Environmental Modelling & Software 48 (2013) 171–182

Contents lists available at SciVerse ScienceDirect

Environmental Modelling & Software

journal homepage: www.elsevier.com/locate/envsoft

Parameter sensitivity analysis of crop growth models based on the extended Fourier Amplitude Sensitivity Test method

Jing Wang[a,b], Xin Li[a,*], Ling Lu[a], Feng Fang[c]

[a] Cold and Arid Regions Environmental and Engineering Research Institute, Chinese Academy of Sciences, Lanzhou, China
[b] Lanzhou Institute of Arid Meteorology, China Meteorological Administration, Key Laboratory of Arid Climatic Change and Reducing Disaster of Gansu Province, Key Open Laboratory of Arid Climate Change and Disaster Reduction of China Meteorological Administration, Lanzhou, China
[c] Lanzhou Regional Climate Center, Lanzhou, China

ARTICLE INFO

Article history:
Received 17 March 2012
Received in revised form
16 June 2013
Accepted 19 June 2013
Available online

Keywords:
Extended FAST
WOFOST crop growth models
Sample size
Parameter variation range
Time-dependent properties
Multivariable output

ABSTRACT

Sensitivity analysis (SA) has become a basic tool for the understanding, application and development of models. However, in the past, little attention has been paid to the effects of the parameter sample size and parameter variation range on the parameter SA and its temporal properties. In this paper, the corn crop planted in 2008 in the Yingke Oasis of northwest China is simulated based on meteorological observation data for the inputs and statistical data for the parameters. Furthermore, using the extended Fourier Amplitude Sensitivity (EFAST) algorithm, SA is performed on the 47 crop parameters of the WOrld FOod STudies (WOFOST) crop growth models. A deep analysis is conducted, including the effects of the parameter sample size and variation range on the parameter SA, the temporal properties and the multivariable output issues of SA. The results show that sample size highly affects the convergence of the sensitivity indices. Two types of parameter variation ranges are used for the analysis, and the results show that the sensitive parameters of the two parameter spaces are distinctly different. In addition, taking the storage organ biomasses at the different growth stages as the objective output, the time-dependent characteristics of the parameter sensitivity are discussed. The results show that several sensitive parameters exist in the grain biomass throughout the entire development stage. In addition, analyzing the twelve sensitive parameters has proven that although certain parameters have no effect on the final yield, they play key roles in certain growth stages, and the importance of these parameters gradually increases. Finally, the sensitivity analyses of different state variable outputs are performed, including the biomass, yield, leaf area index, and transpiration coefficient. The results suggest that the sensitive parameters of various variable processes differ. This study highlights the importance of considering multiple characteristics of the model parameters and the responses of the models in specific phenological stages.

1. Introduction

Crop growth models are a valuable tool for the quantitative analysis of the growth and production of crops and play an important role in crop monitoring, crop yield prediction, field management recommendations, agricultural production potential evaluation, and climate change impact evaluation (Batchelor et al., 2002; Donatelli et al., 2002; Houles et al., 2004; Bouman and van Laar, 2006; Varella et al., 2010). Crop growth models primarily simulate the growth and development of crops, and they encompass the primary biophysical and biochemical processes in the soil–crop–atmosphere system, such as photosynthesis, respiration, transpiration, dry matter partitioning and senescence.

In general, crop growth models are simplifications of the agri-ecological systems that they represent and include many parameters, the determination of which is a major problem for practical operational applications (Makowski et al., 2006). Most parameters are acquired through field observations, which are costly and time consuming (Hsiao et al., 2009), and the acquisition of certain parameters is difficult. Alternative methods are directly derived from

* Corresponding author. Cold and Arid Regions Environmental and Engineering Research Institute, Chinese Academy of Sciences, 320 West Donggang Road, Lanzhou 730000, Gansu Province, China. Tel.: +86 931 4967249; fax: +86 931 4967250.
E-mail addresses: wangjing1102@126.com (J. Wang), lixin@lzb.ac.cn (X. Li).

