Development, uncertainty and sensitivity analysis of the simple SALUS crop model in DSSAT

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ABSTRACT

Simplified approaches to modeling crop growth and development have recently received more attention due to increased interest in applying crop models at large scales for various agricultural assessments. In this study, we integrated the simple version of SALUS (System Approach to Land Use Sustainability) crop model in the widely-used Decision Support System for Agrotechnology Transfer (DSSAT) to enhance the capability of DSSAT to simulate additional crops without requiring detailed parameterization. An uncertainty and sensitivity analysis was conducted using the integrated DSSAT-simple SALUS model to assess the variability in model outputs and crop parameter ranking in response to uncertainties associated with crop parameters required by the model. The influence of year, production level, and location on the effect of crop parameter uncertainty was also investigated.

Parameter uncertainty resulted in a high variability in modeled outputs. Simulated potential above-ground biomass ranged from $1.2\,t\,ha^{-1}$ to $38\,t\,ha^{-1}$ for maize and $4\,t\,ha^{-1}$ to $26.5\,t\,ha^{-1}$ for peanut and cotton, all locations and years considered. The degree of variability was dependent upon the production level, the location, the year, and the crop. Ranking of crop parameters was not significantly affected by the year of study but was strongly related to the production level, location, and crop. The model was not sensitive to parameters related to prediction of the timing of germination and emergence. The most influential parameters were related to leaf area index growth, crop duration, and thermal time accumulation. Findings from this study contributed to understanding the effects of crop parameter uncertainty on the model's outputs under different environmental conditions.

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1. Introduction

Recently crop models have been adopted at scales larger than field levels to assess bi-directional feedbacks between the atmosphere and croplands (Faivre et al., 2004; Bondeau et al., 2007; Osborne et al., 2007; Adam et al., 2011). Some studies have suggested that when operating at larger scales, crop models may be less sensitive to some detailed crop growth processes that were designed for simulating individual plants (Adam et al., 2011; Ewert et al., 2011). In addition, gaps in knowledge of detailed crop parameters for many crops limit the application of complex crop models in global assessment studies (Stehfest et al., 2007). Many modeling communities agree that accommodating a wide range of crops in generic models will not only increase the applicability of the models but also contribute to structuring knowledge common to these crops (Jones et al., 2003; Wang et al., 2002). However, while these generic models have been adopted worldwide, many of them, including the CERES family (Jones and Kiniry, 1986), the CROPGRO

family (Boote et al., 1998) and WOFOST (Supit et al., 1994) exhibit a significant level of details and therefore restrict their use in situations where inputs and parameters required by the model, are not available.

In this study, we integrated in DSSAT (Decision Support System for Agrotechnology Transfer) a robust model yet simple in its parameterization, the simple crop model currently present in SALUS (System Approach to Land Use Sustainability). SALUS (www.salusmodel.net, Basso et al., 2006, 2010) derives from the well-established and validated CERES suite of models with the goal of quantifying the impact of management strategies and their interactions with the soil–plant–atmosphere system on yield and carbon (C), nitrogen (N), and phosphorus (P) dynamics. It contains two modeling approaches, a simple crop model and a complex model. The simple crop model is based on a predetermined leaf area index (LAI) curve that is described in this paper. The complex crop model calculates LAI using cultivar coefficients. The model accommodates various crop rotations, planting dates, plant populations, irrigation, organic and inorganic fertilizer application, and tillage practices. It also simulates plant growth and soil conditions during growing seasons and fallow periods. A version of the model runs on the Internet with simple interfaces (for farmers and extension services) and

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has spatial capabilities. SALUS presents new algorithms for simulating kernel number, plant population effects on bareness and prolificacy, surface runoff, soil water redistribution, upflow from the water table and includes a spatial component for water routing across the landscape (Basso, 2000; Batchelor et al., 2002). SALUS has been tested for soil carbon dynamics (Senthilkumar et al., 2009) crop yield (Basso et al., 2007), plant N uptake and phenology (Basso et al., 2010, 2011), nitrate leaching (Giola et al., 2012; Syswerda et al., 2012), water use efficiency (Ritchie and Basso, 2008) and transpiration efficiency (Basso and Ritchie, 2012).

The simple SALUS crop model (which will be referred to as SALUS-Simple) is based on the modeling approaches used by EPIC (Erosion Productivity Impact Calculator, Williams et al., 1989) and ALMANAC (Agricultural Land Management Alternatives with Numerical Assessment Criteria, Kiniry et al., 1992) to estimate LAI and plant biomass during the season. The current version of the model describes water-limited production with 20 plant parameters and can in principle be parameterized for a range of annual crops and grasses from literature or available data. Comparison between ALMANAC (which calculates LAI and dry matter similarly to SALUS-Simple) and CERES showed that the two models had similar capabilities to simulate variability in maize grain yield across nine U.S. locations (Kiniry et al., 1997).

The implementation of SALUS-Simple in DSSAT led to a number of specific research questions: does the model behave as expected under different environments? What plant parameters exert the largest influence on major model outputs? How do uncertainties in plant parameters translate into variability in these model outputs? Do all the parameters in SALUS-Simple need to be estimated for each maturity group in a species?

A global uncertainty and sensitivity analysis was conducted to address these questions. Since an uncertainty and sensitivity analysis has not been conducted on the SALUS-Simple crop model previously, little is known about the relationship between uncertainties in the plant parameters and variability in key model outputs. Uncertainty and sensitivity analysis is recommended and widely used during model development (Monod et al., 2006). It has been applied for various objectives including verifying model behavior (Confalonieri et al., 2010b), identifying important crop parameters (Pathak et al., 2007) and ranking these parameters with respect to their importance in yield formation (Richter et al., 2010). A detailed review of uncertainty and sensitivity analysis methods was provided by Saltelli et al. (2004), Helton (1993) and Helton et al. (2005). A comparison of the most common sensitivity analysis methods was recently discussed by Confalonieri et al. (2010a).

The goal of this paper was to describe the SALUS-Simple crop model integrated in DSSAT and investigate responses of the model's outputs to crop parameter uncertainty under different environmental conditions. Specific objectives were to: (i) quantify the effect of changes in crop parameters within their ranges of uncertainty, on final biomass, final grain yield and season length of maize, peanut, and cotton; (ii) identify parameters in SALUS-Simple that have the most influential effects on model outputs, and hence need to be estimated with high accuracy; (iii) highlight differences in the effects of crop parameter uncertainty on model outputs under various environmental conditions and at potential and water-limited production levels.

2. Materials and methods

2.1. Overview of the SALUS-Simple crop model

The SALUS-Simple crop model simulates the potential production of an annual crop using less than 20 crop parameters with
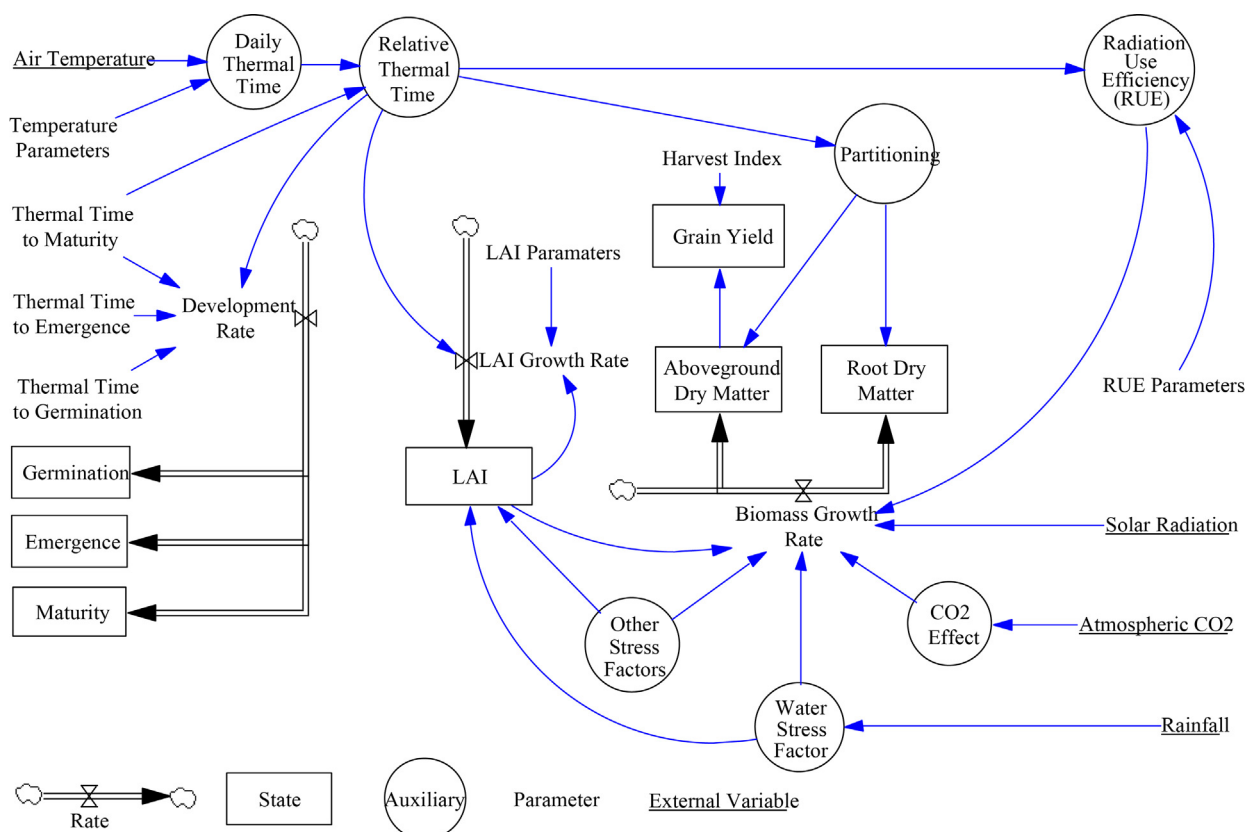

Fig. 1. Diagram depicting the SALUS-Simple model with the main crop growth and development processes.

