Available online at www.sciencedirect.com
ScienceDirect
Agricultural Systems 94 (2007) 141–150
AGRICULTURAL SYSTEMS
www.elsevier.com/locate/agsy

Sensitivity of CERES-Maize simulated yields to uncertainty in soil properties and daily solar radiation

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Received 29 August 2005; received in revised form 27 July 2006; accepted 3 August 2006

Abstract

The sensitivity of CERES-Maize yield predictions to uncertainty in a set of soil-related parameters and solar radiation was evaluated in Pergamino, in the Argentine Pampas. Maize yields were simulated for Pergamino using a 31 years climatic record for a range of values of a group of important model input variables. The input variables considered (and the range evaluated) were: soil nitrogen content at sowing (from 20 to 80 Kg ha^{-1}), soil organic matter content (from 1.75% to 4%), soil water storage capacity (from 150 to 200 mm), soil water content at sowing (from 50% to 100% of total available water), soil infiltration curve number (from 76 to 82) and daily solar radiation (from −20% to 12% of the historical values). Then, a sensitivity analysis using a combination of mathematical and graphical approaches was performed to evaluate the model response to changes in the values of the input variables considered. Moreover, a simplified method based on the evaluation of the model sensitivity at extreme values of the input variables is proposed to evaluate the model non-linear responses with a reduced number of runs. Under the scenario evaluated, representative of the typical maize productions systems of the Argentine Pampas, the model results showed higher sensitivity to changes in radiation (normalized sensitivity were −0.69 and 0.45 for rainfed and irrigated conditions, respectively) than for the soil variables (normalized sensitivity ranged from 0.20 to 0.28). The CERES-Maize model was found to have similar sensitivity for the different soil inputs. Furthermore, some of the variables evaluated (soil curve number, soil water content at sowing and radiation under rainfed conditions) showed an important non-linear response.

Keywords: Crop models; Sensitivity analysis; Maize; Soil parameters; Non-linear responses

1. Introduction

Crop growth models have considerable potential in agricultural research, development of cropping technologies, and the exploration of management and policy decisions (Boote et al., 1996). Crop modeling has provided useful insights about the functioning of crops and agricultural systems and, in particular, about the interactions between crops and their environment (e.g., Meinke and Stone, 1997; Hammer, 1998; Hammer et al., 2002; Messina et al., 1999; Jones et al., 2000). Increasingly, crop models are steering scientific research into the genetic regulation of plant performance and guiding crop breeding (Hammer, 1998; Hammer et al., 2002).

An important limitation to a broader, more effective use of crop growth models is our relatively limited knowledge of uncertainty in the models' results. There are several alternative taxonomies of uncertainty sources (Tatang et al., 1997; Katz, 2002). Following Katz (2002), three major sources of uncertainty can be identified: (a) model structure, (b) measurement error, and (c) natural variability. Model structure

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0308-521X/$ - see front matter
doi:10.1016/j.agsy.2006.08.003

errors arise because of inaccurate treatment of modeled processes, inexact numerical schemes, and inadequate resolutions. This type of uncertainty reflects poor understanding of processes that, therefore, are not well represented in a model (Passioura, 1996).

Measurement errors arise when attempting to measure an unknown physical variable. These errors include both those of a random nature whose magnitude reflects the precision of the instrument on which the measurements are based, and those due to systematic error (Katz, 2002).

Natural variability is a major source of uncertainty for most environmental or geophysical variables, as they exhibit real systematic differences over space and time, as well as inherent randomness. Most variables relevant to crop models (e.g., soil nitrogen or water content at sowing) have high spatial and temporal variability which makes the precise estimation of these quantities difficult and costly. Values for a quantity of interest may be available only for a limited number of sites or conditions. Consequently, many inputs to crop models often are derived through indirect measurements, estimations from other variables (e.g., soil infiltration curve number, solar radiation) or measurements or estimations at sites other than the simulation site must be used to fill data gaps, or be considered as representative. The way in which these derived variables are computed may introduce substantial amounts of uncertainty. Both measurement uncertainty and natural variability uncertainty are associated with incomplete or imperfect knowledge of model inputs such as empirical quantities, simulation initial conditions, and boundary conditions (Tatang et al., 1997).

A better knowledge of the impact of uncertainty in input variables on results from crop models may have several advantages. Firstly, it helps identify important uncertainties for prioritizing additional research (Cullen and Frey, 1999). Also, it provides guidance to improve the quality of assessment practices and decision support systems used in agricultural and environmental decision-making, ultimately improving their reliability, transparency and credibility (Tarantola et al., 2002). Perhaps most importantly, the characterization of uncertainty allows an evaluation of the validity and robustness of model results, and thus guides model use as decision support tools.

There are various methods to evaluate the impacts of uncertainty in model input variables, each involving various degrees of complexity, effort, and data requirements. An overview of several of these methods can be found in Katz (2002). In this paper, we focus on sensitivity analysis (Saltelli, 2002), an important technique to estimate how uncertainty in the output of a model (numerical or otherwise) can be apportioned to different sources of uncertainty in the model input. Sensitivity analysis is hence considered by some as a prerequisite for model building in any setting, be it diagnostic or prognostic (Saltelli, 2002). Indeed, the characterization of uncertainty via sensitivity analysis can play a critical role in model verification and validation throughout the process of model development and refinement (Frey and Patil, 2002).

