Chapter 4
Uncertainties in Simulating Crop Performance in Degraded Soils and Low Input Production Systems

James W. Jones, J. Naab, Dougbedji Fatondji, K. Dzotsi, S. Adiku, and J. He

Abstract Many factors interact to determine crop production. Cropping systems have evolved or been developed to achieve high yields, relying on practices that eliminate or minimize yield reducing factors. However, this is not entirely the case in many developing countries where subsistence farming is common. The soils in these countries are mainly coarse-textured, have low water holding capacity, and are low in fertility or fertility declines rapidly with time. Apart from poor soils, there is considerable annual variability in climate, and weeds, insects and diseases may damage the crop considerably. In such conditions, the gap between actual and potential yield is very large. These complexities make it difficult to use cropping system models, due not only to the many inputs needed for factors that may interact to reduce yield, but also to the uncertainty in measuring or estimating those inputs. To determine which input uncertainties (weather, crop or soil) dominate model output, we conducted a global sensitivity analysis using the DSSAT cropping system model in three contrasting production situations, varying in environments and management conditions from irrigated high nutrient inputs (Florida, USA) to rainfed crops with manure application (Damari, Niger) or with no nutrient inputs (Wa, Ghana). Sensitivities to uncertainties in cultivar parameters accounted for about 90% of yield variability under the intensive

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management system in Florida, whereas soil water and nutrient parameters dominated uncertainties in simulated yields in Niger and Ghana, respectively. Results showed that yield sensitivities to soil parameters dominated those for cultivar parameters in degraded soils and low input cropping systems. These results provide strong evidence that cropping system models can be used for studying crop performance under a wide range of conditions. But our results also show that the use of models under low-input, degraded soil conditions requires accurate determination of soil parameters for reliable yield predictions.

Keywords Crop model • Parameters • Uncertainty • Global sensitivity analysis • Water • Cultivar • Nitrogen

Introduction

Models are increasingly being used as research tools to predict outcomes of cropping systems under different climate, soil, and management conditions in both developed and developing countries. Many papers have been published on research, demonstrating that cropping system models perform adequately for the intended purposes, such as to study impacts of different cultivars, irrigation, fertility, and cultural management practices on yield and other predicted outputs. Many of these studies have emphasized the importance of incorporating climate uncertainty to adequately consider risks to production and profitability (e.g., Hammer and Muchow 1991; Thornton and Wilkens 1998). Impacts of, and adaptation to, climate change have made extensive use of crop models, and now these models are being used for simulating years of crop rotation for projecting long term changes in soil carbon and other properties that affect sustainability of production in different environments.

Typically in these studies, researchers are interested in only a few factors that may limit growth and yield, such as water and nitrogen in addition to climate. However, there may be many factors that limit production in farmers' fields and that present challenges to model users. This is particularly true in developing countries where (1) soils are low in fertility and hold very little water, (2) where farmers typically do not apply fertilizer or irrigate, (3) there is considerable annual variability in climate, (4) weeds, insects and diseases may cause considerable damage the crop, and (5) farming practices are mainly subsistence with low input. Mathews and Stephens (2002) pointed out the difficulties of obtaining inputs to operate cropping system models in developing countries. This presents one of the challenges in reliable use of cropping system models in those countries. However, there is another major challenge that has been ignored in most previous studies, even if inputs for model studies were collected – uncertainty in environmental parameters and inputs. Model developers routinely emphasize the importance of obtaining accurate cultivar coefficients in order to apply cropping system models in local studies, which suggests that without reliable values for these parameters, the models will not adequately simulate the responses to climate and management that users are studying. Little attention has been given to uncertainty analysis of other factors, such as different soil and management inputs relative to prediction of cropping system performance. Based on studies conducted in West Africa, we hypothesized that uncertainty in soil parameters, initial conditions, and nutrient inputs contribute more to prediction uncertainty than cultivar parameters in low input, rainfed cropping systems on soils with low fertility and small water holding capacities. In this study, we used the DSSAT Cropping System Model (CSM) to simulate soil processes and crop growth responses to the harsh conditions in sites with maize in Ghana (using the CERES-Maize) and for millet in Niger (using the CERES-Millet component). Results from these two sites are compared with those for maize production in a high input production system in the USA. In this study, all other management factors, such as plant density, row spacing, etc., were input as fixed values and there was minimal damage due to pests in each of the experiments.

The objectives of this study were (1) to determine sensitivities of the DSSAT – CSM model to uncertainties in parameters for three contrasting cropping systems in low-fertility, sandy soils, and (2) to estimate the uncertainty of simulated crop production as affected by uncertainties in important soil parameters, soil initial conditions, cultivar parameters, and nutrient inputs.

Methods

Experiments

Data from a total of three experiments, two of which were conducted in West Africa (Wa, Ghana and Damari, Niger) and the other in the USA (Gainesville, Florida) were selected for this study. Furthermore, one treatment in each experiment was selected to represent contrasting soil and management conditions for crops commonly grown in each area. Soils in all three experiments were sandy with low water holding capacities and low organic matter contents. Maize was grown in two experiments and millet in the other. The two crops in West Africa were rainfed whereas the maize crop in Gainesville, Florida was irrigated. Soil parameters, initial conditions, management details, and cultivar coefficients were measured and used in prior simulation studies by the authors of those studies. Weeds were controlled in each experiment and there was no evidence of pest damage. Table 4.1 summarizes the overall characteristics and weather conditions for the three experiments used in this study.