Table 1
List of variables used in the description of the SALUS-Simple model.

No.	Variable	Type	Unit	Definition
1	DM	State	g m^{-2}	Mass of total dry matter
2	DLAYR(L)	Auxiliary	cm	Depth of layer L
3	DTT	Auxiliary	°C day	Daily thermal time
4	IPAR	Input	MJ m^{-2} day^{-1}	PAR intercepted by the crop canopy
5	K	Constant	m^2 cm^{-2}	Factor for converting root dry matter from g m^{-2} to g cm^{-2}
6	KCan	Parameter	–	Light extinction coefficient
7	LAI	State	m^2 m^{-2}	Leaf area index
8	LAIP1	Parameter	–	Point on generic LAI curve with coordinates (RelTT = 0.15, RelLAI = RelLAIP1)
9	LAIP2	Parameter	–	Point on generic LAI curve with coordinates (RelTT = 0.50, RelLAI = RelLAIP2)
10	PAR	Input	MJ m^{-2} day^{-1}	Photosynthetically active radiation
11	PlantingDepth	Input	cm	Planting depth
12	PlantPop	Input	plant m^{-2}	Plant density
13	RelTT	Auxiliary	–	Relative thermal time
14	RelLAI	Auxiliary	–	Relative leaf area index
15	RLV(L)	State	cm cm^{-3}	Root length per unit of soil volume in layer L
16	RootDepth	State	cm	Potential root depth growth
17	RootFrac(L)	Auxiliary	–	Factor that determines the fraction of root dry matter in soil layer L
18	Roots	State	g m^{-2}	Mass of root dry matter
19	RootPartCoef	Auxiliary	–	Root partitioning coefficient (fraction of total dry matter present in roots)
20	RowSpacing	Input	cm	Row spacing
21	RUE	Auxiliary	g MJ^{-1}	Radiation Use Efficiency
22	StressFactors	Auxiliary	–	Water and nutrient stress factors
23	Tops	State	g m^{-2}	Mass of aboveground dry matter
24	TTEmerge	Auxiliary	°C	Thermal time from germination to emergence

additional parameters required for water and nutrient-limited production levels. The crop development and growth processes simulated in SALUS-Simple are summarized in Fig. 1. Variables and crop parameters used to describe the SALUS-Simple model in the following sections are summarized respectively in Tables 1 and 2. All rate equations appearing in the description of the model are integrated numerically using the Euler method on a daily time step. Additional model equations are presented in the appendix.

Approaches used in SALUS-Simple to model the total growth duration, LAI, RUE (radiation use efficiency), and grain yield for a single plant are similar to those used in ALMANAC (Kiniry et al., 1992, 1997). However, the current version of SALUS-Simple does not simulate inter-species competition and the effect of vapor pressure deficit on RUE. Unlike ALMANAC, SALUS-Simple predicts the timing of germination and emergence using cultivar-specific parameters. The models differ in their simulation of the effect of cold temperatures and water stress on growth.

2.2. Description of the SALUS-Simple crop model

2.2.1. Plant development

Timing of plant germination is predicted using a fixed thermal time from planting to germination (a crop parameter called *TTGerminate*). Other models have described germination to occur in one day provided soil water conditions are adequate (Jones and Kiniry, 1986) while other authors have used the thermal time approach (Birch et al., 2003). Timing of emergence is also coupled to the plant's thermal environment but dependent on planting depth. Several studies have assessed the relationship between thermal time from germination to emergence (*TTEmerge*) and planting depth (Alessi and Power, 1971; Gupta et al., 1988; Kiniry and Bonhomme, 1991). In the SALUS-Simple model, *TTEmerge* is predicted as a linear function of planting depth, using crop parameters describing the slope and the intercept of the relationship (Table 2). Progress towards maturity is simulated as a fraction of total thermal time from planting to maturity (*TTMature*). This normalized fraction is

Table 2
List of SALUS-Simple crop model parameters and definitions.

| No.	Parameter	Unit	Definition
1	EmgInt	°C day	Intercept of emergence thermal time calculation
2	EmgSlp	°C day cm^{-1}	Slope of emergence thermal time calculation
3	HrvIndex	–	Crop harvest index
4	MaxLAI	m^2 m^{-2}	Maximum expected Leaf area index
5	RelLAIP1	–	Parameter for shape at point 1 on the potential LAI curve
6	RelLAIP2	–	Parameter for shape at point 2 on the potential LAI curve
7	RelTTSn	–	Relative thermal time at beginning of senescence
8	RelTTSn2	–	Relative thermal time beyond which the crop is no longer sensitive to water stress
9	RLWR	cm g^{-1}	Root length to weight ratio
10	RUEMax	g MJ^{-1}	Maximum expected radiation use efficiency
11	SeedWt	g seed^{-1}	Seed weight
12	SnParLAI	–	Parameter for shape of potential LAI curve after beginning of senescence
13	SnParRUE	–	Parameter for shape of potential RUE curve after beginning of senescence
14	StresLAI	–	Factor by which LAI senescence due to water stress is increased between RelTTSn and RelTTSn2
15	StresRUE	–	Factor by which RUE decline due to water stress is accelerated after the beginning of leaf senescence
16	TBaseDev	°C	Base temperature for development
17	TFreeze	°C	Threshold temperature below which crop development and growth stop
18	TOptDev	°C	Optimum temperature for development
19	TTGerminate	°C day	Thermal time from planting to germination
20	TTMature	°C day	Thermal time from planting to maturity
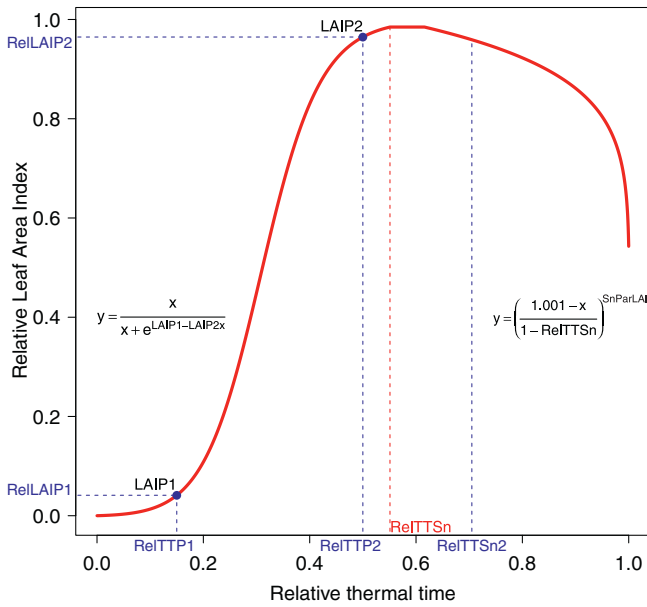
Fig. 2. Generic LAI curve as modeled in SALUS-Simple. Parameters shown are defined in Tables 1 and 2.

the relative thermal time (*RelTT*) which varies from 0 (at planting) to 1 (at maturity).

2.2.2. Leaf area index

The model simulates LAI increase and decline directly using empirical relationships (Kiniry et al., 1992; Adam et al., 2011). During leaf expansion, relative LAI (*RelLAI*, a fraction of maximum LAI under non-stressed conditions) is determined using a sigmoid curve (Fig. 2). To simulate the appropriate shape, the model generates two parameters (*LAIP1* and *LAIP2*) that represent inflexion points on the LAI growth curve, respectively near emergence (*RelTT* = 0.15) and near flowering (*RelTT* = 0.50). The equation of the general LAI curve takes the form:

$$\begin{cases} \text{If } RelTT_t \leq RelTTSn, \\ RelLAI_t = \dfrac{RelTT_t}{RelTT_t + \exp(LAIP1 - LAIP2 \times RelTT_t)} \end{cases} \quad (1)$$

where $RelLAI_t$ represents the relative LAI on day t, prior to the beginning of leaf senescence.

The LAI decline occurs after the relative thermal time to senescence (*RelTTSn*) is reached. The shape of the LAI decline function is controlled by the value of the parameter *SnParLAI*.

$$\begin{cases} \text{If } RelTT_t > RelTTSn, \\ RelLAI_t = \left(\dfrac{1 - RelTT_t}{1 - RelTTSn} \right)^{SnParLAI} \end{cases} \quad (2)$$

where $RelLAI_t$ is now the relative LAI on day t, after the beginning of leaf senescence.