Previous works have dealt with uncertainty in crop models through analyses of the sensitivity of results to variations in input variables such as soil parameters or weather inputs. Liu et al. (1989) carried out a sensitivity test based on available soil, crop and meteorological parameters in Brazil for CERES-Maize (the same model used here). Nonhebel (1994a,b) explored the effects of inaccuracies in temperature and radiation values on results from a model simulating spring wheat growth. Šť'astná and Žalud (1999) explored impacts of three soil input parameters (wilting point, saturated soil water content, and field capacity) on results from the CERES-Maize and MACROS models. Brooks et al. (2001) explored the sensitivity of the Sirius wheat model as a preliminary step leading to the development of a simplified meta-model. Xie et al. (2003) tested the sensitivity of maize and sorghum yields simulated by the Agricultural Land Management Alternatives with Numerical Assessment Criteria (ALMANAC) model in Texas.

The objective of this work is to assess the impact of uncertainty in a group of important (and often difficult/expensive to measure) input variables on maize yields simulated by CERES-Maize, a widely used crop growth model, in the Pampas of Argentina. Two groups of important agronomical model inputs are considered: (i) soil variables (*N* soil content at sowing, soil organic matter content, soil water storage capacity, water soil content at sowing and soil curve number) and (ii) climate variables (daily solar radiation). Moreover, we propose a new approach to evaluate model sensitivity at the extremes of the input variables' range to evaluate potential non-linear model responses without increasing the required number of simulations. We do not address structural uncertainty in this work, thus the CERES-Maize model is treated as a deterministic "black box".

2. Background

2.1. The study area

The geographic focus of this study is the Pampas of central-eastern Argentina (Hall et al., 1992). A large proportion of Argentina's considerable crop production originates in this region. In particular, we consider the area around Pergamino (33°56′ S, 60°33′ W) in the Rolling Pampas, a highly productive region of the Pampas where maize cropping is concentrated (Hall et al., 1992; Paruelo and Sala, 1993). The climate of Pergamino is temperate-humid, with a median annual precipitation of 937 mm, a rainfall maximum in late spring and summer, and a winter minimum. The predominant soils are Argiudolls and Hapludolls (Paruelo and Sala, 1993).

2.2. Sensitivity analysis

Sensitivity analysis (SA) is the study of how the uncertainty in the output of a model (numerical or otherwise) can be apportioned to different sources of uncertainty in the model input. Sensitivity analyses, thus, can be useful for model building in any setting and in any field where models are used (Saltelli, 2002). A thorough description of SA methods can be found in Saltelli et al. (2000). Sensitivity analysis methods have been applied in various fields, including complex engineering systems, economics, physics, social sciences and others (see Saltelli, 1999; Frey and Patil, 2002 for references and examples).

Frey and Patil (2002) identified three major groups of SA methods: mathematical, statistical, and graphical. Our approach involves a combination of mathematical and graphical methods. The mathematical approach allows us to estimate analytical functions that describe precisely the output response to variations in input variables. Derivatives of these functions can be used to estimate sensitivity at the nominal scenario. The graphical approach helps us fit response curves for each input variable and provides an initial qualitative description of non-linearity in the model responses.

Let us identify the output variable (in this case, simulated maize yields) as Y and the input variables as vector $X = (X_1, X_2, \ldots, X_N)$. The sensitivity ($S$) is a measure of change in the model output variable in response to changes in the input variables. Because the variables we consider (see below) have different scales and units of measurement, we use the *normalized sensitivity* as a measure of uncertainty importance. The normalized sensitivity, estimated for each input variable X_j, is defined as the ratio of the relative change in Y by a unit of relative change in X_j (Morgan and Henrion, 1998),

$$S_j = \left[\frac{\partial Y}{\partial X_j}\right]_{X^0} \frac{X_j^0}{Y^0}. \tag{1}$$

The superscript 0, indicates the point $X^0 = (X_1^0, \ldots, X_N^0)$ around which the input variables are varied, referred to as the *nominal scenario*. In addition, let us introduce $Y^0 \equiv Y(X^0)$ as the response value (i.e., maize yield) corresponding to the nominal scenario. The sensitivity is a local indicator which allows us to determine, as long as function Y remains continuous, the first-order response when the input variable changes. For a variation δX_j, the corresponding variation δY is given by

$$\frac{\delta Y}{Y^0} = S_j \frac{\delta X_j}{X_j^0}. \tag{2}$$

The linear approximation (Eq. (2)) is useful when function Y is continuous, with no sharp changes around the nominal scenario. Multiplying both members of Eq. (2) by 100, a relation between errors (expressed as percentage) is obtained:

$$\Delta Y_{\%} = S_j \Delta X_{\%}. \tag{3}$$

If the input variables are assumed to have a statistical distribution (not necessarily Gaussian), the central moment of order two, the variance, gives a measure of the dispersion of values around the statistical mean. The root square of the variance is the standard deviation σ. With the linear approximation, the following relation between standard deviations holds:

$$\sigma_y^2 \approx \sum_{j=1}^{n} \left[\frac{\partial Y}{\partial X_j}\bigg|_{X^0}\right]^2 \sigma_j^2. \tag{4}$$

Using Eqs. (1) and (4) can be rewritten in terms of the sensitivity as

$$\left(\frac{\sigma_y}{Y^0}\right)^2 \approx \sum_{j=1}^{n} S_j^2 \left(\frac{\sigma_j}{X_j^0}\right)^2. \tag{5}$$

As σ_Y and σ_j measure the departure of the variables relative to the mean value, if a proper proportionality constant is introduced, Eq. (5) can be transformed into a relationship between the errors expressed as percentages:

$$\Delta Y_{\%}^2 \approx \sum_{j=1}^{n} S_j^2 \Delta X_{j\%}^2. \tag{6}$$

Eq. (6) indicates that the square of the sensitivity represents the relative weight of the corresponding input variable for the calculation of the total variance of the output.