In the first experiment, maize was grown in 1982 in Gainesville, Florida, (29°41′ N 82°21′ W) with irrigation and high nitrogen input to represent a typical high input production system (Table 4.1). The soil is classified as an Arenic Paleudults Fine Sand and has an average depth of about 180 cm. Soil carbon was 0.64% in the top 20 cm of soil. The experiment consisted of six treatments with different irrigation and nitrogen fertilizer inputs. We used the fully irrigated, high nitrogen fertilizer treatment from this 1982 experiment (Bennett et al. 1989) that is distributed with DSSAT (Jones et al. 2003). Rainfall during the season was high (661 mm), temperature was high, but lowest of the three locations, and the season was 126 days long, the longest of the three locations.

Table 4.1 Site characteristics and season average weather conditions for the three experiments

	Gainesville	Wa	Damari
Location	29°41′ N, 82°21′ W	10°3′ N, 2°30′ W	13°12′ N, 2°14′ E
Altitude, (masl)	54	320	196
Soil			
Classification	Arenic Paleudults	Ferric Lixisol	Kanhaplic Haplustult
Texture	Fine sand	Loamy sand	Loamy sand
Relief	Flat	Flat	Flat
SOC (%)	0.64	0.48	0.15
Soil fertility	Low	Very low	Very low
Runoff potential	Low	Low	High
Seasonal Weather			
Rainfall (mm)	661	738	550
Solar radiation (MJ/m^2/day)	18.4	18.1	21.4
Max Temp (°C)	29.2	30.2	32.8
Min Temp (°C)	15.8	21.6	23.1
Management			
Planting	Tilled	Tilled	Flat
Fertilizer	400 kg ha^{-1} applied	No N, 39 kg ha^{-1} of P	3,000 kg ha^{-1} manure
Irrigation	Yes	No	No

The second experiment involved a maize trial conducted in 2004 by J. B. Naab (Naab 2005; Naab et al. 2008) in Wa, Ghana, using a treatment that had no nitrogen added but adequate P and other inputs (Table 4.1). The experiment site was located in the Upper West Region of Ghana (10°3′ N, 2°30′ W, altitude 320 m above sea level) and has an unimodal rainfall pattern. The average annual rainfall is 1,100 mm falling mainly between April and September. The mean annual temperature in Wa is 27°C. The soil in Wa is characterized as a Ferric Lixisol in the FAO (2001) classification system, with a loamy sand texture, and having a depth of 60 cm. The organic carbon is very low (0.38% in the top 20 cm soil) and available P of 3.26 mg kg^{-1}. This maize experiment was conducted to evaluate maize response to N and P fertilizer applications using 9 treatments in a factorial experiment design. Details of this study are reported in Naab (2005). The treatment with no N and high P fertilizer input (39 kg ha^{-1} of P) was used in this study. This cropping system represents one with low soil N fertility, no N inputs, with high rainfall. Rainfall during the growing season in Wa was 738 mm in 2004, highest among the three sites, and the fields were nearly flat with low surface runoff potential. Although daily maximum temperature average during the season was only 1°C higher than Gainesville, minimum temperature averaged about 6°C higher. The growing season was 98 days long in Wa, 28 days less than in Gainesville.

The third crop was a flat-planted millet treatment in an experiment at Damari (Niger) in 1999 (Table 4.1) with the application of 3,000 kg ha^{-1} manure (Fatondji et al. 2006). Damari is located at Lat 13°12′ N and Long. 2°14′ E, 45 km from Niamey, the capital city of Niger. The long-term average annual rainfall at Damari is 550 mm, which falls between June and September. The long term monthly average minimum and maximum temperatures vary, respectively, between 16°C in January and 28°C in April and May and between 32°C in January and 42°C in April and May. During the experiment in 1999, weather conditions followed this trend; total rainfall for the season was 499 mm (Table 4.1).

The soil at Damari is classified as a Kanhaplic Haplustult (Soil Survey Staff 1998). Table 4.1 shows measured soil properties (0–60 cm) at the experiment site. The soil is highly acidic (pH-H_2O=3.6–4.5), with 84% sand content, with low effective cation exchange capacity (ECEC) (2.8 cmol kg^{-1}), and very low soil water holding capacity. Because of the soil properties and intense rainfall events in the region the soils are prone to surface crusting (Casenave and Valentin 1989) and high runoff. The soil organic carbon ranged from 0.04% to 0.14% (Fatondji et al. 2006), even lower than the typical levels in Niger (about 0.22%, Bationo et al. 2003) and severely limit yield compared to the genetic potential of the site. Table 4.1 (see Fatondji et al. 2012, this volume) summarize soil parameters for the field in which the Damari experiment was conducted. Despite these extreme conditions, farmers are forced to use these soils for producing crops because of limited land availability. Water harvesting technologies are therefore used to assure better soil water conditions for the crop. Treatments in the experiment were combinations of water harvesting using the zai technology in which seeds are planted in pits (Fatondji et al. 2006) vs. flat planting in combinations with nutrient additions (none, straw residue, and manure). In this study, we selected the flat planted, manure treatment in which either water, nutrients, or both could limit crop production. For other details on the experiment and site, see Fatondji et al. (2006).