The rate of LAI increase (prior to the beginning of leaf senescence) is computed as:

$$\frac{dLAI_t}{dt} = \frac{dRelLAI_t}{dRelTT} \cdot \frac{dRelTT}{dt} \times MaxLAI \times StressFactors_t \quad (3)$$

where $dRelLAI_t/dRelTT$ is the slope of the *RelLAI versus RelTT* relationship on day t; $dRelTT/dt$ is the change in relative thermal time from day $t - 1$ to day t.

Calculation of LAI decline rate after the beginning of leaf senescence uses the same relationship (Eq. 3) without the stress factor term ($StressFactors_t$). The effect of water stress on leaf senescence is modeled using *StresLAI* and *RelTTSn2* (Table 2). When water stress

is simulated, the LAI decline parameter is linearly interpolated between *SnParLAI* × *StresLAI* (maximum water stress) and *SnParLAI* (no water stress) during the period *RelTTSn* to *RelTTSn2* when LAI senescence is expected to be more sensitive to water stress.

2.2.3. Total biomass

Photosynthetically Active Radiation (PAR) intercepted by the canopy is approximated using an extinction coefficient and the canopy LAI according to Beer's law (Monsi and Saeki, 1953). The model uses maximum RUE as a crop parameter to compute actual RUE values during the season. Radiation use efficiency decline after the beginning of leaf senescence is similar to LAI senescence and controlled by the equivalent parameters *SnParRUE* and *StresRUE*. The rate of potential total plant dry matter is calculated as the product of RUE and intercepted PAR (Monteith, 1977). Water and nutrient stress factors are applied daily to reduce the rate of potential biomass growth. Plant growth stops in cold environments if the daily thermal time reaches a value smaller than 0.10 °C for 20 consecutive days or if the daily minimum temperature drops below the *TFreeze* temperature threshold (Table 2).

2.2.4. Biomass partitioning and yield

The total biomass produced is partitioned to roots using a coefficient (fraction of total dry matter present in roots) based on work by Swinnen et al. (1994), assuming that 90% of the root mass remain in live roots with the remaining 10% allowed to participate in soil organic matter formation.

$$RootPartCoef_t = 0.45 \times \exp(-1.904 \times RelTT_t) \quad (4)$$

The *RootPartCoef* coefficient reduces exponentially the fraction of total dry matter partitioned to roots, from 0.45 at planting (*RelTT* = 0.0) to 0.067 at maturity (*RelTT* = 1.0). Crop yield is calculated as the product of aboveground biomass and a crop-dependent harvest index (*HrvIndex*). The reduction in harvest index due to water, nutrient or heat stress is not directly accounted for. Ongoing model improvement includes a reduction in the harvest index if a stress condition prevents the crop from accumulating a certain amount of biomass between the beginning of leaf senescence and maturity.

2.2.5. Root dynamics

The model simulates the dynamics of root growth in different soil layers using three main processes: (i) the root front growth, (ii) the root distribution in different soil layers, and (iii) soil impeding factors that modify root front growth and root distribution.

Progression of the root front from the depth of planting to a maximum depth can be modeled using a function of the plant's thermal environment (Jones et al., 1991). The model calculates potential daily root depth increment as 10% of the daily thermal time. Numerous studies showed that the actual root penetration in soil layers is modified by soil strength, soil aeration and soil temperature (Barber, 1971; Jones et al., 1991). In SALUS-Simple, the potential root depth increase is reduced by impeding factors that include saturated soil, dry soil, low soil temperature and a soil hospitality factor.

2.3. Integrating SALUS-Simple in DSSAT

Integration of the SALUS-Simple crop model in DSSAT required structural adaptations to ensure desired communication between the DSSAT cropping system model and the new crop model. Simulation of potential plant growth, development and yield is now performed by SALUS-Simple within DSSAT as described earlier. This type of simulation is executed using a standard DSSAT experiment file (file X) with the cultivar and model name specified for the SALUS-Simple crop model. To simulate the effect of water stress on

plant growth, SALUS-Simple communicates with DSSAT's primary modules in the following way:1.

1. Daily root growth and distribution are computed in the root dynamics subroutine of SALUS-Simple, and root dry matter is converted into root length volume for each soil layer using a root length to weight ratio (RLWR, Table 2);
2. The daily root length volume and the daily LAI calculated by SALUS-Simple are used in DSSAT's soil-plant-atmosphere module to calculate root water uptake and potential plant transpiration;
3. This latter information is used by SALUS-Simple to compute plant water stress as the ratio of total root water uptake to potential plant transpiration.

Therefore, the interface between SALUS-Simple and DSSAT consists of the exchange of information on root growth and distribution, root water uptake, plant LAI and the surface energy balance. The integration of SALUS-Simple in DSSAT required the introduction of the RLWR as a new crop parameter.

2.4. Uncertainty and sensitivity analysis

2.4.1. Sites and analysis settings

For each crop studied, the uncertainty and sensitivity analysis involved a total of 80 treatments resulting from combinations of four locations in the United States (Table 3), two production levels (potential and water-limited) and 10 years of weather data at each location. The analysis was conducted for three crops, maize (*Zea mays* L.), peanut (*Arachis hypogaea* L.) and cotton (*Gossypium hirsutum* L.). Specific soil and weather characteristics at the different locations are summarized in Table 3, which indicates a gradient of decreasing maximum and minimum temperatures with increasing latitude. The locations in Florida, North Carolina, Iowa, and Michigan were used for maize while the sites in Florida, Georgia, North Carolina, and Virginia were used for peanut and cotton. The planting dates used were taken from USDA's publication of usual planting dates in the United States (USDA, 1997). Plant densities for maize, peanut, and cotton were 6.0 plants m^{-2}, 12.9 plants m^{-2}, and 14.0 plants m^{-2}, respectively obtained from Kiniry et al. (1992), Boote (1982) and Ortiz et al. (2009). Soil properties and daily weather data were available from the DSSAT database for Gainesville, Camilla, Ames and Kellogg Biological Station (KBS). Soil survey information from the National Resources Conservation Service's Soil Survey Geographic (SSURGO) database (NRCS, 2010) was used to create DSSAT soil profiles for Clayton and Suffolk. Daily rainfall and temperature for these two locations were obtained from the National Climatic Data Center (NCDC, available online at www.ncdc.noaa.gov). Solar radiation at the two locations was estimated using an improved Bristow–Campbell method (Thornton and Running, 1999).

2.4.2. Uncertainty and sensitivity analysis steps

The uncertainty and sensitivity analysis concentrated on the effect of crop parameter uncertainty on the variability in model outputs and the ranking of crop parameters. It was implemented using a Monte Carlo approach involving four steps that were repeated for each crop and treatment. The first step consisted of defining a probability distribution for each crop parameter in Table 2. A methodology for generating synthetic data, from which the ranges and probability distributions of some of the crop parameters were derived, was developed and described in the following section.

In the second step, a Latin Hypercube (LH) sample (McKay et al., 1979) of the crop parameters was obtained based on their statistical distributions and the correlation structure defined in the first step. For normally distributed and correlated crop parameters, Stein's method for obtaining a LH sample for dependent variables was used (Stein, 1987).

In the third step, the model was evaluated for each combination of crop parameters sampled. Three model outputs were selected for further analysis namely, final aboveground biomass, final grain yield and season length.

In the fourth step, the uncertainty in model outputs was assessed, and their sensitivity to each contributing crop parameter quantified. Uncertainty in model outputs was characterized by the means and variances of the corresponding distributions and cumulative distribution functions (CDFs, Helton et al., 2005). The strength of the sensitivity of a given model output to a crop parameter was quantified using a partial rank correlation coefficient (PRCC, Helton, 1993; Johnson and Wichern, 2002; Marino et al., 2008). The higher the absolute value of the PRCC the more sensitive the model output is to the parameter considered. The PRCC was considered significantly different from 0 when the *p*-value resulting from the PRCC test was smaller than an alpha level of 0.01. To control the effect of collinearity on PRCC values, some crop parameters (*RelTTSn*, *TTMature*, and *SnParRUE* for maize, *TTMature*, and *SnParRUE* for peanut and cotton) due to their high correlations with other parameters were removed from the partial rank correlation analysis. This allowed the reduction of variance inflation factors in the PRCC models to values smaller than 4.0 (Craney and Surles, 2002; O'Brien, 2007).

Differences in PRCC-based crop parameter rankings between two treatments were tested using the top-down concordance coefficient (TDCC, Savage, 1956; Iman and Conover, 1987; Marino et al., 2008). Rankings were considered identical in a top-down sense if the *p*-value resulting from the TDCC test was smaller than an alpha level of 0.05.

