USE OF GLOBAL SENSITIVITY ANALYSIS FOR CROPGRO COTTON MODEL DEVELOPMENT

T. B. Pathak, C. W. Fraisse, J. W. Jones, C. D. Messina, G. Hoogenboom

ABSTRACT. *Crop models range in complexity from simple ones with a few state variables to complex ones having a large number of model parameters and state variables. Determining and understanding how sensitive the output of a model is with respect to model parameters is a guiding tool for model developers. A new cotton model is being developed using the Cropping System Model (CSM)-CROPGRO crop template that allows the introduction of a new crop and its integration with other modules such as soil and weather without changing any code. The main goal of this study was to investigate whether global sensitivity analysis would provide better information on the importance of model parameters than the simpler and commonly used local sensitivity analysis method. Additionally, we were interested in determining the most important crop growth parameters in predicting development and yield and if the model sensitivity to these parameters would vary under irrigated and rainfed conditions. Sensitivity analyses were performed on dry matter yield and length of season model responses for a wet cropping season (year 2003) and a dry cropping season (year 2000) under irrigated and rainfed conditions. Results indicated that global sensitivity analysis improved our understanding of the importance of the model parameters on model output relative to local sensitivity analysis. Results from global sensitivity analysis indicated that the specific leaf area under standard growth conditions (SLAVR) was the most important model parameter influencing cotton yield under both irrigated and rainfed conditions when taking into account its range of uncertainty. Results from local sensitivity analysis indicated that the light extinction coefficient (KCAN) was the most influencing model parameter. In both global and local sensitivity analyses, the duration between first seed and physiological maturity (SD-PM) was the most important parameter for season length response. The differences obtained for global vs. local sensitivity analysis can be explained by the inability of local sensitivity analysis to take into consideration the interactions among parameters, their ranges of uncertainty, and nonlinear responses to parameters.*

Keywords. *Cotton, CROPGRO, Crop models, Global sensitivity analysis, Local sensitivity analysis, Plant growth, Yield.*

The need for information in agriculture is increasing due to market and economic pressures combined with the need for better management of our natural resources. Crop models, widely used as research and teaching tools, are now becoming important tools for agricultural decision makers, as the need for information in agriculture increases. Crop models range in complexity from simple ones with a few state variables to complex ones having large numbers of model parameters and state variables. The Decision Support System for Agrotechnology Transfer (DSSAT) (Jones et al., 1998; Hoogenboom et al., 2004) contains complex dynamic models that simulate crop growth and yield as a function of soil and weather conditions and crop management regimes. DSSAT can also be used to help researchers, extension agents, growers, and other decision-makers to analyze complex alternate decisions (Tsuji et al., 1998).

Cotton (*Gossypium hirsutum* L.) is the single most important textile fiber in the world, accounting for over 40% of total world fiber production. While some 80 countries from around the globe produce cotton, the U.S., China, and India together provide over half of the world's cotton. The U.S., while ranking second to China in production, is the leading exporter, accounting for over one-third of global trade in raw cotton (MacDonald, 2000). Due to the importance of cotton in the world in general, and in the southeastern U.S. in particular, a model to simulate cotton growth and development is currently being developed by the DSSAT crop modeling group. The Cropping System Model (CSM; Jones et al., 2003) contains models of 21 crops based on CROPGRO, CERES, and other models. The new cotton model has been developed using the CSM-CROPGRO template that allows its integration with other modules of the cropping system (Messina et al., 2004). The CROPGRO development team has used this approach in creating models for different species, including brachiaria grass (Giraldo et al., 1998), tomato (Scholberg et al., 1997), and velvet bean (Hartkamp et al., 2002; Boote et al., 2002). CROPGRO was originally developed as a process-oriented model for grain legumes, based on the SOYGRO, PNUTGRO, and BEANGRO models that consider crop carbon, water, and nitrogen balances (Boote et al., 1998). Its ability to represent different crops is attained through input files that define species traits and cultivar attributes (Boote et al., 2002). Outputs from CROPGRO mod-

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els depend on a large number of model parameters associated with the species traits and cultivar attributes.

Determining and understanding how sensitive the simulations of certain model processes are with respect to model parameters is useful for guiding model developers. The effects of particular model parameter on a given output can be determined by measuring the relative influence of the model parameter on model output. Sensitivity analysis is useful for identifying the most and the least important model parameters to the given model output so that it can contribute to the simplification of a model (Saltelli et al., 2000). There are a number of methods and techniques available for performing sensitivity analysis (Saltelli et al., 2004); local and global sensitivity analyses are the most commonly used methods.

Ruget et al. (2002) performed a local sensitivity analysis on the STICS crop simulation model (Brisson et al., 1998) to determine how sensitive the simulation of processes in each module was to the model parameters. Leaf area index was sensitive to all the model parameters of the leaf area index module (crop density, rate of LAI growth, and density effect on tillering), the cumulated root length was sensitivity to two of the model parameters of the root module (rooting depth for half water absorption, and rate of root deepening), whereas mineralization was most sensitive to humification depth. Xie et al. (2003) conducted local sensitivity analysis of the ALMANAC model (Kiniry et al., 1992) to input variables such as solar radiation, rainfall, soil depth, soil plant available water, and runoff curve number and the impact on grain yield of sorghum and maize. They found that runoff curve number change had the greatest impact on simulated yield.