3. Methodology

3.1. Crop model analyzed

The CERES-Maize model within the DSSAT v3.5 shell (Jones et al., 1998; Ritchie et al., 1998) was used to study the effects of uncertainties associated with input variables in typical maize production systems of the Argentine Pampas. This model has been calibrated and validated in several production environments including the Pampas, where it has shown an average error of 17% in predicted maize yields under field conditions (Guevara et al., 1999; Mercau et al., 2001). The information required to run the CERES-Maize model includes: (i) daily weather data (maximum and minimum temperature, precipitation, solar radiation), (ii) soil parameters, including soil moisture and N content at the beginning of simulations, (iii) a description of crop management, and (iv) "genetic coefficients" that describe physiological processes and developmental differences among crop hybrids or varieties.

3.2. Input variables evaluated

Both weather and soil data are important for crop yields, as they describe the basic energy, resources, and environment for crop growth. Within weather or soil data, there are many variables that differ in their relative importance for yield prediction. When developing input data sets, it is valuable to know which variables are most important for simulation accuracy (Xie et al., 2003). We explored the sensitivity of the CERES-Maize model to uncertainty in two groups of important agronomic variables: (i) soil-related variables and (ii) climatic variables (this group included only one variable: daily solar radiation).

Getting field-level values of these variables often involves difficult measurements or significant costs for equipment (e.g., an automated weather station to measure solar radiation) or laboratory processing (e.g., analyses of soil samples from various locations and depths). For this reason, quantifying the importance or influence of uncertainty in these variables on crop model results and subsequent model-based decisions has practical importance. Below we provide a brief description of each input variable considered.

3.2.1. Soil-related variables

Nitrogen content in the soil at sowing time (expressed as NO^{3-} or NH^{4+}) is important to make decisions on fertilization rates. As N is highly mobile in the soil, concentrations of this nutrient are quite variable in space and time. *Organic matter content in the soil* is relevant to the calculation of fertilization rates, as it is used to estimate Nitrogen gains due to mineralization processes. *Soil water storage capacity* indicates the maximum amount of soil water that can be used by plants. It is calculated as the difference between the soil field capacity and the wilting point. Its value depends on the soil texture, structure, and depth. Higher values indicate soils with more chances to overcome moisture deficits and associated crop stresses. *Soil water content at sowing* indicates the amount of soil water available to the plants at sowing, as a percentage of the water storage capacity. This variable provides information about the crop's resilience to eventual water deficits during the growth cycle. *Soil curve number* indicates the partitioning between runoff and infiltration in a precipitation event. It is estimated based on soil texture, field slope, and tillage used. The CERES-Maize implementation is based on the SCS method (Soil Conservation Service, 1972) with some modifications introduced by Williams et al. (1984). A higher curve number indicates that a greater proportion of precipitation will be lost as surface runoff.

3.2.2. Climate-related variables

Daily solar radiation is usually unavailable or costly to measure at the field. Instead, radiation often must be estimated from other variables (e.g., daily temperature range, precipitation), or values must be used from meteorological stations some distance away. Indeed, the Pergamino radiation values in the weather series used for our crop simulations have been derived from sunshine duration values (see Podestá et al., 2004).

3.3. Nominal values and ranges of input variables

The nominal value selected for each input variable describes the mean or most likely value (Patil and Frey, 2004). Table 1 shows the nominal values chosen, the overall range of explored values, and the steps between values for each input variable considered in the sensitivity analyses.

The nominal values for the soil input variables are typical for the Pergamino region, and their overall range encompassed a large proportion of the observed temporal and spatial variability of each variable in the study area (Hall et al., 1992; Satorre, 2001).

The nominal scenario for radiation values (Table 1) was the daily historical record for 1971–2002. To introduce different levels of uncertainty, the entire vector of historical radiation was multiplied by a series of factors. By multiplying the entire series by a constant factor (which would be analogous to simulating a systematic error in radiation measurements) we did not change the consistency among all weather variables in the daily record. The use of a constant multiplier (rather than adding or subtracting a given value from the series) is justified because radiation residuals were found to be proportional to the mean value (Nonhebel, 1994a). To define the range of uncertainty in daily radiation, we considered the typical errors in estimating this quantity from other data (e.g., at locations where radiation is not observed). Errors in estimating solar radiation from sunshine duration typically are around 10% (Nonhebel, 1994a). However, sunshine duration values are not always available and radiation then must be estimated from commonly observed variables (daily temperature, precipitation). Errors in these estimates are larger than those derived from sunshine duration, and can reach about 20% (Podestá et al., 2004). Such large variability, however, may result in non-physical values (i.e., values greater than the extra-terrestrial radiation, or negative values). For this reason, daily solar radiation was varied between −20% and +12% of the historical values.