DSSAT Cropping System Model

The DSSAT version 4.02 Cropping System Model (CSM) (Jones et al. 2003; Hoogenboom et al. 2004) was used to simulate maize or millet in the experiments described above. This model includes the CERES plant growth models (Ritchie et al. 1998; Ritchie and Alagarswamy 1989) and a dynamic soil water, carbon, and nutrient model (Ritchie 1998; Gijsman et al. 2002; Godwin and Singh 1998; Jones et al. 2003; Dzotsi et al. 2010; Porter et al. 2010) that computes daily changes in the status of soils in response to tillage, irrigation, and nutrient applications and the effect of those soil conditions on crop growth and yield. DSSAT is a software environment that embeds the CSM, and this system has been widely used in research on cropping systems analysis for different purposes.

This model was used by researchers in each of the studies that are included in this analysis. In each study, the soil, weather, and management inputs were put into the model, and cultivar parameters were estimated using the crop development, growth, and yield data from the experiments. For example, Dzotsi et al. (2010) and Naab (2005) used the high N and high P treatment in the Wa (Ghana) experiment to estimate cultivar parameters for the Obatanpa maize variety. Fatondji et al. (2012 this volume) estimated cultivar parameters for the local millet variety used in the Damari experiment. These parameters are given as default values in Tables 4.2, 4.3 and 4.4.

Table 4.2 Distributions of the selected parameters for sensitivity analysis for the maize experiment in Gainesville, FL, USA

			Statistic				
Parameter	Parameter Type	Distribution	Default	STDEV	Min	Max	Description
P1	Cultivar	Uniform	265	–	245.1	284.9	Degree days (base 8°C) from emergence to end of juvenile phase
P2	Cultivar	Uniform	0.3	–	0	0.6	Photoperiod sensitivity coefficient (0–1.0)
P5	Cultivar	Uniform	920	–	851	989	Degree days (base 8°C) from silking to physiological maturity
G2	Cultivar	Uniform	990	–	841.5	999.0	Potential kernel number
G3	Cultivar	Uniform	8.5	–	7.22	9.78	Potential kernel growth rate mg/(kernel days)
PHINT	Cultivar	Uniform	39	–	36.08	41.92	Degree days required for a leaf tip to emerge (phyllochron interval) (°C days)
PAW	Soil water	Normal	0.061	0.0073	–	–	Plant available water, volume fraction
PEW	Soil water	Normal	0.2	0.024	–	–	Potential excess water, volume fraction
SLRO	Soil water	Uniform	65	–	60.1	69.9	Soil runoff curve number
SH2O	Soil water	Uniform	0.086	–	0.05	0.11	Initial condition soil water content, volume fraction
SNH4	Soil nutrients	Uniform	0.5	–	0.3	1.5	Initial condition soil ammonium content, mg kg^{-1}
SNO3	Soil nutrients	Uniform	0.1	–	0.05	0.3	Initial condition soil nitrate content, mg kg^{-1}
SAOC	Soil nutrients	Uniform	0.7	–	0.5	1	Total soil carbon, g/100 g
SASC	Soil nutrients	Uniform	0.85	–	0.8	0.95	Stable organic carbon, fraction
ManureN	Management	Uniform	2.53	–	1.85	3.25	Organic nitrogen, percent dry weight basis
FertilizerN	Management	Normal	400	20	–	–	Inorganic fertilizer nitrogen, kg ha^{-1}

Table 4.3 Distributions of the selected parameters for sensitivity analysis for the maize experiment in Wa, Ghana

			Statistic				
Parameter	Type	Distribution	Default	STDEV	Min	Max	Description
P1	Cultivar	Uniform	280	–	259	301	Degree days (base 8°C) from emergence to end of juvenile phase
P2	Cultivar	Uniform	0	–	0	0	Photoperiod sensitivity coefficient (0–1.0)
P5	Cultivar	Uniform	700	–	647.5	752.5	Degree days (base 8°C) from silking to physiological maturity
G2	Cultivar	Uniform	550	–	467.5	632.5	Potential kernel number
G3	Cultivar	Uniform	7.74	–	6.58	8.9	Potential kernel growth rate mg/(kernel days)
PHINT	Cultivar	Uniform	40	–	37	43	Degree days required for a leaf tip to emerge (phyllochron interval) (°C days)
PAW	Soil water	Normal	0.068	0.0082	–	–	Plant available water, volume fraction
PEW	Soil water	Normal	0.231	0.0277	–	–	Potential excess water, volume fraction
SLRO	Soil water	Uniform	61	–	56.4	65.6	Soil runoff curve number
SH2O	Soil water	Uniform	0.183	–	0.143	0.223	Initial condition soil water content, volume fraction
SNH4	Soil nutrients	Uniform	0.5	–	0.25	0.75	Initial condition soil ammonium content, mg kg^{-1}
SNO3	Soil nutrients	Uniform	1.7	–	0.85	2.55	Initial condition soil nitrate content, mg kg^{-1}
SAOC	Soil nutrients	Uniform	0.48	–	0.4	1.0	Total soil carbon, g/100 g
SASC	Soil nutrients	Uniform	0.85	–	0.5	0.95	Stable organic carbon, fraction
ManureN	Management	Uniform	0	–	–	–	Organic nitrogen, percent dry weight basis
FertilizerN	Management	Normal	0	–	–	–	Inorganic fertilizer nitrogen, kg ha^{-1}

Table 4.4 Distributions of the selected parameters for sensitivity analysis for the millet experiment in Damari, Niger