Global sensitivity analysis differs from local methods by accounting for the variance of the model output associated with model parameters over their entire range of uncertainty. Homma and Saltelli (1996) explored methods of global sensitivity analysis of nonlinear models to calculate the fractional contribution of model parameters to the variance of model predictions. Makowski et al. (2006) used global sensitivity analysis to determine the contribution of generic model parameters to the variance of crop model predictions. A sensitivity analysis was performed on three output variables of the AZODYN wheat model (Jeuffroy and Recous, 1999) that included grain yield, grain protein content, and the nitrogen nutrition index. Out of thirteen different model parameters, five were found to have the most influence on grain yield and grain protein content. The only model parameter that affected the nitrogen nutrition index was the ratio of leaf area index to critical nitrogen concentration. This study concluded that model parameters with the least influence on important simulated processes may not need to be accurately estimated.

A sensitivity analysis allows modelers to rank model parameters in order of their influence on model output. Based on the rankings, it can be used to identify model parameters that need a high accuracy in their estimates. Sensitivity analysis can also be used to check whether the behavior of the model output is as expected with respect to change in the input.

For the CSM crop models, it is practically impossible to measure or estimate all the model parameters with a high level of accuracy. The CSM-CROPGRO-Cotton model under development was initially parameterized using data from the literature (Messina et al., 2004) and evaluated for different environmental conditions using those parameters. Thus, there was uncertainty in the values of parameters and how they may affect model output.

This study was conducted for two purposes. The first objective was to determine whether the global sensitivity analysis method would provide information on model performance that differs from the simpler local sensitivity method. This type of sensitivity analysis had not been used in the past with the CSM model. The central hypothesis in this case was that global sensitivity analysis will lead to improved understanding of the importance of model parameters since it accounts for the variance of model output associated with the variance of model parameters over the range of uncertainty for each parameter. The second objective was to determine how sensitive the prototype cotton model predictions are to an important subset of its crop growth and development parameters. Although the prototype model was based on an existing crop model, it was not clear how these model parameters would affect the most critical outputs, such as yield and season length. We also did not know how these effects would differ between rainfed and irrigated conditions. We hypothesized that the sensitivity of yield and season length to changes in model parameters does not vary with weather and irrigation. Results from this study were needed to guide further model parameter estimation efforts for improving the cotton model.

Materials and Methods

Overview of the CSM-CROPGRO-Cotton Model

The cotton model is based on the modular code of the CSM-CROPGRO model (Jones et al., 2003). This model simulates crop growth and development independent of location, season, and crop management system. Its flexible physiological framework provides a convenient template to implement a cotton model that can be immediately integrated with other crop models (Messina et al., 2004). CSM-CROPGRO is composed of several modules that make up a land unit in a cropping system. The primary modules are crop, soil, weather, soil-plant-atmosphere, and management. The soil module integrates information from four submodules: soil water, soil temperature, soil carbon, and nitrogen dynamics. The soil is represented by a one-dimensional profile, consisting of a number of vertical soil layers. The main function of the weather module is to read or generate daily weather data required by the model, including minimum and maximum air temperatures, solar radiation, and precipitation. The soil-plant-atmosphere module computes daily soil evaporation and plant transpiration, while the management module determines when field operations are performed by calling submodules related to planting, harvesting, inorganic fertilization, irrigation, and application of crop residues or organic materials. The crop module can predict the growth and development of a number of different crops; each crop has its own model parameter files. These modules describe the time changes that occur in a land unit due to management and weather.

The CSM-CROPGRO model has three sets of parameters that account for differences in development, growth, and yield between species, ecotypes, and cultivars (Boote et al., 2003). Cultivar parameters are specific to a particular variety, ecotype parameters are for a group of cultivars, and species parameters are common to all cultivars. Mainly, the model cultivar parameters (table 1) are vital to consider for sensitivity analysis.

Table 1. List of cultivar parameters in CSM-CROPGRO-Cotton model.

No.	Parameter	Definition
1	CSDL	Critical short day length, below which reproductive development progresses with no day length effect (for short day plants) (h)
2	PPSEN	Slope of the relative response of development to photoperiod with time (positive for short day plants) (1/h)
3	EM-FL	Time between plant emergence and flower appearance (R1) (photothermal days)
4	FL-SH	Time between first flower and first pod (R3) (photothermal days)
5	FL-SD	Time between first flower and first seed (R5) (photothermal days)
6	SD-PM	Time between first seed (R5) and physiological maturity (R7) (photothermal days)
7	FL-LF	Time between first flower (R1) and end of leaf expansion (photothermal days)
8	LFMAX	Maximum leaf photosynthesis rate at 30°C, 350 ppm CO_2, and high light (mg CO_2/m^2-s)
9	SLAVR	Specific leaf area of cultivar under standard growth conditions (cm^2/g)
10	SIZLF	Maximum size of full leaf (three leaflets) (cm^2)
11	XFRT	Maximum fraction of daily growth that is partitioned to seed + shell
12	WTPSD	Maximum weight per seed (g)
13	SFDUR	Seed filling duration for pod cohort at standard growth conditions (photothermal days)
14	SDPDV	Average seed per pod under standard growing conditions (No. per pod)
15	PODUR	Time required for cultivar to reach final pod load under optimal conditions (photothermal days)
16	KCAN	Canopy light extinction coefficient (species parameter)