The number of model executions was determined by running the model for maize at one location (Gainesville, Florida) for several sample sizes between 500 and 50,000 runs and examining the stability of model outputs. The 50,000 model runs was used as a reference for testing for any statistically significant differences among rankings obtained at different sample sizes using the TDCC test. From this preliminary analysis, sample size-induced increases in mean biomass of up to 7% were noted between 500 and 5000 runs. A sample size of 10,000 model runs was retained to ensure stability in the analysis, which resulted in a total of 800,000 model evaluations (for all 80 treatments) per crop.

2.4.3. Synthetic data and statistical distribution of parameters

A computer experiment was created to determine the distributions and correlations among the following crop parameters:

Table 3
Characteristics of the locations used in the uncertainty and sensitivity analysis.

	Soil	Average solar radiation (MJ m^{-2})	Average maximum temperature (°C)	Average minimum temperature (°C)	Total annual rainfall (mm)
Gainesville, Florida (29.63°, −82.37°)	Millhopper Fine Sand, Typic Paleudults	16.11	27.58	14.66	1271
Camilla, Georgia (31.28°, −84.28°)	Loamy sand, Thermic Arenic Paleudult	16.75	25.76	12.84	1266
Clayton, North Carolina (35.65°, −78.46°)	Norfolk Sandy Clay Loam	13.93	21.67	9.55	1124
Suffolk, Virginia (36.72°, −75.40°)	Suffolk Loamy sand	13.99	20.99	9.62	1183
Ames, Iowa (42.02°, −93.63°)	Typic Hapludoll, Clarion Loam	13.55	15.45	3.54	804
KBS, Michigan (42.41°, −85.41°)	Typic Hapludalf, Kalamazoo Loam	13.68	14.50	4.11	908

Table 4
Specification of treatments used for generating the synthetic data.

	Maize	Peanut	Cotton
Cultivars (4 levels)	Generic long, medium, short, and very short season (DSSAT database)	Spanish type, Early Bunch, Florunner, Southern Runner (Bell et al., 1991)	Acala, Deltapine 77, Deltapine 555, Georgia King (Grimes et al., 1975; Ortiz et al., 2009)
Locations (U.S. states, 4 levels)	Florida, North Carolina, Iowa, Michigan	Florida, Georgia, North Carolina, Virginia	Florida, Georgia, North Carolina, Virginia
Planting dates (3 levels)	Early, medium, late	Early, medium, late	Early, medium, late
Plant population (plants m^{-2}, 3 levels)	4, 6, 8 (Kiniry et al., 1992)	5.6 (Bell et al., 1991) 8.8 (Bell et al., 1987) 12.9 (Boote, 1982)	5 (Fye, 1984) 10.5 (Reddy and Baker, 1988) 14 (Ortiz et al., 2009)
Total number of treatments	144	144	144

HrvIndex, *MaxLAI*, *RelLAIP1*, *RelLAIP2*, *RelTTSn*, *SnParLAI*, *SnParRUE*, *TTMature*. The computer experiment used location, cultivar, plant population and planting date as experimental factors (Table 4). The simulations were conducted at potential production level using CERES-Maize and CROPGRO peanut and cotton models in DSSAT. The genetic coefficients of the cultivars were obtained from the DSSAT database (Tables 5 and 6). *HrvIndex*, *MaxLAI*, *RelTTSn*, and *TTMature* were directly derived from the outputs generated by the computer experiment. Equations (1) and (2) were fitted to the synthetic data to obtain the distributions of *RelLAIP1*, *RelLAIP2*, and *SnParLAI*. The D'Agostino-Pearson's chi-square test for assessing normality based on skewness and kurtosis of data (Zar, 1999) was used to test the assumption of normality in these crop parameters derived from synthetic data. The parameters or their transformed versions were considered normal if the *p*-value from the test was larger than 0.05.

3. Results and discussion

3.1. Synthetic data and crop parameter distribution

A wide range of correlation values were obtained from the synthetic data. The relationship among crop parameters ranged from absolutely uncorrelated (maize's *TTMature* and *SnParLAI*) to strongly correlated (maize's *TTMature* and *MaxLAI*, Table 7). Specific values of the correlations suggested that the assumption of independence among such crop parameters is generally not valid. In studies involving Monte Carlo sampling, the inability to account for these correlations is likely to generate unrealistic combinations of these parameters and result in unstable results.

Results from the synthetic data showed that depending on the crop, *MaxLAI*, *SnParLAI*, *SnParRUE*, and *RelTTSn* needed transformations to attain normality (Table 8). For maize for example, uncertainty in maximum LAI due to variability in cultivar, location, planting date and plant population did not follow a normal distribution. This result was also reflected in our literature review on this parameter that showed a tendency towards positively skewed maximum LAI values.

Uncertainty ranges for parameters not derived from synthetic data were obtained from the literature (Table 8). A comprehensive review of the literature on the variability in the crop parameters can be found in Dzotsi (2012). Such parameters were assumed to have a uniform distribution except for *MaxRUE*, *TBase*, and *TOpt* which

were assigned a normal distribution based on information from the literature (Kiniry et al., 1989; Confalonieri et al., 2010b).

3.2. Maize uncertainty analysis

3.2.1. Overall effect of crop parameter uncertainty

Crop parameter uncertainty resulted in potential model output ranges from 1.2 t ha^{-1} to 38 t ha^{-1} for biomass, 0.7 t ha^{-1} to 18 t ha^{-1} for grain yield and 62 to 185 days for season length, all locations and years considered. Water-limited maximum biomass reached 21 t ha^{-1}, 28 t ha^{-1}, 34 t ha^{-1} and 35 t ha^{-1} respectively in Florida, North Carolina, Iowa and Michigan. These higher water-limited biomass values were simulated in Iowa and Michigan despite the lower mean annual rainfall at these locations (Table 3), which suggested that the distribution of rainfall as well as the soils probably carried more weight in the determination of water stress. The variability in model outputs is due to uncertainty in crop parameters alone. Differences in the effect of parameter uncertainty as influenced by crops and treatments are discussed in the following sections.

3.2.2. Comparison among years at potential level

The means of potential biomass distributions varied between 12 t ha^{-1} (North Carolina) and 18 t ha^{-1} (Michigan) depending on the location (Table 9). For the standard deviations of the distributions of biomass, this range was between 4.8 t ha^{-1} and 7.5 t ha^{-1} at the same respective locations. Differences among the years were more pronounced at higher latitudes. For example, the mean potential biomass in the most productive year differed from the mean potential biomass in the least productive year by 2.1 t ha^{-1}, 1.6 t ha^{-1}, 2.9 t ha^{-1}, and 3.9 t ha^{-1} with increasing latitude. Uncertainties in the distributions of biomass (as measured by the standard deviations) associated with parameter uncertainty were also larger at higher latitudes, meaning that biomass levels, although lower in Florida, were also more stable. The year with highest variability differed from the most stable year in standard deviation of potential biomass by 0.7 t ha^{-1}, 0.9 t ha^{-1}, 1.2 t ha^{-1}, and 2.5 t ha^{-1}, respectively, in Florida, North Carolina, Iowa, and Michigan. While inter-annual differences in the means and standard deviations of the distributions of potential biomass were clearly dependent on latitude, the shapes of the distributions were less affected by location (Fig. 3). Regardless of the year considered, the coefficient of variation (CV) of potential biomass was

Table 5
Growth and development coefficients for the four maize cultivars used in producing the synthetic data.

Definition	DSSAT ID	Very short	Short	Medium	Long
Degree days (base 8 °C) from emergence to end of juvenile phase (°C)	P1	5	110	200	320
Photoperiod sensitivity (day h^{-1})	P2	0.30	0.30	0.30	0.52
Degree days (base 8 °C) from silking to physiological maturity (°C)	P5	680	680	800	940
Potential kernel number (plant^{-1})	G2	820	820	700	620
Potential kernel growth rate (mg day^{-1})	G3	6.60	6.60	8.50	6.00
Phyllochron (°C)	PHINT	38.90	38.90	38.90	38.90

Table 6
Growth and development coefficients for the peanut and cotton cultivars used in producing the synthetic data.

Definition	DSSAT ID	Peanut cultivars				Cotton cultivars			
		Spanish type	Early Bunch	Florunner	Southern Runner	Acala	Deltapine 77	Deltapine 555	Georgia King
Photothermal days from emergence to first flower	EM-FL	17.40	21.90	21.20	22.90	29	34	40	45
Photothermal days from first flower to first pod	FL-SH	7.00	7.60	9.20	8.20	8	8	12	11
Photothermal days from first flower to first seed	FL-SD	17.50	16.50	18.80	18.20	12	15	17	17
Photothermal days from first seed to physiological maturity	SD-PM	62.00	72.40	74.30	82.60	46	49	45	45
Photothermal days from first flower to end of leaf expansion	FL-LF	67	77	85	88	52	75	75	75
Maximum leaf photosynthesis rate, mg CO_2 m^{-2} s^{-1}	LFMAX	1.28	1.34	1.40	1.30	1.1	1.1	1.1	1.1
Specific leaf area, cm^2 g^{-1}	SLAVR	245	270	260	265	250	170	170	170
Maximum size of full leaf, cm^2	SIZLF	16	20	18	17	270	280	300	300
Maximum fraction of daily growth partitioned to seed and shell	XFRT	0.84	0.93	0.92	0.84	0.75	0.9	0.65	0.75
Maximum weight per seed (g)	WTPSD	0.36	1.10	0.68	0.63	0.18	0.18	0.18	0.18
Photothermal days for seed filling per individual seed	SFDUR	29	44	40	40	22	35	35	35
Average seed number per pod	SDPDV	1.65	1.65	1.65	1.65	27	27	27	27
Photothermal days to reach full pod load	PODUR	15	22	24	30	8	8	10	8
Maximum ratio of seed/(seed and shell) at maturity	THRSH	78	75	80	79	74	74	74	74

approximately 40% in Florida, North Carolina, and Iowa. Michigan exhibited the most dramatic CV range, 33–43% (depending on the year).

