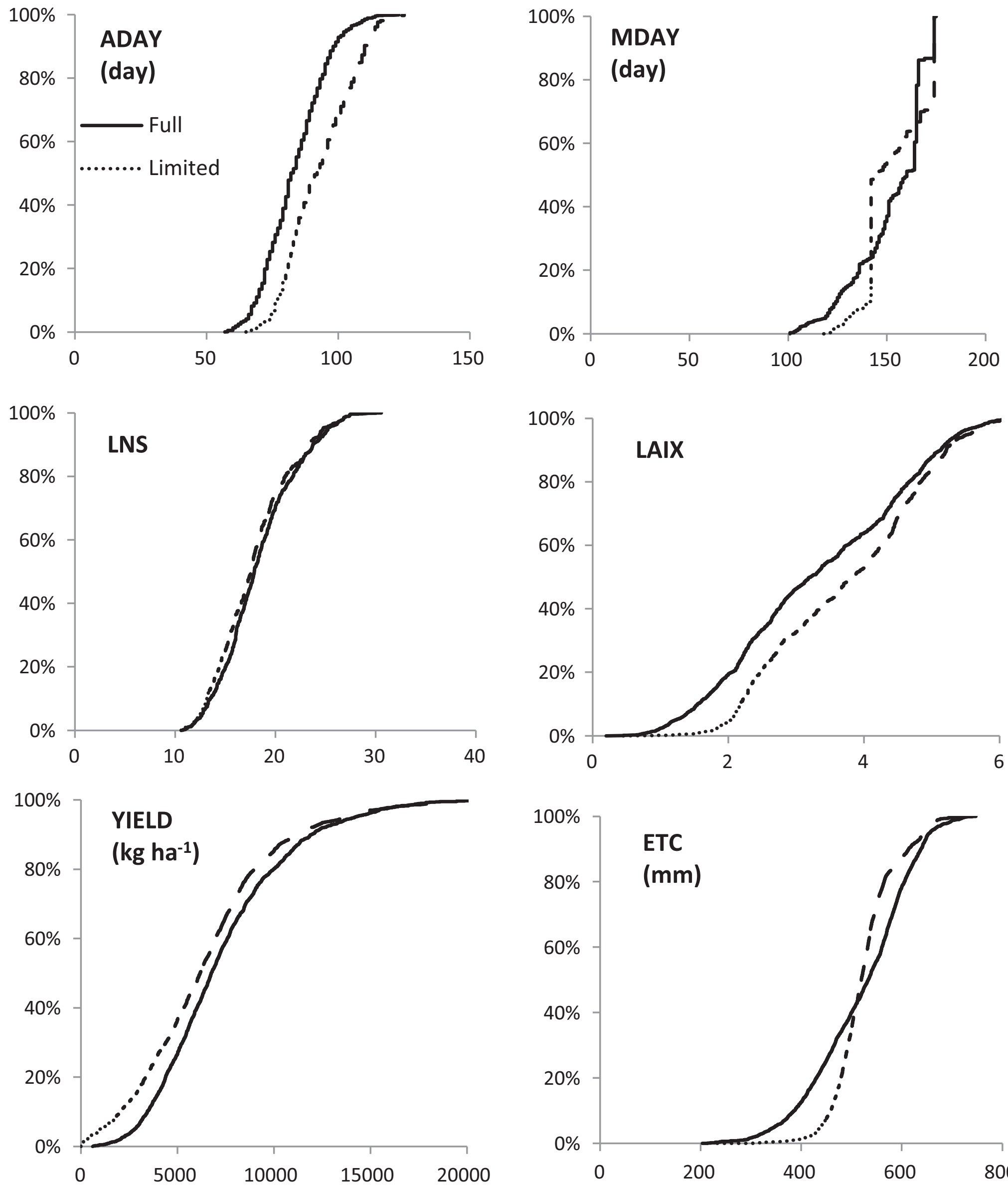

Fig. 3. Uncertainty analysis cumulative distribution functions (CDFs) for CERES-Maize output responses of interest, created from Sobol' model runs. Y-axis indicates cumulative probability (%), *x*-axis unitless unless indicated with the output name.