3.4. Simulation of maize yields

To explore sensitivity to uncertainty in soil-related variables, the CERES-Maize model was run for each considered

Table 1
List of input variables under study, their units, average values (Nominal Scenario) and amount and range of variation

Variable	Symbol	Unit	Nominal value	Range of variation	Variation step
Nitrogen content at sowing	X_1	Kg ha^{-1}	50.0	$20 \leqslant X_1 \leqslant 80$	5.00
Soil organic matter content	X_2	%	2.5	$1.75 \leqslant X_2 \leqslant 4$	0.25
Water storage capacity	X_3	mm	175.0	$150 \leqslant X_3 \leqslant 200$	5.00
Soil water content at sowing	X_4	%	80.0	$50 \leqslant X_4 \leqslant 100$	5.00
Curve number	X_5	None	79.0	$76 \leqslant X_5 \leqslant 82$	1.00
Daily solar radiation	R	MJ m^{-2} day^{-1}	Estimated values in Pergamino historical series (1971–2002)	−20% to +12%	4%

value of an input variable, while holding the remaining variables at their nominal levels (Table 1). When considering solar radiation, the crop model was run for each modified radiation series, using the observed values for the remaining climate variables (maximum and minimum temperature, precipitation) and holding the soil variables at their nominal values (Table 1). Crop responses to changes in solar radiation may depend on the availability of soil water (Nonhebel, 1994a,b). For this reason, we explored sensitivity to uncertainty in solar radiation for two contrasting scenarios: (i) rainfed conditions (typical of the Pergamino region), and (ii) unlimited water supply (i.e., simulated irrigation) during the entire crop cycle. In contrast, when analyzing sensitivity for soil variables, only rainfed conditions were simulated.

Historical (1971-2002) daily weather data (minimum and maximum temperature, precipitation, solar radiation) for Pergamino were used for the crop simulations. The soil was specified as a typical Argiudol of the Pergamino series, with a depth of 180 cm and water storage capacity of 175 mm in the first 150 cm. The genotype considered was DK 752, sown each year on 15 September at a density of seven plants m^{-2}; these constitute typical management options in current maize production systems in the study area. For the sake of simplicity in the interpretation of results, fertilization was not considered in the simulations. Because the model is unable to simulate insect and disease management and weed competition, crop protection was not analyzed in this work.

For each combination of input variables, 31 simulated maize yields were obtained (one for each cropping cycle in the historical record 1971–2002). The yields for all cropping cycles were averaged and the result was considered as the mean model response to each combination of inputs.

3.5. Exploration of model responses

Simulated yields can be plotted as a function of changes in each input variable. These curves represent sections across a response hyper-surface, and they intersect one another at the nominal scenario. The set of fitted functions may be viewed as an explicit, simplified crop yield metamodel. This contrasts with the non-explicit, deterministic CERES-Maize model used to simulate maize yields.

Analytical functions that describe precisely the output response to variations in each input variable were fitted using the software Mathematica (Wolfram, 1988). For example, when exploring soil-related variables ($X_1, \ldots, X_5$, Table 1), the response curve for variable N content at sowing (variable X_1) is formally represented by the function:

$$Y_1(X_1) = Y(X_1, X_2^0, X_3^0, X_4^0, X_5^0). \tag{7}$$

The function that describes the response curve for daily radiation is

$$Y_R(R) = Y(X^0, R). \tag{8}$$

The normalized sensitivity to variation in daily radiation is calculated as

$$S_R = \frac{100}{Y^0}\frac{\partial Y_R}{\partial R}\bigg|_{X^0, R=0}. \tag{9}$$

The percent error in yield is related to the percent error in variable R through:

$$\Delta Y_{\%} = S_R \Delta R_{\%}. \tag{10}$$

The derivatives of the response functions at the nominal scenario provide a local estimator of sensitivity. As we vary one variable at a time, the derivatives used to estimate sensitivity (shown in Eq. (1)) were approximated by

$$\frac{\partial Y}{\partial X_j}\bigg|_{X^0} \approx \frac{\partial Y_j}{\partial X_j}\bigg|_{X_j^0}. \tag{11}$$

3.6. Non-linear model responses

The approach to sensitivity analysis described above is easy to implement, computationally inexpensive, and useful to understand model behavior, but it is limited in some aspects. For instance, any conclusions drawn on the relation between the output and an individual variable are strictly valid around the nominal scenario, unless the model is known to be linear. In contrast, models simulating plant-environment interactions often are complex, non-linear functions of the multidimensional space of input factors. Further, often there are non-negligible interactions among variables (i.e., the effect of changing X_i and X_j is different from the sum of the individual effects) and different sensitivity patterns may predominate in different regions of the input space. As simple approaches to sensitivity analysis are local linear methods, they do not provide information about such global, non-linear responses.

To overcome some of the limitations of local methods for sensitivity analysis, global methods such as combinatorial or Monte Carlo approaches may be used to evaluate the function for scenarios distant from the nominal scenario or to conduct joint parametric analyses (Morgan and Henrion, 1998). The number of required simulations, however, increases rapidly with the number of scenarios considered and can become prohibitive when using computationally expensive models. An intermediate approach is the nominal range sensitivity (NRS) method, in which each input is varied from its low to its high value while keeping other inputs at their nominal values (Frey and Patil, 2002). The NRS approach is more than a local measure, as it evaluates the model for extreme values of each input, but it is less than global because when exploring the effects of one variable it holds all other inputs at their nominal values (Morgan and Henrion, 1998). However, even the NRS method involves a higher computational burden because the number of simulations increases proportionally to the number of nominal scenarios considered.