1364-8152/$ – see front matter © 2013 Elsevier Ltd. All rights reserved.
http://dx.doi.org/10.1016/j.envsoft.2013.06.007

related studies (Confalonieri et al., 2006; Ceglar et al., 2011), but many parameters vary with the environmental conditions, crop cultivars, seasonal variation, and other factors (Confalonieri et al., 2010b; Ceglar et al., 2011; Zhu et al., 2011). Additionally, it is unrealistic to directly apply these parameters to different locations, and model predictions based on inaccurate parameter values are unreliable and not especially meaningful. All of these factors influence the accuracy of the model outputs, and accurate parameter estimation is thus necessary (Guerif and Duke, 2000; Guerif et al., 2006). Many parameter estimation algorithms have been developed, such as the simulated annealing algorithm, genetic algorithm, and Bayesian approaches (Li et al., 2004; Su et al., 2009; Zhu et al., 2011). To a certain extent, these methods solve the problem of difficult-to-acquire parameters, and thus the methods are quite efficient but applicable only to a small number of parameters (Varella et al., 2010). Therefore, the inclusion of many parameters in a single complex crop growth model also presents a problematic observation: it is nearly impossible to simultaneously estimate all of the unknown parameters. In fact, a small number of model parameters are often responsible for most of the variability of the model outputs, whereas most of the other parameters may have only small influences. Therefore, an efficient method for parameter reduction is required (Manache and Melching, 2008; Post et al., 2008). The parameter sensitivity analysis (SA) method is capable of playing this role in identifying sensitive parameters, which is beneficial and allows concentrating efforts on calibrating the sensitive parameters. Those factors with a small contribution may be set to a default value or an observed value. In addition, based on the SA, the balance and robustness of the model can be analyzed for the future improvement and development of the model (Fraedrich and Goldberg, 2000; Confalonieri et al., 2010c). Thus, the parameter SA method has been demonstrated as a beneficial means for understanding, improving and applying models (Chu-Agor et al., 2011; Hirabayashi et al., 2011). In early studies, the parameter SA algorithm was mainly applied to complex hydrological models (Francos et al., 2003) and was subsequently widely expanded to various ecological, crop and environmental models (Asseng et al., 2004; Confalonieri et al., 2006, 2010a; Feyereisen et al., 2006; Luquet et al., 2006; Van Griensven et al., 2006; Wang et al., 2006; Cariboni et al., 2007; Annoni et al., 2011; Miao et al., 2011; Vardit et al., 2011; Sun et al., 2012).

The SA of model parameters is conducted by altering the parameters and observing the corresponding responses in the output variables. Over the past few years, studies of parameter sensitivity have received much critical attention. Many of these studies centered on the development of the SA algorithm (Cukier et al., 1978; Mckay et al., 1979; Yen et al., 1986; Morris, 1991; Sobol, 1993; Saltelli et al., 1999; Van Griensven et al., 2006; Makler-Pick et al., 2011). At first, parameter SA was used to identify the sensitive parameters for model reduction. A local sensitivity method was proposed and obtained by varying one input factor at a time while holding the others fixed at a nominal value. Because this method is efficient, quick and easy to use, it has been commonly applied in many disciplines. Together with the increasingly deep knowledge of model structure and performance, factor interactions have attracted increasing attention. Thus, the concept of global SA was proposed, many global SA algorithms were developed and research in this field has shown considerable progress (Fieberg and Jenkins, 2005; Saltelli et al., 2008). Compared with the local SA algorithms used previously, the global SA method highlights its ability to analyze the output uncertainties over the entire parameter space and determine the comprehensive effects of the parameters on the output. Global SA methods may be divided into three types: screening, regression-based and variance-based (Confalonieri et al., 2010a; Yang, 2011). The screening method is capable of providing parameter rankings, whereas the variance-based method is able to quantify the amount of variance that each parameter contributes to the unconditional variance of the model output (Saltelli et al., 2009). Due to its advantages, the global SA method is quite popular in various fields of science (Ginot et al., 2006; Benson et al., 2008; Manache and Melching, 2008; Miao et al., 2011). However, the global SA algorithm also displays a well-known shortcoming: its heavy computational burden. Together with the enhancement of the knowledge of crop biological processes and their relationships with the ecological environment, more complex processes have been included in the crop growth models with each run; however, these runs require a great deal of time, and performing SA on crop models is thus quite time-consuming. Therefore, scientists have turned to research on the enhancement of the algorithm's efficiency and practicability. The improvement of the sampling strategy is a highly important step with distinct effects on computational efficiency (Helton et al., 2005; Campolongo et al., 2007; Castaings et al., 2012). For example, Helton et al. (2005) suggested that in a complex system, Latin hypercube sampling is preferable over random sampling. However, based on the metamodels, emulation technology has become an important and increasingly expanded area of sensitivity analysis and can also be used to estimate the sensitivity indices (Borgonovo et al., 2012; Ciric et al., 2012; Ratto et al., 2012; Villa-Vialaneix et al., 2012).