3.2.3. Comparison between production levels

As expected, the simulation of water stress resulted in a significant reduction in overall biomass levels and higher variability among the different years (Fig. 3C and D). At all locations, potential CDFs were more similar than water-limited CDFs suggesting that in the presence of water stress, uncertainty in final biomass was more dependent on the year of study. Just like in the case of potential production, the mean biomass gap among the years increased with latitude, meaning that water-stressed biomass was equally more stable across years in Florida and more variable in Michigan. Differences in mean biomass between the driest and the wettest year were up to 4 times larger than at potential production. The individual distributions exhibited higher variability as well (Fig. 3C and D). Coefficients of variations of up to 85% were observed in Florida. Most CVs in water-stressed biomass were larger than the 40% reported at potential production. Interactions between production level and location may be due to the degree of rainfall variability at each location and soil variability among locations. Similar trends in uncertainty results were obtained for maize grain yield at all locations (Table 9).

3.2.4. Maize season length uncertainty

There was no effect of production level on season length uncertainty results because the effect of water stress on growth duration was not modeled for any of the crops studied. Further, uncertainty in season length was more pronounced in Iowa and Michigan than in Florida and North Carolina where crop duration was more stable both within and across years. In terms of means of the yearly distributions of season length, the shortest season differed from the longest season by 6 days in Florida and North Carolina. In contrast, this difference was 18 and 30 days, respectively, in Iowa and Michigan. The yearly distributions were also characterized by CVs ranging from 15% to 17% in Florida and North Carolina and 8% to 21% in Michigan.

3.3. Peanut and cotton uncertainty

3.3.1. Differences in biomass and yield across locations and production levels

Peanut biomass (and yield) was generally lower than that of maize, ranging from 4.0 t ha^{-1} to 26.5 t ha^{-1} at potential level and 1.6 t ha^{-1} to 20 t ha^{-1} at water-limited level. While potential peanut biomass tended to be similar across locations, the highest water-stressed biomass levels were attained in Georgia, North Carolina, and Virginia (Table 9).

Cotton biomass was more location-dependent. For example, maximum potential biomass in any year was highest in Georgia (29 t ha^{-1}) and lowest in North Carolina (23 t ha^{-1}). Maximum water-stressed cotton biomass was still highest in Georgia (22 t ha^{-1}) and lowest at other locations (19–20 t ha^{-1}).

Rainfall had the same effect of increasing the variability among years without modifying the shape of peanut and cotton dry matter distribution (Fig. 3C and D). The CVs ranged from 19% to 33%, which was approximately the same at each location. This result suggested that despite differences in biomass, location had little effect on the ratio of standard deviation to mean biomass. Biomass uncertainty results were similar to those of grain yield (Table 9).

3.3.2. Comparison among yearly distributions of biomass and yield

Differences among the means of peanut biomass distributions were smaller in Florida than other locations, indicating that as

Table 7
Pearson correlation coefficients between crop parameters derived from synthetic data for maize, peanut, and cotton.

|	HrvIndex	MaxLAI	RelLAIP1	RelLAIP2	RelTTSn	SnParLAI	TTMature
Maize							
HrvIndex	1	−0.70	−0.64	0.38	−0.67	0.10	−0.74
MaxLAI	−0.70	1	0.72	−0.43	0.81	0.10	0.91
RelLAIP1	−0.64	0.72	1	−0.20	0.52	−0.08	0.75
RelLAIP2	0.38	−0.43	−0.20	1	−0.78	−0.43	−0.55
RelTTSn	−0.67	0.81	0.52	−0.78	1	0.22	0.87
SnParLAI	0.10	0.10	−0.08	−0.43	0.22	1	0.07
TTMature	−0.74	0.91	0.75	−0.55	0.87	0.07	1
Peanut							
HrvIndex	1	−0.19	−0.33	0.05	−0.33	0.33	−0.31
MaxLAI	−0.19	1	0.65	0.57	−0.10	−0.59	0.85
RelLAIP1	−0.33	0.65	1	0.65	−0.30	−0.18	0.49
RelLAIP2	0.05	0.57	0.65	1	−0.72	0.06	0.50
RelTTSn	−0.33	−0.10	−0.30	−0.72	1	−0.38	−0.11
SnParLAI	0.33	−0.59	−0.18	0.06	−0.38	1	−0.51
TTMature	−0.31	0.85	0.49	0.50	−0.11	−0.51	1
Cotton							
HrvIndex	1	−0.83	−0.28	0.73	−0.59	0.70	−0.54
MaxLAI	−0.83	1	0.33	−0.70	0.53	−0.60	0.45
RelLAIP1	−0.28	0.33	1	0.01	0.06	0.09	0.19
RelLAIP2	0.73	−0.70	0.01	1	−0.81	0.54	−0.26
RelTTSn	−0.59	0.53	0.06	−0.81	1	−0.30	0.06
SnParLAI	0.70	−0.60	0.09	0.54	−0.30	1	−0.49
TTMature	−0.54	0.45	0.19	−0.26	0.06	−0.49	1
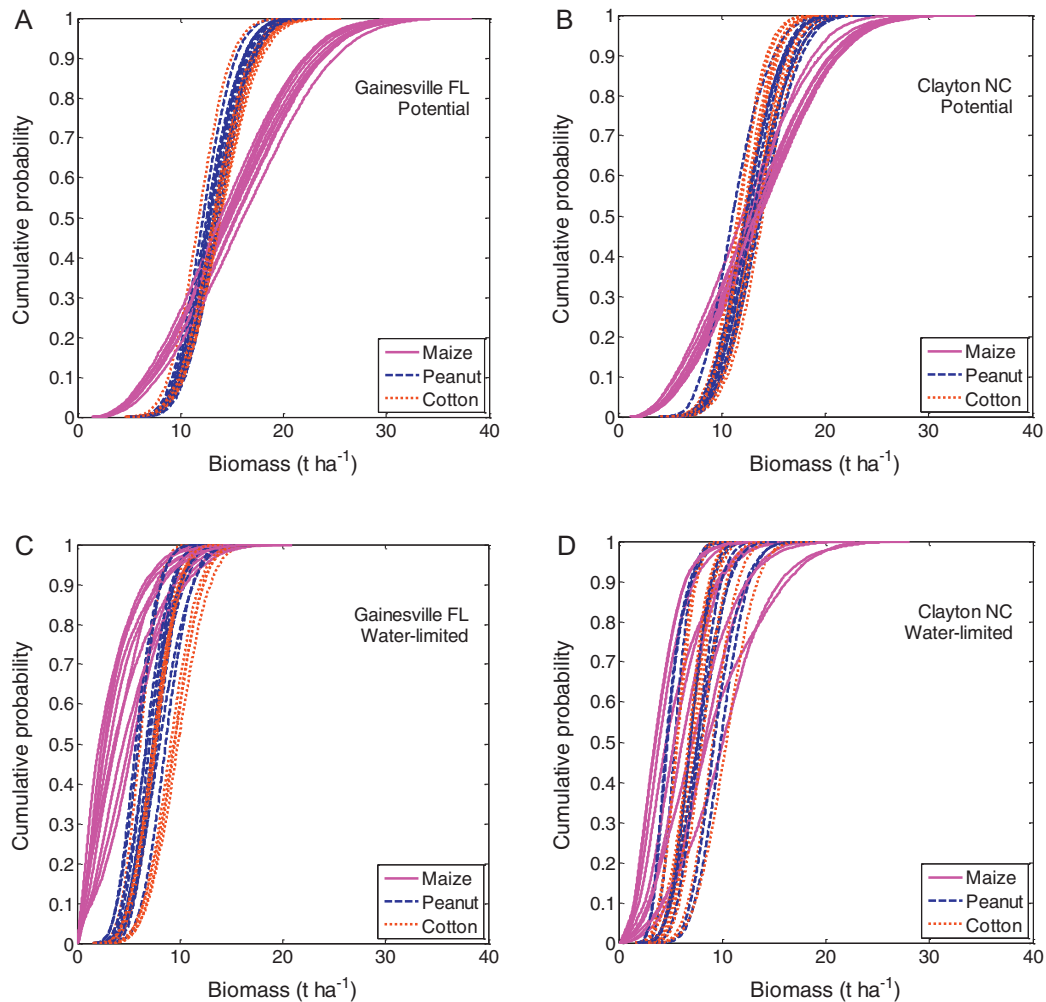
Fig. 3. Cumulative distribution function of maize, peanut and cotton potential and water-limited biomass over the 10 years of the study in Gainesville (A and C) and Clayton, North Carolina (B and D). Each line represents one of the 10 years and shows the effect of crop parameter uncertainty.