			Statistic				
Parameter	Type	Distribution	Default	STDEV	Min	Max	Description
P1	Genetic	Uniform	170.0	–	144.5	195.5	Degree days (base 8°C) from emergence to end of juvenile phase
P20	Genetic	Uniform	12.0	–	11.8	12.2	Critical photoperiod or the longest day length (in hours) at which development occurs at a maximum rate
P2R	Genetic	Uniform	150.0	–	127.5	172.5	Extent to which phasic development leading to panicle initiation is delayed for each hour increase in photoperiod above P_2O.
P5	Genetic	Uniform	450.0	–	382.5	517.5	Thermal time (degree days above a base temperature of 10°C from beginning of grain filling (3–4 days after flowering) to physiological maturity)
G1	Genetic	Uniform	1.00	–	0.7	1.3	Scaler for relative leaf size
G4	Genetic	Uniform	0.770	–	0.54	1.00	Scaler for partitioning of assimilates to the panicle (head)
PHINT	Genetic	Uniform	43.00	–	36.55	49.45	Degree days required for a leaf tip to emerge (phyllochron interval) (°C days)
PAW	Soil water	Normal	0.036	0.00432	–	–	Plant available water, volume fraction
PEW	Soil water	Normal	0.301	0.03612	–	–	Potential excess water, volume fraction
SLRO	Soil water	Uniform	98	–	90	100	Soil runoff curve number
SH2O	Soil water	Uniform	0.086	–	0.05	0.11	Initial condition soil water content, volume fraction
SNH4	Soil nutrients	Uniform	0.010	–	0.3	1.5	Initial condition soil ammonium content, mg kg^{-1}
SNO3	Soil nutrients	Uniform	0.007	–	0.05	0.3	Initial condition soil nitrate content, mg kg^{-1}
SAOC	Soil nutrients	Uniform	0.150	–	0.5	1	Total soil carbon, g/100 g
SASC	Soil nutrients	Uniform	0.920	–	0.8	0.95	Stable organic carbon, fraction
ManureN	Management	Uniform	2.530	–	2.03	3.03	Organic nitrogen, percent dry weight basis
FertilizerN	Management	Normal	0	–	–	–	Inorganic fertilizer nitrogen, kg ha^{-1}

Global Sensitivity Analysis

We conducted a global sensitivity analysis on the three systems described above with contrasting climate, soil, and management inputs. We also quantified the uncertainties in yield predictions associated with 16 soil water, soil nutrient, and cultivar parameters.

Parameters in the Sensitivity Analysis

Parameters for sensitivity analysis were selected based on past experiences in adapting crop models to a wide range of soils, climates, and management conditions. Parameters that are usually missing when adapting crop models for a new location are those associated with the cultivars grown there – the cultivar parameters in the DSSAT CSM. Thus, a basic requirement in new situations is to perform experiments and measure crop development, growth and yield to calibrate or estimate the cultivar parameters. Although these parameters should be estimated using data on crops grown under non-limiting resource conditions such as adequate nutrient and water supply with minimal pest damage (Hunt et al. 1993; Boote et al. 2003), this is often not the case. In most cases, crop data are only available for sub-optimal and rainfed trials. The estimation of crop cultivar parameters using such data from crops grown under nutrient or water deficits may not be reliable and would contribute to uncertainty in those parameters. Even though the default parameters for maize and millet listed in Table 4.2 are those reported by researchers who performed the experiments, inherently there are uncertainties associated with these values.

The second set of parameters selected for sensitivity and uncertainty analyses was for the soil water balance, which computes daily amounts of water available in the root zone for crop uptake. Even though researchers may collect soil samples and determine water retention properties in the laboratory, these lab-measured estimates of field water holding characteristics may be inadequate for use in the model because they often fail to capture the field-scale spatial heterogeneity (Ritchie 1998). In addition, model simulation of soil water infiltration is based on a widely-used runoff curve number technique (Williams 1991) that uses the curve number (SLRO) as its defining parameter. This parameter and its determination are highly empirical, and thus its estimates are highly uncertain. Two other parameters that we selected for study are based on the lower limit of water below which plants are not able to extract water (SLLL), the drained upper limit (SDUL), and saturated soil water content (SSAT), and initial soil water content. These parameters are plant available water (PAW, which is (SDUL-SLLL)) and water storage capacity above SDUL (PEW, which is (SSAT-SDUL)).

A final set of five parameters were those associated with soil fertility and its management. Four of the parameters were initial condition estimates for ammonium, nitrate, total soil carbon, and stable soil carbon. Under non-fertilized crops, these factors are very important determinants of nutrient supply during their growing season. A fifth parameter is the input amount of fertilizer N (either inorganic or organic).

Default values and ranges of uncertainty were selected for the 16 parameters. The default values were those previously reported by researchers who used the models to study each of the three experiments; these were available in the DSSAT v4.02 (Hoogenboom et al. 2004) data files. Uniform distributions were used for most parameters. Ranges for the cultivar parameter distributions were based on prior experience in uncertainties obtained when estimating coefficients using field data. Although cultivar parameter uncertainties were not known for the cultivars in these studies, we used the same uncertainty ranges for each location so that differences in sensitivities among the locations could be attributed to location differences instead of differences in parameter uncertainties. Uncertainties in PAW and PEW soil water parameters were described by normal distributions based on a study by He (2008). Tables 4.2, 4.3 and 4.4 show the distributions of the selected parameters for three experiment sites in this study.