We introduce here a new approach that allows us to explore sensitivity beyond the nominal scenario without using complicated methods and without increasing the number of simulations required. Our approach is based on the calculation of derivatives of the fitted response functions $Y_j(X_j)$ at the extremes of the variability range of each variable. Let us take a two-variable example. Instead of evaluating the derivative of Y only at (X_1^0, X_2^0), the idea is to perform the derivation with respect to X_1 also at $(X_{1\min}, X_2^0)$ and $(X_{1\max}, X_2^0)$ and, similarly, with respect to X_2 at $(X_1^0, X_{2\min})$ and $(X_1^0, X_{2\max})$. These derivations can be done without additional model runs; we use the fitted functions described above. In contrast, if the NRS method were used for X_1, new model runs would have to be performed changing X_2 values at the nominal points $(X_{1\min}, X_2^0)$ and $(X_{1\max}, X_2^0)$. The result of this example would be three Y vs. X curves corresponding to each of the three nominal scenarios for X_1. Similarly, the number of required model runs would increase for each additional variable considered.

If the following definitions are made:

$$Y_j^{\min} \equiv Y_j(X_j^{\min}), \text{ and} \tag{12}$$

$$Y_j^{\max} \equiv Y_j(X_j^{\max}), \tag{13}$$

with $X_j^{\min}$ and $X_j^{\max} (1 \leqslant j \leqslant 5)$ being the lowest and highest considered values for variable X_j, sensitivities at the extremes of the range considered can be calculated as

$$S_j^{\min} = \left[\frac{\partial Y_j}{\partial X_j}\right]_{X_j^{\min}} \frac{X_j^{\min}}{Y_j^{\min}}, \text{ and} \tag{14}$$

$$S_j^{\max} = \left[\frac{\partial Y_j}{\partial X_j}\right]_{X_j^{\max}} \frac{X_j^{\max}}{Y_j^{\max}}. \tag{15}$$

$S_R^{\min}$ and $S_R^{\max}$ are calculated using Eq. (9) evaluated in the minimum and maximum of R respectively.

4. Results and discussion

4.1. Sensitivity analysis of soil-related variables

The simulated maize yield at the nominal scenario for all soil variables was 5854 kg ha^{-1} (yields averaged over all years in the historical climate record). Fig. 1a–e show the average maize yields simulated by varying one soil variable at a time while holding the others at their nominal values. Expressions for the analytical functions fitted to these curves and the sensitivity values estimated for each variable are shown in Table 2.

The availability of soil nitrogen increases crop biomass production and growth rate during critical stages, leading to higher yields. For this reason, the simulated maize yields strongly responded to the two nitrogen-related variables considered. Maize yield increased in response to nitrogen content at sowing (X_1; Fig. 1a). Similarly, higher values of soil organic matter were associated with increased maize yields (X_2; Fig. 1b), since the higher the soil organic matter content, the higher the N released through mineralization of organic matter. Maize yields responded strongly to simulated variations in both soil nitrogen and organic matter content because the range of values considered for these variables were relatively low in comparison with the average crop consumption (200–300 kg N ha^{-1}). Yield responses may be less marked with higher N fertilization rates (in this work, fertilization was not simulated).

All three water-related soil variables influence the amount of water available for crop growth, and thus have effects on maize yields. The soil water storage capacity (X_3; Fig. 1c) defines the capacity of the soil to supply water for crop growth in the absence of precipitation or irrigation, and thus influences the ability of the crop to overcome temporary water stresses. Maize yields increased with higher soil storage capacities (Fig. 1c). The amount of water available in the soil at sowing also influences the ability of the crop to withstand water shortages, at least during initial growth stages. Consequently, higher values of soil water available at sowing (X_4; Fig. 1d) also resulted in increased maize yields. Higher soil curve numbers (X_5; Fig. 1e) are associated with a decrease in the proportion of precipitation that infiltrates the soil and becomes available to the crop. Higher curve numbers, therefore, are associated with lower maize yields (Fig. 1e). Variations founded in maize yields in response to changes in water-related soil variables may be modified according to precipitations levels during crop cycle (e.g. responses may be less marked in those years with high precipitation).

From responses showed in Fig. 1a–e and analytical fitted functions describing these responses, we estimated sensitivity of each soil-related variable by differentiating Eq. (11) and replacing the result into Eq. (1). Normalized sensitivities for each variable were:

$$\begin{aligned} &S_1 = 0.25; \quad S_2 = 0.20; \quad S_3 = 0.27; \\ &\quad S_4 = 0.20; \quad S_5 = -0.28. \end{aligned} \tag{16}$$

Now, replacing the last sensitivities into Eq. (6), the percentage error in yield for the study case can be expressed as

$$\begin{aligned} \Delta Y_{\%}^2 \approx{} & (0.25)^2 \Delta X_{1\%}^2 + (0.20)^2 \Delta X_{2\%}^2 + (0.27)^2 \Delta X_{3\%}^2 \\ & + (0.20)^2 \Delta X_{4\%}^2 + (0.28)^2 \Delta X_{5\%}^2. \end{aligned} \tag{17}$$

For all soil variables, the response is attenuated with regards to the introduced uncertainty. For example, if nitrogen content is overestimated by 10%, simulated yields are overestimated by only about 2.5%.