Site and Experiment Description

Sensitivity analyses were conducted for two cropping seasons: 2003, for which we had observed data collected in an experiment conducted at the C. M. Stripling Irrigation Research Park (SIRP), Camilla, Georgia (31° 11' N, 84° 12' W), and 2000, which was a dry year to compare the results from irrigated and rainfed conditions. Daily weather data consisting of maximum and minimum temperature, solar radiation, precipitation, and wind speed were obtained from a local weather station at SIRP (www.georgiaweather.net). Maximum temperatures varied from 24°C to 33°C, minimum temperatures varied from 10°C to 22°C, and average temperatures varied from 18°C to 27°C. The extremes for minimum temperatures occurred at the end of the growing season. Long-term average precipitation (1939 to 2003) for June and July was 131.1 and 150.9 mm, respectively. During the 2000 cropping season, the total precipitation for June and July was 63.2 and 102.4 mm, respectively. In 2003, June and July precipitation totaled 139.9 and 203.6 mm, respectively. Unlike 2003, no field experiment was conducted during 2000. The main reason for performing the sensitivity analysis for this year was to include a dry cropping season. Comparison of dry and wet years would allow us to evaluate the hypothesis that the importance of model parameters does not vary with irrigated and rainfed conditions.

A 34 ha field was planted with a late-maturing cotton variety, DP 555, using a conventional tillage system. The field was sown during the first week of May with a plant population of approximately 110,000 plants per hectare. The soil type at the study site was classified as an Orangeburg loamy sand (fine-loamy, siliceous, thermic Typic Paleudults) (source: Mitchell County SCS map, USDA Soil Conservations Service). The experiment had two treatments: one was rainfed, and the other was irrigated. All other inputs were the same for both treatments.

Sensitivity Analysis

The principle of sensitivity analysis is first to generate output variability associated with the variability of input, and second to assign the simulated output variability to the model parameters that affect it the most (Ruget et al., 2002). The most crucial step in sensitivity analysis is the selection of the model parameters and their uncertainty ranges. Including a large number of model parameters for global sensitivity analysis would result in an unrealistically high number of simulation runs and an impractical computational load (Thorsen et al., 2001).

Local sensitivity analysis was performed on the entire set of cultivar model parameters listed in table 1 and on one of the species parameters, light extinction coefficient (KCAN). Messina et al. (2004) recommended that KCAN should be considered as a cultivar or ecotype parameter because initial estimates of KCAN from literature data showed variations between and within seasons, with planting dates, and between cultivars (Rosenthal and Gerik, 1991; Milroy et al., 2001; Milroy and Bange, 2003; Bange and Milroy, 2004). The main reason for including KCAN in the sensitivity analysis was to help answer the question whether KCAN was sufficiently important to warrant its inclusion as an ecotype parameter. Results from this local sensitivity analysis were used to select model parameters for the global sensitivity analysis.

Local Sensitivity

Local sensitivity is often used to provide a normalized measure for comparing sensitivity of a model to several parameters. In order to measure relative sensitivity of an output relative to a particular model parameter, only that parameter is changed in the vicinity of a base value; all other parameters are fixed to their base values. Local sensitivity was calculated for model responses using the base and ±5% changes in the base value. Sensitivity indices were obtained by computing the change in the output relative to changes in parameters. Relative sensitivity for dry matter yield and season length was defined as follows:

$$\sigma_r\left(\frac{Y}{\theta}\right)=\frac{\partial Y/Y}{\partial\theta/\theta} \tag{1}$$

$$\sigma_r\left(\frac{M}{\theta}\right)=\frac{\partial M/M}{\partial\theta/\theta} \tag{2}$$

where Y is simulated dry matter yield, and M is simulated length of the growing season obtained for each level of an individual model parameter (θ) while keeping all other model parameters at their base values. The terms $(\partial Y/Y)$ and $(\partial M/M)$ represent fraction changes in simulated outputs for dry matter and season length, respectively, relative to the fraction changes in inputs $(\partial\theta/\theta)$, and the terms $\sigma_r(Y/\theta)$ and $\sigma_r(M/\theta)$ represent dry matter yield and season length local sensitivities, respectively.

Global Sensitivity

Measuring model sensitivity for each model parameter θ separately with all other model parameters fixed at their single base values prevents the detection and quantification of interactions. A key aspect of most global sensitivity methods is the ability to take these interactions into account.