Global Sensitivity Analysis

The method for the global sensitivity analysis followed that by Sobol (1993), which is similar to an analysis of variance. Multiple sets of parameters were created using Monte Carlo random sampling from the parameter distributions for running the model to produce output responses that were then analyzed. The variances of response variables were decomposed into the contributions from the various input parameter variations over their ranges of uncertainties (Monod et al. 2006). With 16 parameters or factors, the decomposition of the total variance $\operatorname{var}(\hat{Y})$ in any response Y, such as grain yield, can be summarized by:

$$\operatorname{var}(\hat{Y}) = \sum_{i=1}^{16} D_i + \sum_{i<j} D_{ij} + \ldots + D_{1\ldots16} \tag{4.1}$$

where D_i is the variability associated with the main effect of parameter i, and D_{ij} is the variability associated with the interaction between parameters i and j. Sensitivity indices (S_i) are derived from the decomposition of total variance in Eq.4.1 by dividing the variance attributed to uncertainty in each parameter by $\operatorname{var}(\hat{Y})$:

$$S_i = D_i / \operatorname{var}(\hat{Y}) \tag{4.2}$$

Interactive sensitivity indices can also be computed if needed, based on the D_{ij} terms in Eq. 4.1. In our case, we computed the main effect indices for each parameter along with the total sensitivity, TS_i, to each parameter, i, considering its interactive effects with other parameters, given by:

$$TS_i = \frac{D_i + D_{i2} + \cdots + D_{i\cdots16}}{\operatorname{var}(\hat{Y})} \tag{4.3}$$

The software package SimLab v2.2.1 (Saltelli et al. 2004; SimLab 2005), designed for multiple model runs with probabilistically selected model inputs using Monte Carlo sampling of distributions, was coupled with the DSSAT CSM model to perform the global sensitivity analysis.

The DSSAT-Maize and Millet model runs were executed using each randomly generated sample of input parameters. Distributions of simulated biomass and grain yield were generated, and first order and total sensitivities of these outputs to each uncertain input parameters were computed using the Sobol decomposition of variances. This method requires $N(16+1)$ model runs for the calculation of the first-order sensitivity indices of 16 factors, where N is the number of randomly sampled parameter scenarios. We used N = 2,048, which resulted in a total of 34,816 sample sets of input parameters for each site. The parameter conversion and automatic model running were implemented using the R language (R Development Core Team 2009). In essence, these model runs create a mapping from the distribution of parameter uncertainties to the distribution of output uncertainties. We then used the results of these model runs to determine (1) the uncertainty in model predictions for each site, and (2) the input variables with uncertainties that contributed most to yield prediction uncertainty.

Results and Discussion

Simulated grain yield varied with input levels in all the three experiments. For Florida, where the maize crop was fertilized and irrigated, the yield varied between 10,000 and 14,000 kg ha^{-1}, with 12,000 kg ha^{-1} being the most likely model outcome (Fig. 4.1). Maize yield under rainfed conditions and with no N input at Wa (Ghana) varied between 400 and 5,000 kg ha^{-1} but a yield of 1,500 kg ha^{-1} was most likely. In Niger, simulated millet yields varied between 350 and 1,700 kg ha^{-1} with a modal yield of 800 kg ha^{-1}. The fact that the modal yields from the uncertainty analysis were near the observed yields indicates that the model, as calibrated by researchers who conducted those experiments, were about the same as observed. Observed mean grain yields for the treatments used in the experiments from Gainesville, Florida, Wa, Ghana, and Damari, Niger were 11,881, 417, and 705 kg ha^{-1}, respectively. The variabilites in yields shown in Fig. 4.1 were due to the uncertainties in parameters as defined in Tables 4.2, 4.3 and 4.4. Furthermore, uncertainties in yield were higher in absolute terms in Gainesville and Niger, as seen in the spread of these two yield distributions (Fig. 4.1), but the ratios of variances to means were much higher in Ghana and Niger than in Gainesville. One of the main simulation results is that even under a given set of weather conditions at a given location, a range of yields can be realized, primarily due to the variability of inputs. These types of model outputs may provide a more realistic representation of the variable yield outcomes commonly observed on farmers' fields.

Figure 4.2 shows the fractions of total variability in yield that were due to uncertainties in the 16 parameters for the intensive management system at the Gainesville site.

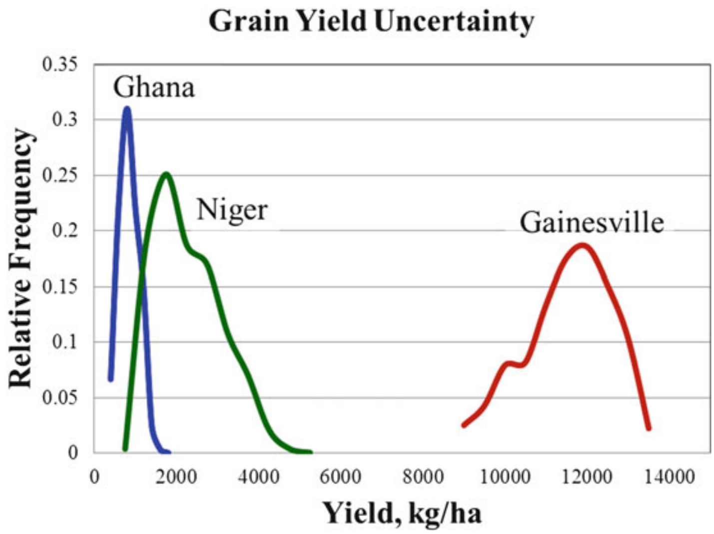

Fig. 4.1 Uncertainty in simulated grain yield for three locations (Gainesville, Florida; Wa, Ghana; and Damari, Niger) that had sandy soils with low nutrient and low water holding capabilities. This graph shows probability distributions that were simulated when taking into account uncertainties in cultivar, soil water, and soil nutrient parameters