Table 8
Statistical distributions of SALUS–Simple crop parameters for maize, peanut, and cotton.

Crop parameter	Distribution[a]	Maize		Peanut		Cotton	
		Parameters[b]	Source	Parameters[b]	Source	Parameters[b]	Source
EmgInt	Uniform	22–47	(Alessi and Power, 1971; Gupta et al., 1988)	15–59.5	(Ketring and Wheless, 1989; Robertson et al., 2002)	15–59.5	(Ketring and Wheless, 1989; Robertson et al., 2002)
EmgSlp	Uniform	2.6–7.6	(Alessi and Power, 1971; Gupta et al., 1988)	5.5–7.6	(Angus et al., 1981; Gupta et al., 1988)	5.5–7.6	(Angus et al., 1981; Gupta et al., 1988)
HrvIndex	Normal	0.46 (0.09)	Synthetic data; (Kiniry et al., 1992, 1995)	0.43 (0.05)	Synthetic data; (Bell and Wright, 1998)	0.41 (0.06)	Synthetic data; (Ko et al., 2009)
MaxLAI	Normal	1.67 (0.53)	Synthetic data; (Kiniry et al., 1995; Lindquist et al., 2005)	31.30 (14.12)	Synthetic data; (Kiniry et al., 2005)	3.86 (0.88)	Synthetic data; (Ko et al., 2009)
LAIP1	Normal	3.47 (0.61)	Synthetic data	3.84 (0.42)	Synthetic data	4.97 (0.78)	Synthetic data
LAIP2	Normal	14.89 (2.43)	Synthetic data	13.10 (0.97)	Synthetic data	15.38 (2.66)	Synthetic data
RelTTSn	Normal	0.48 (0.06)	Synthetic data; (Kiniry et al., 1995)	0.38 (0.50)	Synthetic data	0.83 (0.09)	Synthetic data
RelTTSn2	Uniform	0.55–0.90	–	0.55–0.90	–	0.55–0.90	–
RLWR	Uniform	798–12,000	(Barber, 1971; Follett et al., 1974; Allmaras et al., 1975; Grant, 1989; Jones et al., 1991)	6500–9500	(Boote et al., 1985; Robertson et al., 2002)	6500–9600	(Van Noordwijk and Brouwer, 1991; Robertson et al., 2002)
MaxRUE	Normal	3.50 (0.70)	(Kiniry et al., 1989; Lindquist et al., 2005)	2.10 (0.30)	(Robertson et al., 2002; Kiniry et al., 2005)	2.50 (0.17)	(Gallagher and Biscoe, 1978; Ko et al., 2009)
SnParLAI	Normal	3.12 (0.67)	Synthetic data; (Kiniry et al., 1995)	0.10 (0.02)	Synthetic data	0.05 (0.03)	Synthetic data
SnParRUE	Normal	3.12 (0.67)	Synthetic data; (Kiniry et al., 1995)	0.10 (0.02)	Synthetic data	0.05 (0.03)	Synthetic data
StresLAI	Uniform	1–10	–	1–10	–	1–10	–
StresRUE	Uniform	1–10	–	1–10	–	1–10	–
TBaseDev	Normal	8.50 (0.50)	(Warrington and Kanemasu, 1983; Narwal et al., 1986; Hatfield et al., 2008)	11.50 (0.83)	(Boote et al., 1985; Hatfield et al., 2008)	12.50 (0.83)	(Reddy, 1994; Ko et al., 2009)
TOptDev	Normal	29.50 (1.50)	(Kiniry and Bonhomme, 1991; Kiniry et al., 1992)	32.75 (1.25)	(Ong, 1985; Bell and Wright, 1998)	31.00 (1.33)	(Reddy, 1994; Roussopoulos et al., 1998)
TTGerminate	Uniform	7–30	(Muchow and Carberry, 1989; Hayhoe et al., 1996)	9–42	–	10–45	–
TTMature	Normal	1508 (344)	(Narwal et al., 1986; Kiniry et al., 1992)	1743 (138)	Synthetic data; (Ketring and Wheless, 1989)	1995 (277)	Synthetic data; (Wanjura and Supak, 1985)

[a] Transformations of the synthetic data were necessary to achieve normality for some crop parameters. For maize: a power 0.5 transformation was used for MaxLAI, and SnParLAI and SnParRUE were multiplied by an arbitrary normal distribution with mean 10 and standard deviation 2. For peanut: a power 2 transformation was used for MaxLAI and RelTTSn. For cotton: a power 0.5 transformation was used for RelTTSn.
[b] Actual values of the parameters of the statistical distributions reflecting transformations applied. Lower and upper bound values are shown for uniform distributions and mean (standard deviation) are shown for normal distributions.

Table 9
Minimum and maximum values of mean biomass, grain yield and season length (based on 10,000 simulations) over the 10 years of the study for maize, peanut, and cotton.

Location	Biomass (kg ha^{-1})		Grain yield (kg ha^{-1})		Season length (days)	
	Potential	Water-limited	Potential	Water-limited	Potential	Water-limited
Maize						
Gainesville, FL	14180	2905	6173	1229	101	101
	16327	5738	7129	2493	107	107
Clayton, NC	12372	3802	5374	1647	107	107
	13948	10071	6084	4399	114	114
Ames, IA	14712	7437	6411	3260	112	112
	17618	14905	7688	6483	130	130
KBS, MI	14537	6719	6390	2873	117	117
	18448	14968	8077	6532	147	147
Peanut						
Gainesville, FL	12257	5844	5227	2491	119	119
	13796	8701	5886	3715	124	124
Camilla, GA	13058	6234	5563	2670	118	118
	14971	9433	6394	4034	125	125
Clayton, NC	11312	4852	4826	2069	131	131
	13829	9931	5908	4252	149	149
Suffolk, VA	12402	6859	5289	2937	133	133
	14591	11701	6239	5000	163	163
Cotton						
Gainesville, FL	11846	6156	4839	2517	152	152
	14028	9870	5720	4018	158	158
Camilla, GA	14336	6832	5854	2766	156	156
	15779	9433	6445	3825	171	171
Clayton, NC	11574	5605	4723	2285	162	162
	13972	10393	5723	4240	197	197
Suffolk, VA	10524	7296	4286	2962	163	163
	14361	11017	5884	4498	212	212

found for maize, potential and water-limited biomass was more stable under changes in weather across years. For cotton, Georgia was the location with the highest stability in mean biomass (Table 9). Georgia demonstrated also the narrowest range of standard deviation of biomass distribution for both peanut and cotton. The yearly distributions of potential biomass were less variable when compared to maize (CVs of approximately 20% compared to maize's 40%).

3.3.3. Season length uncertainty

Peanut and cotton season length distributions shared similar characteristics, although growth duration was larger for cotton. Mean season length increased with latitude (Table 9). Standard deviation also increased in the same direction but only for peanut because in addition to longer crop durations, cotton was often affected by the occurrence of "early maturity" due to freezing in cooler environments. Therefore, uncertainties in cotton (and peanut to a lesser extent) season length in cooler environments were compounded by the slow accumulation of thermal time (due to a larger base temperature, Table 8) that increased the crop duration and resulted in multimodal season length distributions. The yearly distributions of season length were characterized by CVs of order of magnitude approximately half those of maize's season length distributions. These CVs ranged from 8% to 15% for peanut and 0.4% to 14% for cotton.

3.4. Sensitivity analysis

3.4.1. Relationship between model output and crop parameter

Fig. 4 shows PRCC values corresponding to the most frequently statistically-significant parameters for biomass, for the first year of the simulation at both production levels and two locations. These results indicated that regardless of the location and production level, RLWR, SnParLAI, SnParRUE, and TOpt were negatively related to grain yield while TBase, MaxRUE, MaxLAI, TTMature, RelTTSn, and HrvIndex were positively related to grain yield. Likewise, TOpt and HrvIndex were negatively related to season length while TBase and

MaxLAI were positively related to season length. Biomass showed a relationship similar to that of grain yield except for HrvIndex that was weakly-negatively related (Table 10). The consistency of these relationships across locations was an indication that they reflected the model structure rather than a specific location. The strength of these relationships varied, however, depending on location, production level and model output (Table 10), and determined the importance of each parameter in the sensitivity analysis treatments.

3.4.2. Effect of year on parameter ranking

Ranking of crop parameters was not affected by the year of study at all locations and for all model outputs examined. This result means that differences in the yearly distributions of model outputs noted on Fig. 3 did not result in significantly different rankings of crop parameters. The TDCC test of differences between parameter rankings in different years for each combination of location and production level produced a p-value consistently smaller than 0.05. The stability of parameter rankings means that model output sensitivity to crop parameter uncertainty was orthogonal to weather variability among the years considered in this study.