Factorial design is a method of global sensitivity analysis that allows for simultaneous evaluation of the influence of many model parameters. It follows the classical theory of experimental design in which nature is replaced by the simulated crop model (Box and Draper, 1987). In this study, selection of model parameters for global sensitivity analysis was based on results from the local sensitivity analysis. A simplification of the deterministic model can be used to represent the two output state variables, dry matter yield (Y) and season length (M), as a function of model parameters:

$$Y = f(\theta) \text{ and } M = f(\theta) \tag{3}$$

where θ = model parameters.

Complete factorial design uses all possible combinations of chosen factors and levels. For example, eight model parameters and three levels would create 3^8 combinations. For such a factorial experiment, the analysis can be expressed by decomposing the function $Y = f(\theta)$ and $M = f(\theta)$ into main effects and interactions:

$$\begin{aligned} Y_{abcdefgh} &= \mu + \alpha_a + \beta_b + \ldots + \varepsilon_h + \eta_{ab} + \ldots + \eta_{gh} \\ &+ \eta_{abc} + \ldots + \eta_{fgh} + \eta_{abcd} + \ldots + \eta_{efgh} \\ &+ \eta_{abcde} + \ldots + \eta_{defgh} + \eta_{abcdef} + \ldots + \eta_{cdefgh} \\ &+ \ldots + \eta_{abcdefg} + \ldots + \eta_{bcdefgh} + \eta_{abcdefgh} \end{aligned} \tag{4}$$

$$\begin{aligned} M_{abcdefgh} &= \mu + \alpha_a + \beta_b + \ldots + \varepsilon_h + \eta_{ab} + \ldots + \eta_{gh} \\ &+ \eta_{abc} + \ldots + \eta_{fgh} + \eta_{abcd} + \ldots + \eta_{efgh} \\ &+ \eta_{abcde} + \ldots + \eta_{defgh} + \eta_{abcdef} + \ldots + \eta_{cdefgh} + \\ &+ \ldots + \eta_{abcdefg} + \ldots + \eta_{bcdefgh} + \eta_{abcdefgh} \end{aligned} \tag{5}$$

where $Y_{abcdefgh} = f(a, b, c, d, e, f, g, h)$ and $M_{abcdefgh} = f(a, b, c, d, e, f, g, h)$ denote the model responses of dry matter yield and growing season length, respectively, when $\theta_1 = a$, $\theta_2 = b$, $\theta_3 = c$, $\theta_4 = d$, $\theta_5 = e$, $\theta_6 = f$, $\theta_7 = g$, and $\theta_8 = h$; μ is the overall mean of the model responses; $\alpha_a, \beta_b, \ldots, \varepsilon_h$ represent the main effects of model parameters $\theta_1, \theta_2, \ldots, \theta_8$ when $\theta_1 = a$, $\theta_2 = b, \ldots, \theta_8 = h$; and η_{ab} is the interaction between a and b, η_{gh} is the interaction between g and h, and so on.

The overall response variability can be separated into factorial terms as follows:

$$\sum_{abcdefgh} (Y_{abcdefgh} - \mu)^2 = m\sum_a \alpha_a^2 + m\sum_b \beta_b^2 + \sum_{ab} \eta_{ab}^2 + \ldots \tag{6}$$

where

$\sum_{abcdefgh} (Y_{abcdefgh} - \mu)^2$ is the total sum of squares (SS_T) and represents the total variability in the model responses.

$m\sum_a \alpha_a^2$ is the sum of squares (SS_1) associated with the main effect of m levels of model parameters θ_1, and so on. The NCSS (Hintze, 2004) statistical software was used for calculating the sum of squares of the main effects and interactions for the complete factorial design.

For the sensitivity analysis of a deterministic model, the main interest lies in comparing the contributions of the factorial terms to the total variability. The main effect sensitivity ($S_{i\,=1\text{ to }8}$) indicates the relative importance of individual model parameter uncertainty and can be calculated by dividing the corresponding main effect sum of squares by the total sum of squares (eq. 7):

$$S_i = \frac{SS_i}{SS_T} \tag{7}$$

Interaction sensitivity indices are measures of the interactive influences of the model parameters on the output variance and were calculated by dividing the interaction sum of squares of the model parameters by the total sum of squares.

Global sensitivity indices indicate the overall impact of model parameters on the output variance when model parameters vary over their entire range of uncertainty. Global sensitivity indices for selected model parameters were calculated by the following equation:

$$S_{global(i)} = \frac{SS_i + SS_{i,\sim i}}{SS_T} \tag{8}$$

where $S_{global\,(i)}$ indicates global sensitivity index, SS_i is the main effect sum of squares, $SS_{i,\sim i}$ is interaction sum of squares, and SS_T is total sum of squares, for parameters i = 1 to 8.