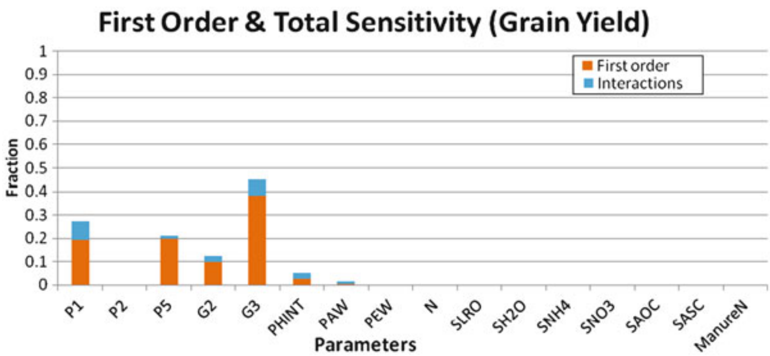

Fig. 4.2 Global sensitivity indices for the Gainesville, Florida site showing the fraction of total grain yield uncertainty that was due to uncertainties in each parameter. The first six are cultivar parameters, which dominated the uncertainty in yield at this site

The lower bars in this stacked-bar figure show first order sensitivity indices Eq. 4.2 for the parameters whereas the very top of the bar shows total sensitivities to each factor Eq. 4.3. Sensitivities to cultivar coefficients were high at this site (accounting for about 90% of the uncertainty). In contrast, sensitivity indices for water and nutrient parameters were very low, accounting for less than 10% of the final yield uncertainty. This is not a surprising result because intensive management provided water and nutrients that were high enough in Gainesville to obscure most effects of

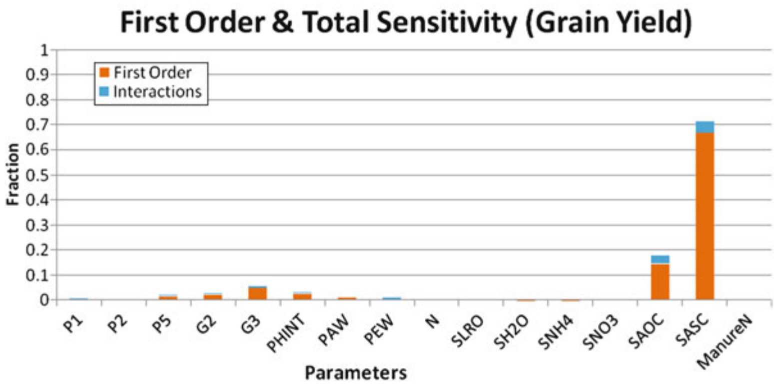

Fig. 4.3 Global sensitivity indices for the Wa, Ghana site showing the fraction of total grain yield uncertainty that was due to uncertainties in each parameter. The two soil carbon parameters dominated the uncertainty in yield at this site

variability in each of the parameters and inputs that would limit yield. In essence, yields in this site were high for all combinations of water and nutrient-related parameters, varying mostly due to cultivar coefficients.

Results were considerably different for the Wa, Ghana location where observed maize yield was 417 kg ha^{-1} (Fig. 4.3). At this site with very low soil nutrient levels, N was mostly supplied by mineralization of soil organic matter during the growing season. Thus, the amount of carbon in the soil and its level of stability were the dominant parameters. As total soil carbon (SAOC) and stable soil carbon (SASC) varied over their levels of uncertainty, mineralization of N for plant growth varied considerably and yield was influenced accordingly. It was somewhat surprising that the effect of stable carbon was higher than total soil carbon. However, if SASC is a large fraction of the total soil C, then very little mineralization would occur even for relatively high SAOC values for these sandy soils. At this site, over 80% of the total yield variability was due to uncertainties in soil carbon characteristics (SAOC and SASC), mostly due to first order effects. The remaining yield uncertainty (less than 20%) was mostly due to cultivar parameters.

In Damari, Niger, water was the most limiting factor for the treatment used in this study, which received 3,000 kg ha^{-1} of manure. Rainfall was lower and runoff was high due to soil crusting. This was clearly shown by the sensitivity factors. The soil water holding capacity (PAW) was the parameter with the highest first order sensitivity whereas the runoff coefficient (SLRO) was second. Together, the water parameters accounted for about 55% of the yield uncertainty. One very interesting result was the interactive effects of soil water and soil nutrient parameters (Fig. 4.4). Although the first order sensitivities of yield to nutrient parameters were very low (less than 1%), the interactive effects of all of the nutrient parameters were high. Considering these interactions, over 85% of the uncertainty of millet grain yield was accounted for. Sensitivities to cultivar parameters were also very low in this site, accounting for less than 13% of the simulated yield variability.