The absolute values of normalized sensitivities for all five soil variables lie in the range 0.2–0.3, suggesting that these variables have comparable importance on the overall uncertainty, at least around the nominal scenario. Saltelli (1999) warned that simple sensitivity analysis approaches cannot be used to rank the impact of different uncertain input variables in determining the variation of the output under examination, unless the model is known to be linear or the range of variation around the nominal scenario is small. However, as the conditions defined for the nominal soil scenario are quite common in the target area, our results provide first-order conclusions about how accurately each variable should be described to realistically simulate grain yields.

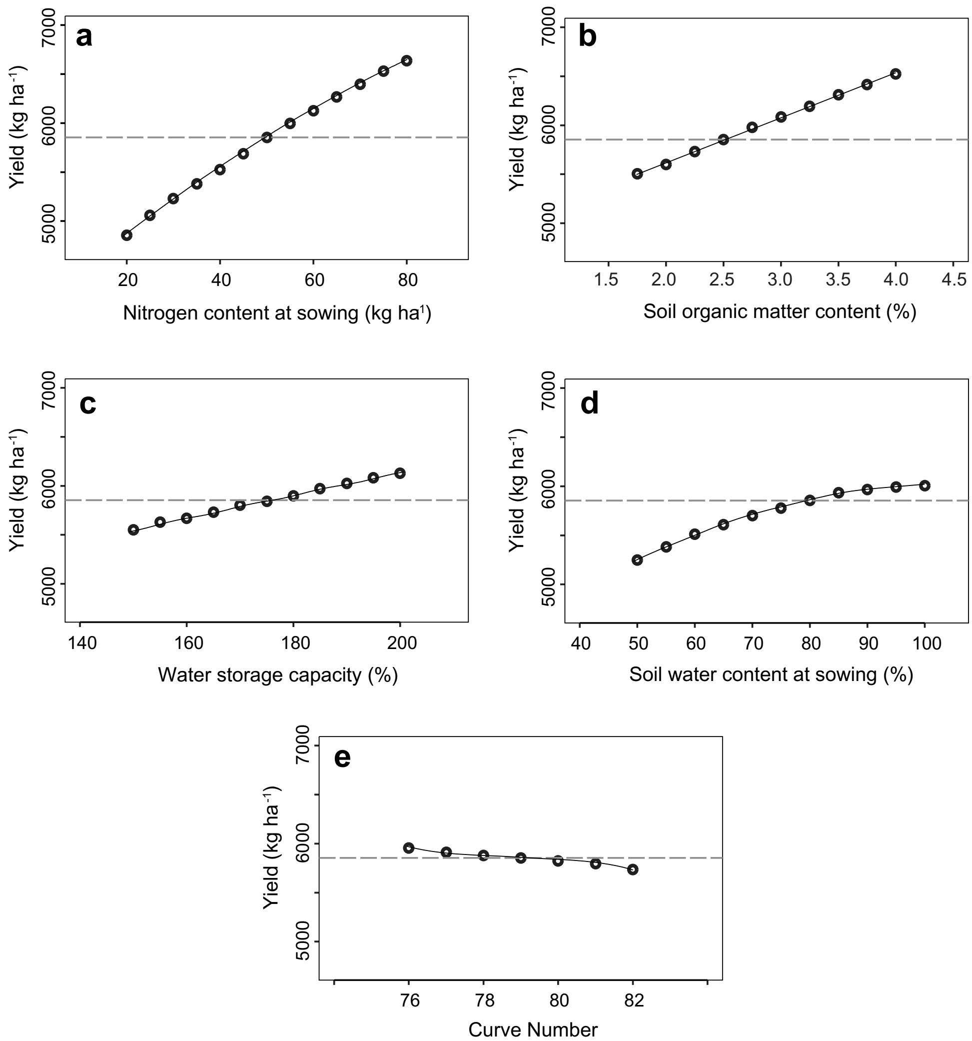

Fig. 1. Maize yield variations in response to changes in different soil input variables: (a) yield variations in response to different levels of nitrogen content at sowing, (b) yield variations in response to changes in soil organic matter content, (c) yield variations in response to changes in soil water storage capacity, (d) yield variations in response to changes in soil water content at sowing, and (e) yield variations in response to changes in the soil curve number parameter. The points correspond to simulated values and lines to equations in Table 2.