Global sensitivity analysis apportions the output variability to the variability in model parameters covering their entire range space, and hence it was important to decide the ranges of the selected model parameters. The ranges of model parameters should be chosen such that they represent the expected extreme values of those parameters. The ranges of some of the model parameters (SLAVR, KCAN, and XFRT) were obtained from the literature (Bange and Milroy, 2000; Milroy et al., 2001; Milroy and Bange, 2003; Reddy et al., 1992; Reddy et al., 1993; Reddy et al., 1991; Messina et al., 2004).

Published data by Wright and Sprenkel (2006) on the length of different growth stages were used to determine the ranges of the model parameters that deal with crop development duration. Information on certain crop growth stages was not available in the published literature, so in order to make maximum use of the available dataset it was assumed that the ratio of the parameters on crop growth stages for the cotton model was the same as the ratio of those parameters for the soybean model. Data for soybean parameters were obtained from Boote et al. (2003). In the cases of SFDUR and PODUR, no information on ranges was available. Instead of using an arbitrary range, the percentage variance from the mean value for soybean parameters was applied to the base cotton model parameters.

Results and Discussion

Local Sensitivity Analysis

Model parameters that were selected for global sensitivity analysis based on the initial local sensitivity analysis are

Table 2. Local sensitivity indices with respect to selected model parameters for dry matter yield.

Parameter	Base Value	Year 2000 Irrigated	Year 2000 Rainfed	Year 2003 Irrigated	Year 2003 Rainfed
KCAN (θ_1)	0.720	3.11	2.65	3.32	3.32
EM-FL (θ_2)	27.87	1.45	0.83	1.76	1.76
FL-SD (θ_3)	11.65	0.43	0.44	0.34	0.34
SD-PM (θ_4)	27.68	0.62	0.69	0.79	0.79
SLAVR (θ_5)	170.0	1.76	0.99	1.91	1.91
XFRT (θ_6)	0.720	0.40	0.84	0.37	0.37
SFDUR (θ_7)	35.0	0.21	0.19	0.03	0.03
PODUR (θ_8)	8.00	0.09	0.12	0.13	0.13

Table 3. Local sensitivity indices with respect to selected model parameters for season length.

Parameter	Base Value	Year 2000 Irrigated	Year 2000 Rainfed	Year 2003 Irrigated	Year 2003 Rainfed
KCAN (θ_1)	0.72	0	0	0	0
EM-FL (θ_2)	27.87	0.31	0.32	0.32	0.32
FL-SD (θ_3)	11.65	0.10	0.10	0.10	0.10
SD-PM (θ_4)	27.68	0.42	0.43	0.43	0.43
SLAVR (θ_5)	170	0	0	0	0
XFRT (θ_6)	0.72	0	0	0	0
SFDUR (θ_7)	35	0	0	0	0
PODUR (θ_8)	8	0	0	0	0

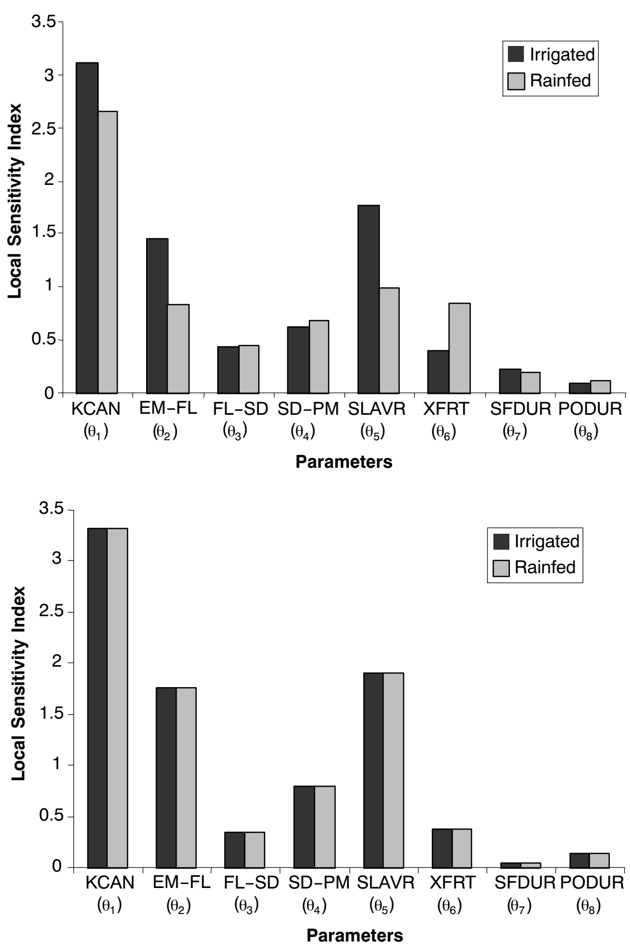

Figure 1. Local sensitivity indices for irrigated and rainfed conditions for 2000 (top) and 2003 (bottom).

shown in tables 2 and 3. Sensitivity indices of the other parameters were either zero or very small. For both treatments and years, KCAN was the parameter that most affected dry matter yield simulation results. For the 2000 rainfed condition, magnitudes and orders of local sensitivity indices were different from 2000 irrigated condition and 2003 irrigated and rainfed conditions (table 2, fig. 1). As an example, dry matter yield was more sensitive to XFRT than EM-FL for 2000 rainfed conditions, whereas it was vice versa for all other cases. One reason for such differences could be because the model is non-linear in its responses and local sensitivity analysis does not consider the range of uncertainty. Only three model parameters (EM-FL, FL-SD, and SD-PM) affected the response of season length. The time between first seed and maturity (SD-PM) was the model parameter that influenced season length the most (table 3).