In addition, certain scientists place additional emphasis on this question throughout the entire application process. For example, the convenience and simplicity of performing SA have been highlighted. Based on these requirements, a specific software program known as SimLab has been developed for implementing the SA algorithm (SimLab, 2009), and certain studies have focused on the analysis of SA results for different locations, crop varieties, field management, and climate zones (Francos et al., 2003; Confalonieri et al., 2010b; Foscarini et al., 2010; Richter et al., 2010). Francos et al. (2003) proposed that the sensitivity of the model output to its input parameters might depend on the value and range of the variation of the investigated parameters. Based on the global sensitivity analysis combined with the Latin-hypercube and one-factor-at-a-time methods, Van Griensven et al. (2006) analyzed the sensitivity of catchment models for two catchments and showed that the parameter rankings were dependent on the variables, location and time period of the simulation. Confalonieri et al. (2010a) believed that the key to SA is that it should occur in a context that describes the soil and weather environment under modeling and must explicitly declare the conditions. DeJongea et al. (2012) compared the respective parameter sensitivities under irrigation and non-irrigation conditions. According to the results of the cited study, for the full irrigation treatment, the most sensitive parameter is that of the crop cultivar, whereas for the limited irrigation treatment, the parameter of water holding capacity is the most sensitive. A conclusion may also be drawn from the works of Luquet et al. (2006) and Confalonieri et al. (2006), which stated that the results of SA depend on the model complexity and the number of crop parameters included in the analysis and the environment. In addition, certain research works have focused on the convergence of parameter sensitivity measures (Annoni et al., 2011; Benedetti et al., 2011; Yang, 2011; Tarantola et al., 2012). For example, Nossent et al. (2011) showed that the choice of calculation for the Monte Carlo integrals could highly affect the convergence of the sensitivity analysis results. Sieber and Uhlenbrook (2005) also examined the statistical convergence of sensitivity analysis with increasing sample size and determined the sample size. The above studies prove that when performing SA, many impact factors must be considered to obtain a reliable factor importance ranking, including the parameter sample size, the natural properties of the parameters and the models, environment, and crop variety.

Furthermore, in the parameter sensitivity analysis of crop growth models, the yield and aboveground biomass at maturity are usually set as the objective outputs, and the parameter space is usually derived from the reference or ground observations. However, few studies of SA have focused on the parameter sensitivity during the process of crop growth, other variable outputs, or the effects of the parameter space on SA. Lamboni et al. (2009) used the ANOVA method to perform dynamic parameter SA on the winter wheat dry matter model (WWDM) and the CERES-EGC model and proposed that the values of the sensitivity indices vary widely over time. The actual function of the parameters can be examined by observing the sensitivity variation of each parameter and the sensitivity of other outputs. Therefore, the dynamic assessment of the parameter sensitivity of crop growth models can provide new insights into the models and model structures and is thus beneficial to model improvement and development.