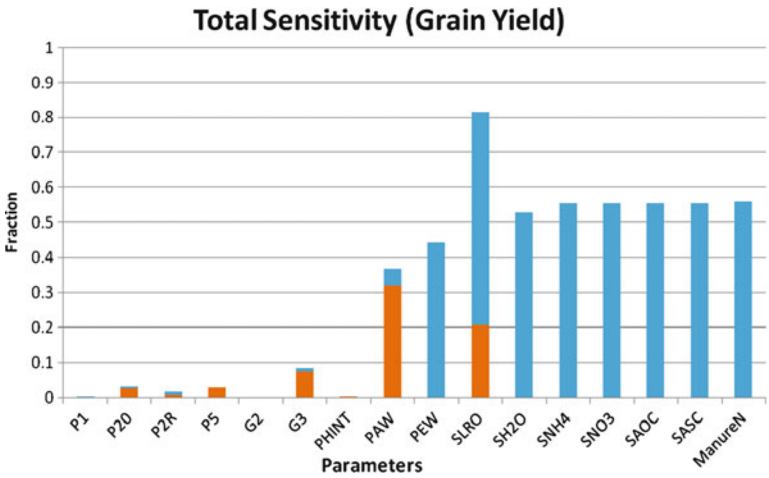

Fig. 4.4 Global sensitivity indices for the Damari, Niger site showing the fraction of total grain yield uncertainty that was due to uncertainties in each parameter. The soil water holding and runoff parameters (*PAW* and *SLRO*) had the highest first order influence on simulated uncertainty in yield at this site. Nutrient parameters also interacted with other parameters when considering total sensitivities

A comparison of sensitivities among sites shows that uncertainties in parameters of factors that limit yield in each site had the highest influence on uncertainties in simulated yields. This information should be considered by those who use cropping system models at locations where yields are low due to one or more limiting factors. Accurate input parameters are needed for those yield-limiting factors. Otherwise, uncertainties in their values can have major effects on uncertainties in simulated yields and other model outputs. This study showed cases where cultivar parameters, soil water parameters, and nutrient parameters can dominate uncertainties in simulated yields, depending on the production situation being studied. Another implication of these findings is that one should not estimate cultivar parameters using observed crop growth variables from studies in which soil limitations restrict crop growth. Varying these cultivar parameters may have little or no effect on simulated crop growth and yield results due to water, nutrient, or other factors that may severely limit growth and yield.

This study showed that sensitivities of simulated yields to soil parameters can dominate those for cultivar parameters in degraded soils and low input cropping systems. In effect, much more attention needs to be paid to the determination of input soil properties than has hitherto been the case. Undoubtedly, the determination of soil properties often entails high costs and is often time consuming. However, recent advances in measurement techniques using simple field soil testing kits should provide a feasible means for data collection in variable landscapes for use in modeling work.

Conclusions

Contributions of factors to simulated overall yield uncertainties in three contrasting production situations were expressed by sensitivity indices in this chapter. Sensitivities due to cultivar parameters were high under intensive management in Florida and low in harsh environments (Ghana and Niger). We also concluded that sensitivities to soil water parameters were low under intensive management (Florida) and nutrient-limited (Ghana) environments, but high in degraded soil of Niger when nutrients were supplied via manure. Sensitivities to C and N parameters were low in Florida and Niger when nutrients were supplied but high in Ghana when no nutrients were applied. Our results showed that some parameters may not have high first order sensitivities yet have major influences on model outputs via interactions with other factors. Sensitivities to soil parameters dominate those for cultivar parameters in degraded soils and low input cropping systems. This study also showed that some parameters may not have high first order sensitivities yet have major influences on model outputs via multi co-linearity and interactions with other factors.

In low input farming systems, other uncertainties that were not considered in this study are likely to be dominant in some situations. In particular, biotic stresses caused by weed competition, plant diseases and insect damage may greatly influence yield, and there are inherent uncertainties in the type, magnitude, and timing of biotic stresses due to the difficulties in measuring and modeling these yield-reducing factors. Uncertainty and sensitivity analysis methods used in this paper to study uncertainties in cultivar and soil inputs can also be used for those factors if the distributions of these factors can be estimated. This research further highlights the need for more attention to uncertainties in model predictions under a range of production situations. Global sensitivity analysis is needed to help ensure that field-scale parameter estimates are anchored in an understanding of model behavior for specific cropping systems.

References

Bationo A, Mokwunye U, Vlek PLG, Koala S, Shapiro BI (2003) Soil fertility management for sustainable land use in the West African Sudano-Sahelian zone. In: Gichuru MP et al (eds) Soil fertility management in Africa: a regional perspective. Academy Science Publisher & Tropical Soil Biology and Fertility, Nairobi, pp 253–292

Bennett JM, Mutti LSM, Rao PSC, Jones JW (1989) Interactive effects of nitrogen and water stresses on biomass accumulation, nitrogen uptake, and seed yield of maize. Field Crop Res 19:297–311

Boote KJ, Jones JW, Batchelor WD, Nafziger ED, Myers O (2003) Genetic coefficients in the CROPGRO-soybean model: links to field performance and genomics. Agron J 95:32–51

Casenave A, et Valentin C (1989) Les états de surface de la zone sahelienne; Influence sur l'infiltration. Les processus et les facteurs de réorganisarion superficielle. (ed) ORSTOM – Institut Français de Recherche Scientifique pour le Développement en Coopération. Collection Didactiques. Paris, pp 65–190