(median 82 days for full irrigation, 92 days for full irrigation). There were some differences in the uncertainty range between treatments for MDAY, with high frequency in several cases as indicated by sharply vertical lines (Fig. 3). The only difference between irrigation treatments for LNS was a minimal increase for full irrigation over limited irrigation. Simulated LAIX was found to be higher for limited irrigation than full irrigation (median 3.21 for full irrigation, 3.82 for limited irrigation). The UA for ETC indicated a broader range for full irrigation than for limited irrigation, i.e., full irrigation exhibited respective 5% and 95% CIs of 346 and 656 mm but limited irrigation indicated 5% and 95% CIs of 439 and 645 mm, respectively. Finally, YIELD exhibited higher values under full irrigation than under limited irrigation over the entire probability range.

4. Discussion

Because the Morris μ^* and Sobol' ST_i results had such a high correlation, the remainder of this paper will refer to the sensitivity of a parameter in a general sense rather than in specific terms of SA method (i.e., Morris or Sobol'). It is important to consider that the results for Morris were found with 170 runs and a simpler algorithm than the more complicated Sobol' algorithm which required 2080 runs (with $n = 160$ cycles to determine sample size). While Saltelli (1999) recommends n in the range of 100 or higher, Saltelli et al. (2005) also note that n is typically in the range of 500–1000. Preliminary Sobol' runs performed for this study indicated that sensitivity obtained with $n = 160$ had results indistinguishable to $n = 1200$, and we expect that increasing the total number of Sobol' runs would only give the same results at additional cost. Regardless, the Morris and Sobol' methods served equally well in terms of not only ranking the input parameters, but also in quantifying relative total sensitivity of the input parameters. Similar results were found by Campolongo et al. (2007) when assessing the sensitivity of a chemical reaction model for dimethylsulphide (DMS). As the Morris method is less computationally expensive, it may be preferred over the Sobol' method for many types of SA studies. However, caution must be used in this approach as interactions and nonlinearity are difficult to distinguish based on Morris screening results alone (Saltelli et al., 2000a). For example, in a previous study Campolongo and Saltelli (1997) performed both Morris and Sobol' analyses using the GMSK model to simulate the oceanic production of DMS, evaluating 34 factors, and found that the Pearson correlation coefficient (r) between the Morris and Sobol' methods was 0.66, a much lower value than consistently found in this study. Campolongo and Saltelli (1997) go on to suggest a procedure matching accuracy and cost that would include a Morris analysis followed by a Sobol' analysis on a subset of selected inputs, just as was conducted in this study. However, simple linear correlations between the two methods were very high in our case. Confalonieri et al. (2010b) used the rice model WARM to conduct SAs using the Morris method, three regression-based methods, and two variance-based methods (E-FAST and Sobol'), finding that the simpler SA methods including Morris gave comparable results to the more computationally expensive Sobol' method.

CERES-Maize output responses ADAY, MDAY, and LNS had no notable sensitivity difference between treatments, indicating that anthesis and maturity timing (as well as successive leaf tip appearances) are generally insensitive to the effects of water stress. This is contradictory to some observed field responses, for example Farre and Faci (2006) observed delays in maize flowering and maturity due to water stress, and DeJonge et al. (2011) observed differences in total leaf count for the same field experiment used in this study. Abrecht and Carberry (1993) observed delayed leaf tip emergence, tassel emergence, silking, and onset of grain filling due to varying amounts of water stress. For the CERES-Maize LAIX, YIELD, and ETC output responses, water holding capacity was an extremely important factor in regard to sensitivity under limited irrigation, as the sensitivity is highly dependent upon the water management objectives. For full irrigation, none of the model output responses evaluated in this study exhibited significant sensitivity to the soil parameters SLLL or SDUL. However, under limited irrigation, these input parameters were very important in terms of total sensitivity, especially SLLL which was the most sensitive input parameter for both LAIX and ETC (Table 3). This indicates that much more attention is required in estimating SLLL and SDUL for limited irrigation simulations than for full irrigation simulations, especially SLLL as it is a main limiting factor for leaf area growth, crop yield, and ET (Fig. 2). Interactions are also important to consider, for example in LAIX under limited irrigation SLLL has a large interaction (0.09), likely with P1 and PHINT as no other inputs show a large amount of interaction (Fig. 2). SLDR was also an influential input in regard to ETC under limited irrigation, as increased drainage out of the soil profile limits the model's ability to meet ET demand, and also had a large interaction with other parameters (0.17). Where these interactions exist, all parameters should be considered simultaneously instead of one at a time, and this GSA study illustrates this importance.