The main objective of this study is to examine the influence of the natural properties of the parameters and models on the parameter SA results in crop growth models. In this work, the natural properties primarily note the parameter variation range, temporal characteristics and multivariable output of the models. In addition, the impact of the parameter sample size on the convergence of the sensitivity measures is discussed. With its generic characteristic, the WOrld FOod STudies model (WOFOST) has become popular worldwide (Van Keulen and Wolf, 1986; Supit et al., 1994). In this study, the WOFOST model is used for parameter SA, and a global SA algorithm known as the extended Fourier Amplitude Sensitivity Test (EFAST) is adopted for parameter sensitivity.

The remainder of the paper is organized as follows. The theoretical backgrounds of the WOFOST model and the sensitivity analysis method as well as the data required for model runs are briefly introduced in the Materials and methods section. This section also includes four numerical experiment schemes for the parameter SA: the convergence of the SA with increasing sample size, the impact of the parameter variation range on the parameter SA, the temporal characteristics of the parameter SA, and the parameter sensitivity of multivariable outputs. The results of this study are described in detail in the Results and discussion section. Finally, the last section summarizes the main observations of the study and suggests lines for further research.

2. Materials and methods

2.1. WOFOST crop growth models

The WOFOST model is a mechanistic crop growth model developed by Wageningen University in the Netherlands and is derived from the SUCROS model (Van Keulen et al., 1982). Based on different crop parameters, the WOFOST model may be applied to most crops. The WOFOST model is a classical light-use efficiency model, which simulates crop growth as a function of irradiation, temperature and crop properties. It describes plant growth using the phenological development of the crop as a growth control factor and uses light energy and CO_2 assimilation as growth driving processes. Next, the daily dry matter accumulation is calculated, and each organ of the plant is constructed using the partition factor. The WOFOST model encompasses the primary biophysical and biochemical processes. The output values are the daily crop growth rates, and the growth status is determined via time integration. The three crop development stages (DVS) are expressed using dimensionless variables, with zero representing emergence, one representing anthesis, and two representing maturity. The WOFOST model is capable of simulating both the potential and water-limited production conditions. An optimal water supply is assumed in the potential condition. The water-limited growth effect is represented by the ratio of actual evapo-transpiration to potential evapo-transpiration. The implementation and detailed structure of the WOFOST model have been described by Supit et al. (1994).

The WOFOST model provides the default crop parameter sets for different crops. For detailed parameter definitions, the reader may refer to the WOFOST model document. Certain parameters of the WOFOST model are organized in tables, and their values are altered according to the crop's phenological stages, which are determined by the accumulation of thermal time and include the specific leaf area (SLATB), the maximum leaf CO_2 assimilation rate (AMAXTB), and other biomass partition parameters. For these parameters, the specific parameter values during key periods are provided in the parameter file. For example, for the parameter SLATB, the parameter file provides the SLATB at the DVS of 0.00, 0.78 and 2.00, and the $SLATB_{0.00}$, $SLATB_{0.78}$ and $SLATB_{2.00}$ are subsequently treated as three parameters. In addition, certain parameters, e.g., the reduction factor for the maximum leaf CO_2 assimilation rate (TMPFTB), are also functions of the mean temperature, and the management of these factors is similar to that of the SLATB.

2.2. Data and management

The crop growth simulation scenario is assumed for a 2008 implementation in the Yingke Oasis of Gansu Province in northwestern China, which is a major irrigated agricultural region. The climate in this region is temperate, with a mean annual temperature of 7.6 °C, a mean annual precipitation of 117 mm and a mean annual evaporation of 2390 mm. The soil of this region is sandy loam, and corn is the main grain crop (Yang and Liu, 2010) and has therefore been chosen as an example crop for simulation using WOFOST in this study.

Meteorological data are taken from an automated weather station (AWS) located at the Yingke experimental station (100°25′E, 38°51′N) (Li et al., 2009, 2011). This AWS provides measurements of the maximum and minimum air temperature, precipitation, daily total solar radiation, relative humidity, and wind speed and direction, and these data have been pre-processed for driving crop growth models. Every phenological stage of corn is recorded as well. Based on these meteorological data and phenological investigations, two phenological parameters are computed, TSUM1 and TSUM2, which are, respectively, the effective temperature sum from emergence to anthesis and from anthesis to maturity.