Global Sensitivity Analysis

Based on the local sensitivity analysis results of all the cultivar model parameters and one species model parameter, eight parameters were selected for global sensitivity analysis (table 4). Tables 5 and 6 show the calculated global sensitivity indices for dry matter yield and season length, taking into account all main effects and interactions related to corresponding model parameter. The first ten interaction terms in order of their magnitudes of sensitivity indices are listed in table 5.

Unlike local sensitivity indices, global sensitivity indices were consistent in terms of order of sensitivity across rainfed and irrigated conditions and years. For a given management condition and year, SLAVR had the highest sensitivity index, followed by KCAN. Two model parameters, PODUR and SFDUR, showed the least influence on dry matter yield across both treatments and years. For lower specific leaf areas, thicker and smaller leaves would reduce light capture and net photosynthesis. On the other hand, for higher specific leaf areas, leaves are thinner and larger, resulting in increased light capture and hence increased net photosynthesis. Thus, changing SLAVR would indirectly affect canopy net photosynthesis, which eventually affects growth and yield. KCAN was the second most important parameter for dry matter yield. The light extinction coefficient, KCAN, is used to compute light interception depending on leaf area index. The highest interaction effect was obtained between KCAN and SLAVR. The model parameter XFRT was the third most important model parameter for crop yield. Parameter values of SLAVR and KCAN mainly control leaf expansion and light capture and hence control daily assimilates. XFRT regulates the partitioning of daily assimilates that goes to seed. XFRT being the third most important parameter, its interaction with SLAVR and KCAN being the second and third most important interactions was logical.

For 2000, irrigated and rainfed conditions provided similar sensitivity indices (fig. 2). There were small differences in the values due to irrigation and year; however, the order of importance of model parameters was consistent. Year 2003 was a wet year and hence, even under rainfed conditions, the indices were consistent in terms of values and order. Overall, global sensitivity indices did not show variations in order of importance with different treatments.

Season length was sensitive to only three model parameters, EM-FL, FL-SD, and SD-PM. Season length is mostly determined by parameters that control the duration of differ-

Table 4. Model parameters and their range of uncertainty selected for the global sensitivity analysis.

Parameter	Uncertainty Range Min.	Base	Max.	Reference for Uncertainty Range
KCAN (θ_1)	0.5	0.72	0.95	Rosenthal and Gerik, 1991; Milroy et al., 2001; Milroy and Bange, 2003; Bange and Milroy, 2004
EM-FL (θ_2)	27.72	27.87	28.02	Wright and Sprenkel, 2006
FL-SD (θ_3)	9.03	11.65	14.27	Wright and Sprenkel, 2006; Boote et al., 2003
SD-PM (θ_4)	21.46	27.68	33.91	Wright and Sprenkel, 2006; Boote et al., 2003
SLAVR (θ_5)	90	170	250	Reddy et al., 1992; Reddy et al., 1993; Reddy et al., 1991
XFRT (θ_6)	0.5	0.72	0.95	Reddy et al., 1992; Reddy et al., 1993; Reddy et al., 1991
SFDUR (θ_7)	31.12	35	38.88	Boote et al., 2003
PODUR (θ_8)	5.82	8	10.18	Boote et al., 2003

Table 5. Global sensitivity indices for dry matter yield including main effects and interactions.