The UA results offer some interesting insight into the behavior of the model (Table 5 and Fig. 3). There was little difference in sensitivity between irrigation treatments for ADAY and MDAY. However, the UA showed a shift in ADAY for limited irrigation, which may partially be due to delayed crop planting for some limited irrigation treatments, but more likely due to sensitivity to some unknown response not evaluated in this study. Responses also varied between irrigation treatments for MDAY, with the CDFs crossing each other twice and both having strong vertical lines, indicating crop maturity at the same date for many simulations. This trend can be explained as an interaction between the weather inputs, the irrigation treatment, and model code that indicates maturity (or simulation end) under specific conditions. LNS essentially exhibited the same uncertainty between irrigation treatments, with a slight decrease in LNS under limited irrigation; these differences are illustrated in Fig. 2 where a very small sensitivity to soil water parameters is seen for limited irrigation. For LAIX, there was a very broad range in uncertainty for both treatments, and interestingly the CDF and statistics for full irrigation indicated lower LAIX values than under limited irrigation. Upon closer examination of the results, in many cases LAIX was higher for full irrigation than for limited irrigation as expected, but limited irrigation had higher LAIX values overall. This trend is likely due to increased partitioning to leaf biomass when the crop is under water stress. It is also important to consider that LAIX indicates the maximum LAI over the season and under stressed conditions the LAI will often spike and decrease quickly because of senescence. Future studies may consider using an average LAI during a specific developmental stage; however, with differing treatments and input parameters the growth stages obviously would be dynamic and difficult to glean from the outputs. As expected, YIELD was higher for full irrigation than limited irrigation across the uncertainty range. The 95% CI indicates predicted yields of 14,190 kg ha^{-1} under full irrigation, numbers that are typically unrealistic under these climatic conditions. These high simulated yields may be due to unique combinations of input parameters that maximize yield, for example large values for input parameters RUE P2, G2, G3. At higher cumulative probabilities, ETC was higher for full irrigation than for limited irrigation, as would be expected (i.e., the 95% CI predicts 656 mm for full irrigation and 645 mm for limited irrigation). However, as ETC decreases, the values were actually higher for limited irrigation (i.e., the 5% CI predicts 346 mm for full irrigation and 439 mm for limited irrigation). This trend supports the conclusion of DeJonge et al. (2011) that CERES-Maize tends to overpredict evapotranspiration while the crop is under water stress.

Ma et al. (2011) describe a systematic calibration of cultivar parameters for DSSAT models, in which they suggest calibrating these inputs based on phenology first, followed by biomass, LAI, and yield. As this GSA study shows, the calibration method described by Ma et al. (2011) may be appropriate in a study that observes no water stress. However, the difference in input sensitivity in regard to limited irrigation treatments found in this study provides a unique opportunity to perform a systematic calibration of datasets for water stressed conditions, such as those used in DeJonge et al. (2011), and could provide guidance for other DSSAT modelers to improve calibrations under limited water conditions. Such a calibration would be roughly based on the method described by Ma et al. (2011) by calibrating or parameterizing individual output responses to observed values based on which influential inputs can be solved for the most easily. However, this new calibration method would also acknowledge the strong influence that water holding capacity has on outputs such as LAI and yield. In this study, no output response was overly sensitive to P2 so the recommended default value for this parameter could likely be used. PHINT also was not an overly sensitive parameter in this study, but could be estimated based on observations of successive leaf tip appearances and growing degree days. Once PHINT is known, P1 can then be estimated by matching ADAY for both treatments and LNS for full irrigation only (as we know that limited irrigation, the model will not correctly predict observed leaf number). With P1 and PHINT known, only P5 is left to estimate to fit MDAY. At this point, LAIX (and leaf area index throughout the season, for that matter) should match closely for full irrigation. Soil hydraulic parameters SLLL and SDUL can then be estimated within acceptable levels for the known soil type, and should help closely match leaf area index for the limited irrigation treatment. Ma et al. (2011) recommend using SLPF to improve simulations, but this study found all relevant outputs to be insensitive to changes in SLPF. While RUE has not traditionally been documented in past studies as a calibration parameter, this study suggests it could be evaluated within reasonable ranges. RUE can also be used to make smaller adjustments to LAIX, as it provides some sensitivity without interactions, and obviously has a high influence on YIELD. Finally, YIELD can be fitted by finding values for G2 and G3, whereas ETC can be fitted by defining SLDR. Without full testing, it is impossible to speculate if such a systematic method of calibration would be worthwhile, but it is certainly worth considering in future studies as another extension of this GSA.