Table 2
Yield functions Y and sensitivity S of each variable analyzed

	$Y(x)$	S
Soil-related parameters (X)		
Nitrogen content at sowing (X_1)	$Y_1(X_1) = 4117 + 39.63X_1 - 0.10X_1^2 - 1.40\sin(\pi X_1/10)$	0.25
Soil organic matter content (X_2)	$Y_2(X_2) = 4702 + 458.4X_2$	0.20
Water storage capacity (X_3)	$Y_3(X_3) = 3575 + 14.45X_3 - 0.08X_3^2 - 6.64\sin[\pi(X_3 - 175)/8]$	0.27
Soil water content at sowing (X_4)	$Y_4(X_4) = 3234 + 52.87X_4 - 0.25X_4^2 + 5.89\sin[\pi X_4/10]$	0.20
Curve number (X_5)	$Y_2(X_2) = 8443 + 42.39X_2 - 0.95X_2^2 + 214.6\sin[\pi(X_2 - 79)/6] - 31.26\sin[\pi(X_2 - 79)/3]$	−0.28
Radiation (R)		
80% of water content at sowing and rainfed	$Y_{Rr}(X_{Rr}) = 5844.88 - 40.68R - 0.65R^2$	−0.69
Irrigation	$Y_{Ri}(X_{Ri}) = 8170.23 + 37.13R + 7.85\cos\left(\frac{\pi R}{4}\right)$	0.45

4.2. Sensitivity analysis of daily solar radiation

The simulated maize yield at the nominal scenario for daily solar radiation under rainfed conditions was 5854 kg ha^{-1} (yields averaged over all years in the historical climate record). For the simulations assuming irrigation, the average simulated maize yield was 8202 kg ha^{-1}. Fig. 2a–b show average maize yields simulated by varying daily solar radiation while holding the remaining climate variables at their historical values and soil variables at nominal values; the two panels correspond to rainfed (a) and irrigated (b) conditions respectively. Expressions for

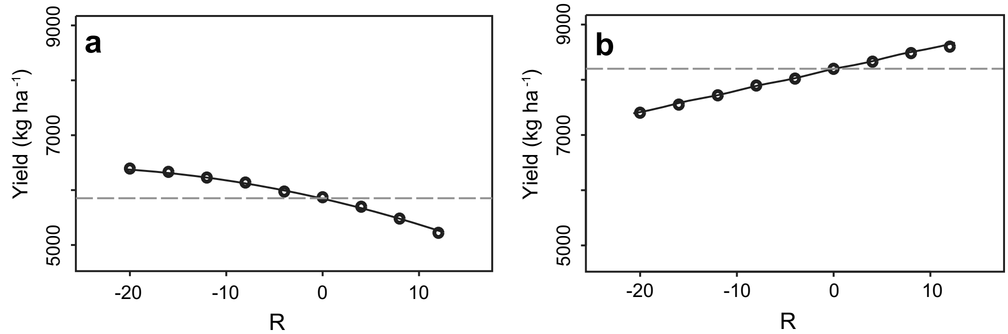

Fig. 2. Maize yield variations in response to changes in daily solar radiation under two cropping water conditions: (a) 80% of soil water content at sowing and rainfed, and (b) unlimited water supply (crop irrigated along the entire cycle). The points correspond to simulated values and lines to equations in Table 2.

the fitted analytical functions, together with the estimated sensitivity values, are shown in Table 2.

The response of maize yield to different radiation levels depends on the availability of soil water. Under non-limiting water conditions, higher radiation values help to maintain higher photosynthesis rates during the entire crop cycle, resulting in greater biomass production and yields. In contrast, under water-limited conditions higher radiation values increase soil evaporation and plant transpiration during early crop stages. As a result, the amount of water available during the crop's critical stages (i.e., silking and start of grain filling) may be lower, resulting in higher likelihood of water stress and low yields. These results are consistent with those obtained by Nonhebel (1994a,b) for simulated irrigation and rainfed conditions for spring wheat. Xie et al. (2003) observed that variability in solar radiation resulted in smaller variations in maize yields under irrigated conditions than for a rainfed scenario.

The sensitivity of the CERES-Maize model to changes in radiation seems to be higher than for the soil-related variables (normalized sensitivities are −0.69 and 0.45 for rainfed and irrigated conditions, versus 0.20–0.28 for the soil variables). For the rainfed situation, an overestimation of global radiation produces an underestimation in yield, whereas the opposite occurs for the irrigated condition.

4.3. Non-linear responses

Estimated sensitivities at the extremes of the range for each input variable are shown in Fig. 3. Two major response patterns appear to exist for the evaluated variables: near-linear and non-linear. Simulated yields showed