	2000 Irrigated Sensitivity Indices		2000 Rainfed Sensitivity Indices		2003 Irrigated Sensitivity Indices		2003 Rainfed Sensitivity Indices	
Parameter	Main Effects & Interactions	Global Indices	Main Effects & Interactions	Global Indices	Main Effects & Interactions	Global Indices	Main Effects & Interactions	Global Indices
KCAN (θ_1)	0.3848	0.4802	0.4109	0.4976	0.3761	0.4832	0.3762	0.4832
EM-FL (θ_2)	0.0002	0.0022	0.0002	0.0022	0.0002	0.0023	0.0002	0.0023
FL-SD (θ_3)	0.0057	0.0122	0.0065	0.0131	0.0058	0.0132	0.0058	0.0132
SD-PM (θ_4)	0.0203	0.0359	0.0196	0.0325	0.0165	0.0311	0.0165	0.0310
SLAVR (θ_5)	0.4491	0.5451	0.4262	0.5132	0.4549	0.5631	0.4550	0.5631
XFRT (θ_6)	0.0224	0.0479	0.0291	0.0532	0.0182	0.0400	0.0182	0.0400
SFDUR (θ_7)	0.0002	0.0009	0.0001	0.0010	0.0000	0.0011	0.0000	0.0011
PODUR (θ_8)	0.0004	0.0020	0.0007	0.0027	0.0010	0.0029	0.0010	0.0029
KCAN × SLAVR	0.0716	n/a	0.0651	n/a	0.0855	n/a	0.0855	n/a
KCAN × XFRT	0.0107	n/a	0.0100	n/a	0.0089	n/a	0.0089	n/a
SLAVR × XFRT	0.0096	n/a	0.0102	n/a	0.0082	n/a	0.0082	n/a
SD-PM × SLAVR	0.0065	n/a	0.0045	n/a	0.0059	n/a	0.0059	n/a
KCAN × SD-PM	0.0053	n/a	0.0046	n/a	0.0047	n/a	0.0047	n/a
KCAN × SD-PM × XFRT	0.0038	n/a	0.0029	n/a	0.0034	n/a	0.0034	n/a
FL-SD × SLAVR	0.0018	n/a	0.0017	n/a	0.0020	n/a	0.0020	n/a
KCAN × FL-SD	0.0015	n/a	0.0016	n/a	0.0016	n/a	0.0016	n/a
KCAN × SD-PM × SLAVR	0.0010	n/a	0.0006	n/a	0.0011	n/a	0.0010	n/a
EM-FL × FL-SD × SD-PM	0.0006	n/a	0.0006	n/a	0.0006	n/a	0.0006	n/a

Table 6. Global sensitivity indices for season length including main effects and interactions.

	2000 Irrigated Sensitivity Indices		2000 Rainfed Sensitivity Indices		2003 Irrigated Sensitivity Indices		2003 Rainfed Sensitivity Indices	
Parameter	Main Effects & Interactions	Global Indices	Main Effects & Interactions	Global Indices	Main Effects & Interactions	Global Indices	Main Effects & Interactions	Global Indices
EM-FL (θ_2)	0.0040	0.0339	0.0043	0.0344	0.0040	0.0343	0.0040	0.0343
FL-SD (θ_3)	0.1756	0.2058	0.1826	0.2127	0.1990	0.2307	0.1990	0.2307
SD-PM (θ_4)	0.7829	0.8142	0.7732	0.8038	0.7589	0.7896	0.7589	0.7896
EM-FL × FL-SD × SD-PM	0.0163	n/a	0.0154	n/a	0.0165	n/a	0.0165	n/a
FL-SD × SD-PM	0.0076	n/a	0.0072	n/a	0.0077	n/a	0.0077	n/a
EM-FL × SD-PM	0.0073	n/a	0.0071	n/a	0.0064	n/a	0.0064	n/a
EM-FL × FL-SD	0.0063	n/a	0.0067	n/a	0.0074	n/a	0.0074	n/a

ent crop growth stages. In our study, three duration model parameters were selected that covered the whole crop season length. SD-PM was the most important model parameter affecting season length, partly due to greater uncertainty in this parameter, followed by FL-SD and EM-FL (table 6).

Comparison of Local and Global Sensitivity Analysis Results

For comparing local and global sensitivity analysis results, only rankings were taken into consideration. The reason for that was because the local sensitivity index is the ratio of percentage change in the output response to the percentage change in the model parameter, whereas the global sensitivity index is the measure of percentage contribution of an individual model parameter to overall output variance.

Based on local sensitivity results, KCAN was the most important model parameter for cotton dry matter yield, followed by SLAVR, which was opposite to global sensitivity results (table 7). The main reason for these differences was because local sensitivity analysis focuses on the local impact of parameters on the model response, where model parameters varied in small intervals around their base values. For nonlinear models, finding the most important model parameter with such sparse domain coverage may be misleading. On the other hand, global sensitivity analysis takes into account the main effects and interactions between parameters over their entire uncertainty ranges.