3.4.3. Sensitivity to maize biomass and grain yield

At all four locations, EmgInt, EmgSlp, and TTGerminate were not significant (p-value from PRCC test smaller than 0.01) at both potential and water-limited levels. By design, RelTTSn2, StresLAI, and StresRUE were not expected to be significant at potential production because they are used only when water stress occurs. In Florida and North Carolina, the order of importance of the parameters at potential production was MaxLAI, TTMature, RelTTSn, MaxRUE, SnParLAI, SnParRUE, RelLAIP1, TOpt, TBase, RelLAIP2, and HrvIndex. A similar ranking was observed in Iowa and Michigan (Table 10a).

At water-limited level, RLWR became an important parameter for biomass at all locations (with PRCC values as high as 0.77 in Florida) for two main reasons. First, the RLWR determined how much root length was produced and available for crop water
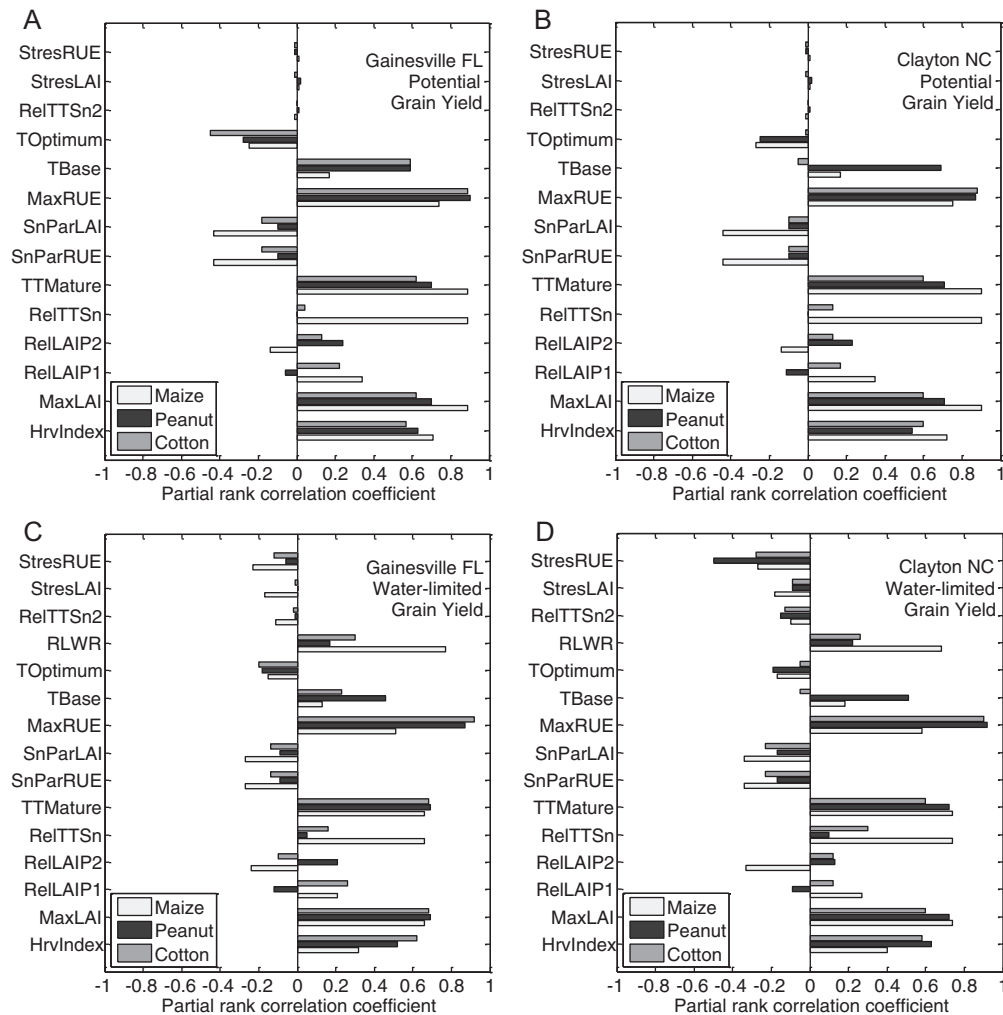
Fig. 4. Partial rank correlation coefficients between potential and water-limited maize, peanut and cotton grain yield and significant SALUS-Simple crop parameters in the first year of the study in Gainesville, Florida (A and C) and Clayton, North Carolina (B and D).

uptake, hence played a major role in the calculation of plant water stress. Second, the uncertainty range of this parameter, as determined from the literature was relatively wide (Jones et al., 1991). *MaxLAI*, *TTMature*, *RelTTSn*, *MaxRUE*, *RLWR*, *SnParLAI*, and *SnParRUE* were consistently ranked (in this order) as the most influential parameters except in Florida where *RLWR* was ranked first. The order of the remaining parameters, *RelLAIP1*, *RelLAIP2*, *TOpt*, *TBase*, *StresLAI*, *StresRUE*, *RelTTSn2*, and *HrvIndex* varied with location but generally *TBase* seemed to be more influential at higher latitudes (Iowa and Michigan) while *TOpt* was more important in Florida and North Carolina.

Rankings for biomass and grain yield were similar. The major difference between these two model outputs was that for grain yield, a new influential parameter, *HrvIndex*, emerged with PRCC values as high as 0.70 in Florida (Fig. 4), which was expected since the portion of biomass in grain yield is the harvest index.

3.4.4. Maize season length

Production level did not influence season length sensitivity because as mentioned earlier for uncertainty analysis, SALUS-Simple does not account for the effect of water deficit on growth duration. Although the sensitive parameters were not affected by location, their ranking was. Crop parameters with PRCC values larger or equal to 0.1 were *TTMature*, *RelTTSn*, *MaxLAI*, *TOpt*, *RelLAIP1*, *TBase*, *RelLAIP2*, *HrvIndex* in this order (in Florida). In Iowa

and Michigan, *TBase* was ranked second instead, underlining the higher influence of *TBase* in cooler climates. For example, in Florida, *TBase* had a PRCC of 0.34 while *TOpt* had a PRCC of 0.42. In Michigan, the order of importance of the PRCC was reversed to 0.36 (for *TBase*) and 0.10 (for *TOpt*).

3.4.5. Peanut and cotton

The major drivers of crop growth and development namely *MaxLAI*, *TTMature*, *MaxRUE*, *HrvIndex*, LAI parameters and temperature parameters were also significant for peanut and cotton biomass and grain yield. The main differences with maize could be summarized as follows: (i) the significant parameters had either large or small PRCC values, suggesting that only a few parameters were truly influential on growth and development of these two crops. Top ranked parameters were *MaxLAI*, *TTMature*, *MaxRUE*, *TBase*, *TOpt*, and *HrvIndex* with their relative importance varying with location and model output (Table 10); (ii) the *RLWR* did not appear to be a major determinant of water-limited biomass and grain yield (values of PRCC as low as 0.13 were obtained in Virginia); (iii) peanut season length variation was essentially dominated by *TBase*, *MaxLAI*, and *TTMature* with PRCC values of 0.80, 0.62, and 0.62 respectively in Florida (all other parameters had PRCC values equal to or smaller than 0.40 in absolute value); (iv) cotton season length variation could be essentially attributed to *TBase* and *TOpt* (in Florida) and *TBase* alone (in

Table 10
PRCC between total crop biomass and significant crop model parameters at four locations: (a) maize, (b) peanut, and (c) cotton.

(a)

	Gainesville, FL		Clayton, NC		Ames, IA		KBS, MI	
	Potential	Water	Potential	Water	Potential	Water	Potential	Water
HrvIndex	−0.16	−0.09	−0.16	−0.13	−0.15	−0.08	−0.13	−0.15
MaxLAI	0.93	0.65	0.94	0.74	0.93	0.75	0.92	0.79
TTMature	0.93	0.65	0.94	0.74	0.93	0.75	0.92	0.79
RelTTSn	0.93	0.65	0.94	0.74	0.93	0.75	0.92	0.79
RelLAIP1	0.44	0.2	0.44	0.27	0.42	0.21	0.4	0.33
RelLAIP2	−0.18	−0.23	−0.17	−0.33	−0.16	−0.16	−0.15	−0.37
SnParLAI	−0.54	−0.26	−0.53	−0.33	−0.53	−0.33	−0.5	−0.4
SnParRUE	−0.54	−0.26	−0.53	−0.33	−0.53	−0.33	−0.5	−0.4
MaxRUE	0.81	0.5	0.81	0.57	0.81	0.65	0.81	0.6
TBaseDev	0.21	0.13	0.21	0.17	0.21	0.07	0.22	0.24
TOptDev	−0.32	−0.15	−0.32	−0.17	−0.26	−0.1	−0.09	−0.1
RLWR	0	0.77	0	0.68	0	0.67	0	0.53
RelTTSn2	−0.01	−0.10	−0.01	−0.09	−0.01	−0.16	−0.01	−0.15
StresLAI	0.00	−0.16	0.00	−0.17	0.00	−0.19	−0.01	−0.20
StresRUE	0.01	−0.23	0.01	−0.26	0.01	−0.27	0.02	−0.29

(b)