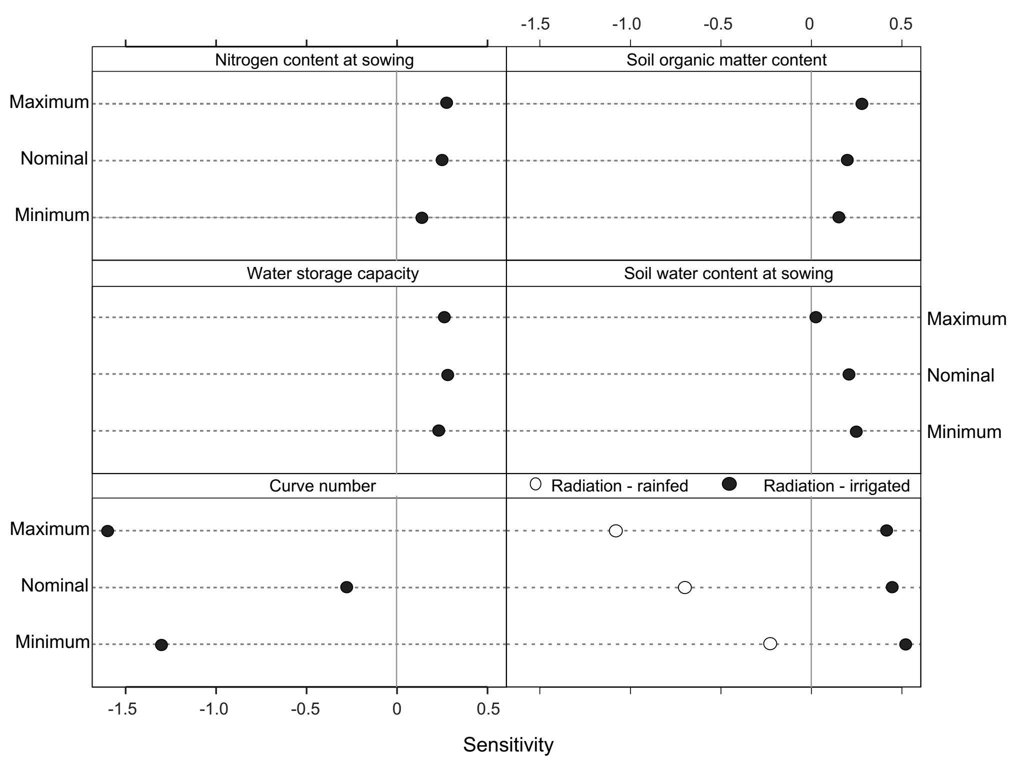

Fig. 3. Sensitivities of maize yield predictions in the central (nominal values) and extremes points.

a near-linear response to variations in N content at sowing (X_1), organic matter content (X_2), water storage capacity (X_3) and changes in radiation under irrigated conditions. That is, sensitivities for these variables did not change much throughout the range of variability considered. The lack of noticeable change in sensitivities may be due to the fact that, under conditions typical of the target area, the range of values explored for soil variables is not large enough to reach saturation in crop responses to N levels or water content. However, the estimated sensitivities could change under different conditions. For example, higher fertilization rates would decrease the importance of initial nitrogen content or N inputs from mineralization of organic matter. Similarly, sensitivity to water-related variables would decrease in years with high precipitation.

Non-linear simulated responses are most apparent for soil water content at sowing (X_4), soil curve number (X_5), and radiation under rainfed conditions. These results are consistent with those shown in Figs. 1d and e, 2c, where relatively marked changes are observed for the slopes of the functions fitted to simulated yields. At the extremes of the range of values considered for soil curve number, the estimated sensitivities are lower than -1. Because of its high normalized sensitivity, one may think that uncertainty in curve number would magnify greatly the errors in simulated yields. Nevertheless, as the uncertainty for soil curve number is lower than for other variables analyzed (this is reflected in the narrow range of values considered), the impacts on overall error in yields will be limited.

5. Summary and conclusions

An important limitation to a more effective use of crop growth models is our relatively limited knowledge of uncertainty in the models' results. Surprisingly, despite the wide use of these models in many regions and for many purposes, there is a relatively small body of literature (see Section 1) on the effects of uncertainty in input variables on model results.

A sensitivity analysis approach was used to evaluate the response of yields simulated by the CERES-Maize crop model to uncertainty in a set of important soil and climatic input variables. A combination of mathematical and graphic approaches allowed us to define the basic shape of responses to changes in each input variable and, subsequently, to fit analytic functions that described those responses. The fitted curves may be viewed as part of an explicit, simplified crop yield meta-model, and thus can be used to replace model simulations in some situations. Near the nominal scenario, all soil variables considered have comparable incidence on yield uncertainty. In contrast, the effects of uncertainty in solar radiation appear to be more important on simulated yields than those of soil variables. However, even for radiation, possible errors in the input variables around the central values would be dampened by the model.

Simple approaches to sensitivity analysis often involve local linear methods that do not provide information about potential non-linear model responses. Various approaches have been proposed to address this shortcoming, but the number of simulations required often increases rapidly and can become prohibitive when using computationally expensive models. In this paper we introduce a new approach to explore sensitivity beyond the nominal scenario without increasing the number of simulations required. The approach is based on the calculation of derivatives of fitted response functions at the extremes of the variability range of each variable. Application of the proposed approach helped us identify portions of the input variable space (e.g., high or low soil curve numbers) where uncertainty is actually magnified by the model and interpretation of results should be careful.

The characterization of uncertainty in model responses to input variables has important implications for model design and interpretation, and for future data collection efforts. The variability in simulated yields that occurs over the range of uncertainty of the inputs represents a fundamental limit to the accuracy that models can achieve. Thus, there are likely to be no benefits for yield prediction by including excessive detail in crop models (Brooks et al., 2001). Also, understanding the impact of uncertainty of different variables on model results helps to set priorities for collection of enhanced input data sets. For instance, the large importance on crop model results of solar radiation values (detected in this work and others) suggests that attention should be focused on improving the availability and quality of radiation observations or estimations. Further, the characterization of uncertainty, together with a realistic assessment of the quality of available input data, allows an appropriate evaluation of the validity and robustness of model results, and guides interpretation of results for decision support.

Acknowledgement

This work was supported by funds from the US National Science Foundation's Biocomplexity in the Environment program (grants 0119851 and 0410348). Additional funds were provided by NOAA's Office of Global Programs Climate and Societal Interactions program. F.E.B is doctoral fellow and E.H.S. is a researcher from Argentina's National Council for Science and Technology (CONICET).

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