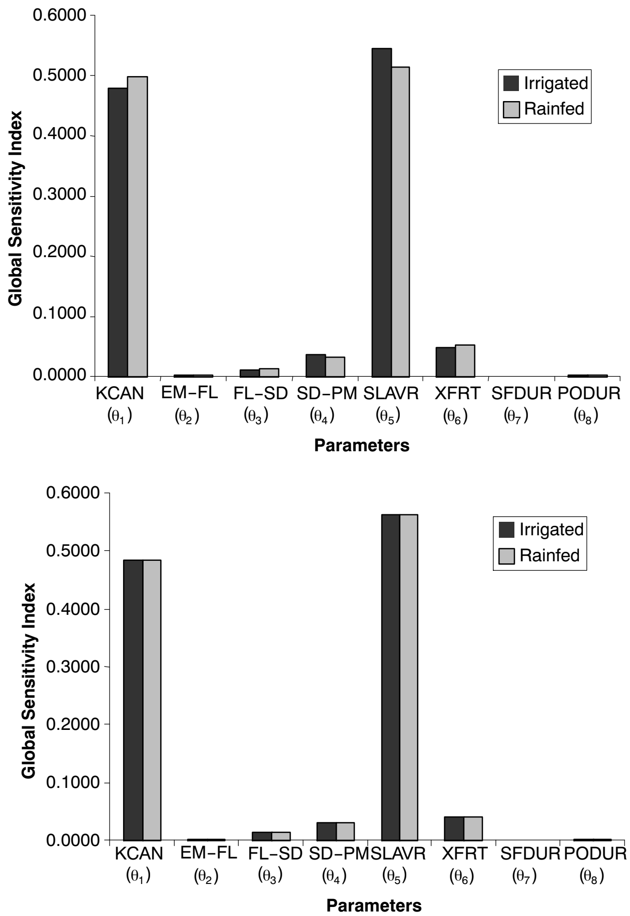

Figure 2. Global sensitivity indices for irrigated and rainfed conditions for the year 2000 (top) and 2003 (bottom).

Table 7. Model parameter rankings based on local and global sensitivity indices for dry matter yield.

Parameter	Year 2000 Irrigated	Year 2000 Rainfed	Year 2003 Irrigated	Year 2003 Rainfed
Local sensitivity analysis rankings				
KCAN (θ_1)	1	1	1	1
EM-FL (θ_2)	3	4	3	3
FL-SD (θ_3)	5	6	6	6
SD-PM (θ_4)	4	5	4	4
SLAVR (θ_5)	2	2	2	2
XFRT (θ_6)	6	3	5	5
SFDUR (θ_7)	7	7	8	8
PODUR (θ_8)	8	8	7	7
Global sensitivity analysis rankings				
KCAN (θ_1)	2	2	2	2
EM-FL (θ_2)	6	6	6	6
FL-SD (θ_3)	5	5	5	5
SD-PM (θ_4)	4	4	4	4
SLAVR (θ_5)	1	1	1	1
XFRT (θ_6)	3	3	3	3
SFDUR (θ_7)	8	8	8	8
PODUR (θ_8)	7	7	7	7

For this study, irrigated and rainfed conditions for dry and wet years were used to compare local sensitivity and global sensitivity analyses results. The model parameter rankings did not change with years and treatments for global sensitivity analysis, whereas they varied among the years and treatments for local sensitivity analysis. Both methods provided similar results for two variables (PODUR and SFDUR), showing that model sensitivity over the range of parameter uncertainty was small. Such information can be useful to focus additional research and possibly to simplify the model by reducing the number of model parameters that one has to estimate.

Table 8. Model parameter rankings based on local and global sensitivity indices for season length.

Parameter	Year 2000 Irrigated	Year 2000 Rainfed	Year 2003 Irrigated	Year 2003 Rainfed
Local sensitivity analysis rankings				
EM-FL (θ_2)	3	3	3	3
FL-SD (θ_3)	2	2	2	2
SD-PM (θ_4)	1	1	1	1
Global sensitivity analysis rankings				
EM-FL (θ_2)	3	3	3	3
FL-SD (θ_3)	2	2	2	2
SD-PM (θ_4)	1	1	1	1

Season length response was sensitive to only three model parameters, EM-FL, FL-SD, and SD-PM (table 8). Of these three, SD-PM was the most important model parameter, followed by FL-SD and EM-FL, respectively. These rankings were the same for both local and global sensitivity analysis. The reason for season length response being sensitive to only three model parameters was because those model parameters were the only ones among the selected parameters for the analysis that can affect the duration of crop growth stages.

Summary and Conclusions

This study evaluated how sensitive the cotton model predictions were to a selected set of model parameters. Local and global sensitivity analyses were used to determine dry matter yield and season length sensitivity to model parameters under irrigated and rainfed conditions for two cropping seasons. Results demonstrated that, in accordance with our first hypothesis, global sensitivity analysis improved our understanding of how sensitive the prototype cotton model was to the selected set of parameters over the ranges of parameter uncertainties. In addition to accounting for the variance of model output associated with the variance of model parameters over the entire range on uncertainty, it had the advantage of considering the interactions among model parameters. The most influencing model parameter on dry matter yield was the specific leaf area (SLAVR). Local sensitivity analysis indicated that the extinction coefficient (KCAN) was the most influencing model parameter.

The global sensitivity analysis results also demonstrated that, consistent with our second hypothesis, sensitivity of dry matter yield and season length to the selected set of model parameters did not vary between irrigated and rainfed conditions or with years. However, that was not true for local sensitivity analysis. Results from this study indicated that more research is needed to reduce the range of uncertainties of both KCAN and SLAVR. Experiments have shown variations in KCAN values for different cultivars, and hence it was suggested that it should be included in an ecotype set of model parameters rather than in a species file. That suggestion was supported by the results of this study. The parameters selected for this study were associated with cotton growth and development. Additional studies are needed to assess model sensitivity to soil water and nitrogen parameters, which were held constant for this study.

Global sensitivity analysis can be a valuable tool for application with large, highly non-linear models, such as the DSSAT-CSM models. However, the use of a complete factorial design and analysis of variance can result in a large number of simulation runs when there are many model parameters. The choice of model parameters to be evaluated should be considered with care, taking into account available resources.

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