	Gainesville, FL		Camilla, GA		Clayton, NC		Suffolk, VA	
	Potential	Water	Potential	Water	Potential	Water	Potential	Water
HrvIndex	−0.22	−0.17	−0.2	−0.23	−0.24	−0.2	−0.21	−0.21
MaxLAI	0.73	0.71	0.72	0.66	0.72	0.73	0.7	0.69
TTMature	0.73	0.71	0.72	0.66	0.72	0.73	0.7	0.69
RelLAIP1	−0.03	−0.09	−0.02	−0.21	−0.09	−0.06	−0.06	−0.22
RelLAIP2	0.23	0.22	0.22	0.16	0.23	0.12	0.2	0.13
RelTTSn	0.02	0.07	0.02	0.13	0.01	0.12	0.01	0.08
SnParLAI	−0.12	−0.11	−0.12	−0.18	−0.11	−0.19	−0.11	−0.18
SnParRUE	−0.12	−0.11	−0.12	−0.18	−0.11	−0.19	−0.11	−0.18
MaxRUE	0.91	0.89	0.93	0.93	0.88	0.93	0.9	0.89
TBaseDev	0.61	0.45	0.58	0.59	0.7	0.53	0.68	0.61
TOptDev	−0.3	−0.18	−0.35	−0.36	−0.25	−0.19	−0.1	−0.11
RLWR	0	0.19	0	0.3	0	0.24	0	0.13
RelTTSn2	0.01	0.00	0.02	−0.13	0.01	−0.16	0.01	−0.16
StresLAI	0.03	0.01	0.03	−0.08	0.03	−0.09	0.03	−0.07
StresRUE	0.00	−0.06	−0.01	−0.48	−0.01	−0.52	−0.01	−0.44

(c)

	Gainesville, FL		Camilla, GA		Clayton, NC		Suffolk, VA	
	Potential	Water	Potential	Water	Potential	Water	Potential	Water
HrvIndex	−0.14	−0.07	−0.14	−0.1	−0.02	−0.05	0.03	0.01
MaxLAI	0.66	0.71	0.63	0.6	0.65	0.62	0.68	0.66
TTMature	0.66	0.71	0.63	0.6	0.65	0.62	0.68	0.66
RelLAIP1	0.23	0.26	0.21	0.29	0.19	0.13	0.22	0.06
RelLAIP2	0.16	−0.08	0.15	0.22	0.17	0.14	0.2	0.13
RelTTSn	0.05	0.18	0.03	0.29	0.15	0.31	0.18	0.29
SnParLAI	−0.2	−0.15	−0.2	−0.28	−0.12	−0.25	−0.09	−0.14
SnParRUE	−0.2	−0.15	−0.2	−0.28	−0.12	−0.25	−0.09	−0.14
MaxRUE	0.9	0.93	0.89	0.9	0.9	0.91	0.91	0.91
TBaseDev	0.61	0.25	0.65	0.31	−0.07	−0.04	−0.35	−0.26
TOptDev	−0.47	−0.2	−0.42	−0.17	0	−0.05	0.11	0.05
RLWR	0	0.31	0	0.29	0	0.26	0	0.15
RelTTSn2	0.01	−0.02	0.01	−0.12	0.01	−0.13	0.01	−0.05
StresLAI	0.00	−0.01	0.00	−0.10	−0.01	−0.09	−0.01	−0.04
StresRUE	0.00	−0.12	−0.01	−0.26	0.01	−0.28	0.01	−0.14

Virginia) with respective PRCC values of 0.87, −0.72, and 0.57. All other significant parameters had PRCC values smaller than 0.30.

3.5. Discussion

Sensitivity analysis results indicated that *EmgSlp*, *EmgInt*, and *TTGerminate* (used to predict timing of germination and emergence) did not play a significant role in the prediction of biomass, grain yield or season length within their ranges of uncertainty. These findings were in agreement with the modeling philosophy of other authors who did not predict germination explicitly based on a thermal time approach (Jones and Kiniry, 1986).

Among the influential parameters identified, three categories could be distinguished: parameters directly related to biomass accumulation (*MaxRUE*, *SnParRUE*), LAI parameters (*MaxLAI*, *RelLAIP1*, *RelLAIP2*, *RelTTSn*, *SnParLAI*), and temperature parameters (*TOpt* and *TBase*). In addition, some parameters, because of the specific role they played in determining targeted model outputs or production levels, were always significant in those situations. Conditional model uncertainty and sensitivity of this type was well-demonstrated in the study by Jones et al. (2012).

Table A.1
Additional SALUS-Simple model equations.

Process simulated	Equation	Relevant studies
Timing of emergence	$TTEmerge = EmgInt + EmgSlp \times PlantingDepth$	(Alessi and Power, 1971; Gupta et al., 1988)
Light interception	$IPAR_t = PAR_t \times (1 - \exp(-KCan \times LAI_t))$	(Monsi and Saeki, 1953)
Canopy extinction coefficient	$KCan = 1.5 - 0.768 \times \left(PlantPop \times (0.01 \times RowSpacing)^2 \right)^{0.1}$	(Flenet et al., 1996)
Rate of total dry matter growth	$\frac{dDM_t}{dt} = IPAR_t \times RUE_t$	(Monteith, 1977)
Rate of root dry matter growth	$\frac{dRoots_t}{dt} = 0.9 \times RootPartCoef_t \times \frac{dDM_t}{dt}$	(Monteith, 1977; Swinnen et al., 1994)
Rate of aboveground biomass growth	$\frac{dTops_t}{dt} = (1 - RootPartCoef_t) \times \frac{dDM_t}{dt}$	(Monteith, 1977; Swinnen et al., 1994)
Potential rate of root depth growth	$\frac{dRootDepth_t}{dt} = 0.1 \times DTT_t$	(Jones et al., 1991)
Growth rate of root length per unit soil volume for each soil layer L	$\frac{dRLV_t}{dt}(L) = RLWR \times \frac{dRoots_t}{dt} \times DLAYR(L) \times RootFrac_t(L) \times K$	(Barber, 1971; Jones et al., 1991)

Biomass and grain yield were highly sensitive to *MaxRUE* because in the model this crop parameter controlled the conversion of intercepted light into dry matter. Biomass and grain yield were also highly sensitive to LAI parameters because they defined the maximum capacity of the canopy to capture light (*MaxLAI*), determined how fast this capacity could be reached (*RelTTSn*, *RelLAIP1*, and *RelLAIP2*), or lost (*SnParLAI*). The sensitivity of season length to *MaxLAI* was mainly due to the high correlation between *MaxLAI* and *TTMature* for maize and peanut (Table 7). Season length in crop models has been found to be generally sensitive to crop duration parameters (for example, Pathak et al., 2007). In this study, temperature parameters that controlled the accumulation of thermal time were highly influential on season length. Optimum temperature and RUE have been found (in other studies using RUE-based crop models) as the most influential crop parameters (Confalonieri et al., 2010a). The high sensitivity of *TBase* was also underlined in the sensitivity analysis by Richter et al. (2010) who reported it as a parameter of considerable importance for a wheat model.

4. Conclusions

Variability in crop yield, total dry matter and season length simulated by SALUS-Simple was strongly dependent on crop parameter uncertainty. Although the model uses simplified relationships to represent LAI and dry matter production, the pattern and magnitude of the relationships between crop parameters and model outputs were consistent with typical responses of crop physiological processes to the environment. Sensitivity analysis results indicated that the model's response to crop parameter uncertainty was not affected by the year considered but was dependent upon crops, model outputs, production levels and locations. A large number of crop parameters were found to be influential on the model outputs studied with their relative importance varying with the situation considered. Since common applications of crop models involve one or a combination of these situations, it is adequate to infer that all 15 significant parameters are important for accurate crop predictions. Additionally, variability in model outputs may be dependent on how well crop parameters' distributions represent the true parameters' uncertainty. Obtaining parameter uncertainty ranges is usually complicated by the variability in measurement methods used in the literature, which may inflate measurement errors themselves. The definition of crop parameter uncertainty using a more complex crop model not only improved the statistical distributions obtained but also provided a means to calculate correlations among selected parameters. These correlations ensured that realistic combinations of crop parameters were used.

Our study concentrated primarily on crop parameter uncertainty and discussed results for crops, model outputs, production levels and environmental conditions. We did not consider uncertainty in model inputs due to spatial heterogeneity in soil properties or highly variable weather inputs such as rainfall. Contributions of these inputs to the overall model output uncertainty could be quantified if they were considered to be uncertain. In addition, the consideration of longer term weather variability could demonstrate a significant influence of the year on uncertainty and sensitivity analysis results. Findings reported in this study assisted with identifying parameters that require accurate estimation for reliable prediction of crop performance. The model shows promises for estimating LAI and dry matter for a number of crops or grasses in integrated assessment studies. A parameter estimation for maize, peanut and cotton that accounts for the uncertainty information derived from this study will constitute our next step in the development and integration of SALUS-Simple in DSSAT.

Appendix A. Appendix: Additional SALUS-Simple model equations

Additional model equations are presented in Table A.1. Variables and parameters are defined respectively in Tables 1 and 2.

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