5. Summary and conclusions

Two types of SA were performed on full and limited irrigation treatments of corn using the CERES-Maize crop model and five years of observed full and limited irrigation schedules and weather. In addition, an UA was conducted using CDFs created from the Sobol' SA simulation outputs. Model outputs evaluated included growth timing of anthesis date and maturity, total leaf number per stem, maximum leaf area index, crop yield, and cumulative evapotranspiration. Inputs, which were systematically varied throughout an acceptable range of values, included crop cultivar parameters, soil hydrologic parameters, and radiation use efficiency. The Morris SA method was used to eliminate completely insensitive parameters prior to performing the more computationally intensive Sobol' method. In this study, results comparing Morris mean and Sobol' total sensitivity index showed very high correlation between the two (Table 4), indicating that the computationally cheaper Morris method could have been used as the sole indicator of input sensitivity.

For the full irrigation treatment, outputs were mostly sensitive to crop cultivar parameters. This was anticipated as CERES-Maize has been known to perform best in non-water stressed environments and the crop cultivar parameters have historically been used for calibration (DeJonge et al., 2011). However, in the limited irrigation treatment outputs for leaf area index, yield, and evapotranspiration were highly influenced by the SLLL and SDUL input parameters (which define water holding capacity). Evapotranspiration was also highly sensitive to drainage rate (SLDR) in both treatments, and crop yield was most sensitive to radiation use efficiency (RUE) in both treatments. For both treatments, anthesis date and maturity date were not sensitive to soil hydraulic parameters and had the same sensitivity between treatments, unsurprising as in CERES-Maize these outputs are strictly a function of thermal time and have no reaction to available water (although the UA showed slight differences between irrigation treatments). There were no differences in sensitivity or uncertainty between treatments for leaf number per stem, a trend expected based on the DeJonge et al. (2011) results. For LAIX, the UA indicated higher values for limited irrigation than for full irrigation, and future studies are recommended to use a time-averaged value for LAI instead of the maximum value. Although for YIELD the UA indicated higher values for full irrigation, analysis of ETC showed higher evapotranspiration for the limited irrigation treatment in the lower range of values, indicating a need for further investigation as to why CERES-Maize tends to overpredict evapotranspiration while the crop is under water stress.

It is a well-known fact that identifying influential model parameters, in a specific arena of application, is of primary importance for all types of models, in this case the agroecosystem (and specifically crop) modeling community. This is true for aiding not only efficacious parameterization and calibration, but also for model development and enhancement itself. This study shows that as prediction problems related to water availability in agriculture become more complex, our analysis techniques need to evolve and progress to better represent and quantify how crop growth models behave under water limited environments. Although this study focused on CERES-Maize parameter sensitivity and output uncertainty, a future study should focus on model sensitivity to water stress and how those functions are calculated. The ability to better quantify crop development delay under water stress is a potential model improvement as indicated by this SA. The current version of CERES-Maize shows little phenological timing or growth response (in the form of total leaf count) to water stress, as these outputs are strictly functions of thermal time (DeJonge et al., 2011). Saseendran et al. (2008a) review several examples of observed maize phenology delay due to water stress, and emphasize that crop models that simulate water stress should emphasize these effects. One possibility for future improvement of CERES-Maize would be to adopt an approach similar to the APSIM (Agricultural Production Systems Simulator) v 5.0 generic plant module. For example, between the stages of emergence and flowering, the calculated daily thermal time in APSIM is scaled back by water and N stresses, causing delayed phenology under stress (Saseendran et al., 2008a). It is also notable that DeJonge et al. (2011) reported underestimation of LAI under limited irrigation while ET was overestimated, and UA in this study actually indicates higher ET under water stress in some cases. To obtain a full understanding of contributors to these output biases, an evaluation of CERES-Maize water stress sub-procedures is suggested to supplement this GSA study.

Finally, the linkage between sensitivity analysis and model parameterization/calibration is not always well-defined or readily apparent for the casual or even advanced crop modeler. As real-world management paradigms change, for example limited irrigation of crops, the models that are used to simulate these management changes will need to adjust appropriately. For example, formerly suggested CERES-Maize calibration methods for non-stressed crops may not be adequate in cases that include, or even focus on, water stress. Therefore, a new methodology for systematic calibration of CERES-Maize, based on sensitivity indices for the two irrigation treatments, is proposed for future evaluation. This calibration method focuses on the strong influence that water holding capacity has on outputs such as LAI and yield, and may potentially improve CERES-Maize predictive ability under limited water conditions where water stress is commonly encountered during the vegetative growth stage.

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