Dzotsi KA, Jones JW, Adiku SGK, Naab JB, Singh U, Porter CH, Gijsman AJ (2010) Modeling soil and plant phosphorus within DSSAT. Ecol Model 221:2839–2849
FAO (2001) Lecture notes on the major soils of the world. World Soil Res Rep. 289 pp
Fatondji D, Bationo A, Tabo R, Jones JW, Adamou A, Hassane O (2012) (this volume) Water use and yield of millet under the zai system: understanding the processes using simulation
Fatondji D, Martius C, Bielders C, Vlek P, Bationo A, Gérard B (2006) Effect of planting technique and amendment type on pearl millet yield, nutrient uptake, and water use on degraded land in Niger. Nutr Cycl Agroecosyst 76:203–217
Gijsman AJ, Hoogenboom G, Parton WJ, Kerridge PC (2002) Modifying DSSAT crop models for low-input agricultural systems using a soil organic matter-residue module from CENTURY. Agron J 94:462–474
Godwin DC, Singh U (1998) Nitrogen balance and crop response to nitrogen in upland and lowland cropping systems. In: Tsuji GY, Hoogenboom G, Thornton PK (eds) Understanding options for agricultural production. Springer, Dordrecht, pp 55–78
Hammer GL, Muchow RC (1991) Climatic risk in crop production: models and management for the semi-arid tropics and subtropics. CAB International, Wallingford, pp 205–232
He J (2008) Best management practice development with the CERES-maize model for sweet corn production in North Florida. PhD dissertation, University of Florida, Gainesville, 329 pp
Hoogenboom G, Jones JW, Wilkens PW, Porter CH, Batchelor WD, Hunt LA, Boote KJ, Singh U, Uryasev O, Bowen WT, Gijsman AJ, du Toit AS, White JW, Tsuji GY (2004) Decision support system for agrotechnology transfer version 4.0, [CDROM]. University of Hawaii, Honolulu
Hunt LA, Pararajasingham S, Jones JW, Hoogenboom G, Imamura DT, Ogoshi RM (1993) GENCALC: software to facilitate the use of crop models for analyzing field experiments. Agron J 85:1090–1094
Jones JW, Hoogenboom G, Porter CH, Boote KJ, Batchelor WD, Hunt LA, Wilkens PW, Singh U, Gijsman AJ, Ritchie JT (2003) The DSSAT cropping system model. Eur J Agron 18(3–4): 235–265
Matthews RB, Stephens W (2002) Crop-soil simulation models: applications in developing countries. CABI Publishing, Wallingford, 280 pp
Monod H, Naud C, Makowski D (2006) Uncertainty and sensitivity analysis for crop models. In: Wallach D, Makowski D, Jones JW (eds) Working with dynamic crop models: evaluation, analysis, parameterization, and applications. Elsevier, Amsterdam, pp 84–87
Naab JB (2005) Measuring and assessing soil carbon sequestration by agricultural systems in developing countries, 2004 annual report. Savanna Agricultural Research Institute, Wa
Naab JB, Koo J, Traore PCS, Adiku SGK, Jones JW, Boote KJ (2008) Carbon Enhancing Management Systems(CEMS): estimation of soil carbon sequestration potential in smallholder farming systems in Northern Ghana. Technical bulletin 2008–3, ABE Department, University of Florida, Gainesville, 11 pp
Porter CH, Jones JW, Adiku S, Gijsman AJ, Gargiulo O, Naab JB (2010) Modeling organic carbon and carbon-mediated soil processes in DSSAT v4.5. Oper Res Int J 10(3):247–278
R Development Core Team (2009) R: a language and environment for statistical computing. R Foundation for Statistical Computing, Vienna. ISBN 3-900051-07-0
Ritchie JT (1998) Soil water balance and plant water stress. In: Tsuji GY, Hoogenboom G, Thornton PK (eds) Understanding options for agricultural production. Springer, Dordrecht, pp 41–54
Ritchie JT, Alagarswamy G (1989) Genetic coefficients for CERES models. In: Virmani SM, Tandon HLS, Alagarswamy G (eds) Modeling the growth and development of sorghum and pearl millet. ICRISAT research bulletin no. 12. ICRISAT, Patancheru, pp 27–34
Ritchie JT, Singh U, Godwin DC, Bowen WT (1998) Cereal growth, development and yield. In: Tsuji GY, Hoogenboom G, Thornton PK (eds) Understanding options for agricultural production. Springer, Dordrecht, pp 79–98
Saltelli A, Tarantola S, Campolongo F, Ratto M (2004) Sensitivity analysis in practice: a guide to assessing scientific models. Wiley, Chichester
SimLab (2005) SimLab Ver. 2.2. Reference manual

Sobol IM (1993) Sensitivity estimates for non-linear mathematical models. Math Model Comp Exp 1(4):407–414

Soil Survey Staff (1998) Keys to soil taxonomy, 8th edn. USDA/NRCS, Washington, DC

Thornton PK, Wilkens PW (1998) Understanding options for agricultural production: systems approaches for sustainable agricultural development. Kluwer, Dordrecht, pp 329–345

Williams JR (1991) Runoff and water erosion. In: Hanks RJ, Ritchie JT (eds) Modeling plant and soil systems. Agronomy monograph #31, American Society of Agronomy, Madison