Corn was hole seeded on April 20 and harvested on September 22 in 2008. The row spacing was 55 cm, and the plant spacing was 22 cm. Detailed field management measures at the experimental station, such as the irrigation amount and fertilization amount, are listed in Table 1. Throughout the entire growth period, the amounts of irrigation and fertilizer were sufficient with an irrigation amount that reached 885 mm and a fertilizer amount that completely met the nutrient needs of the crops.

In addition, the required soil input data, i.e., the soil physical properties, soil water retention, and hydraulic conductivity, were obtained during the investigation at the local agro-meteorological experimental station, and the groundwater level was obtained from the local water service department. Due to the relatively deep groundwater level in the region, the WOFOST model was used without consideration of the groundwater.

2.3. Sensitivity analysis method

The EFAST is a global and quantitative SA algorithm that may be applied to complex nonlinear and non-monotonic models (Saltelli et al., 1999, 2010). In this study, the EFAST is used to analyze the parameter sensitivity of the WOFOST model for corn. The main sensitivity index and total sensitivity index of each parameter are obtained via an analysis of the impacts of the input factors on the output variance. The method is developed based on the Fourier Amplitude Sensitivity Test (FAST) algorithm and Sobol's algorithm. The FAST provides a high-efficiency sampling

Table 1
Field management measures at the Yingke experimental station from 2008.

Irrigation		Fertilizer				
Date	Irrigation amount	Date	Fertilizer name	Fertilizer amount	Nitrogen amount	Phosphorus amount
May 18	150 mm	April 5	Diammonium phosphate	300 kg ha^{-1}	21.2%	23.5%
June 15	150 mm	April 5	Organic fertilizer	6 m^3 ha^{-1}	1.6%	0.68%
July 16	180 mm	May 16	Diammonium phosphate	225 kg ha^{-1}	21.2%	23.5%
August 15	180 mm	May 16	Complex-fertilizer	225 kg ha^{-1}	10%	10%
September 8	225 mm	June 15	Urea	225 kg ha^{-1}	46%	
		June 15	Complex-fertilizer	225 kg ha^{-1}	10%	10%
		August 14	Ammonium nitrate	525 kg ha^{-1}	35%	

method based on a suitably defined search curve, which is capable of scanning the entire parameter space and obtaining the quantitative sensitivity measures in terms of the individual contributions of each parameter to the output variance. However, the FAST method is not able to calculate the higher interaction terms of the parameters with respect to the output variance. Sobol's algorithm is capable of calculating the total sensitivity index and provides an indication of the overall effect of a given parameter by considering all possible interactions of that parameter with the others (Sobol, 1993). However, Sobol's method uses the Monte Carlo method, which carries a high computational demand. Therefore, by integrating the merits of FAST and Sobol's algorithm, the EFAST provides a method that possesses the characteristics of high efficiency and accuracy in addition to the ability to compute the interaction effects among parameters. In recent years, due to these advantageous properties, the EFAST has recently become more popular in hydrological, ecological, and meteorological modeling (Varella et al., 2010; Miao et al., 2011; Reusser et al., 2011; Pandya et al., 2012). The source code for EFAST can be downloaded from the website http://sensitivity-analysis.jrc.ec.europa.eu/software/index.htm.

Because it is a variance-based method, the EFAST algorithm primarily includes two steps: sampling and sensitivity index calculation (Chan et al., 1997; Saltelli et al., 1999). First, a highly efficient and uniform sampling procedure is performed via a transformation function. Next, using the Fourier Amplitude Sensitivity Test, the quantitative sensitivity indices are obtained. The main formulations are given as follows:

$$E(Y) = \frac{1}{2\pi}\int_{-\pi}^{\pi} f(s)\mathrm{d}s \tag{1}$$

$$Var(Y) = \frac{1}{2\pi}\int_{-\pi}^{\pi} f^2(s)\mathrm{d}s - [E(Y)]^2 \approx \sum_{j=-\infty}^{\infty}\left(A_j^2+B_j^2\right) - \left(A_0^2+B_0^2\right) \approx 2\sum_{j=1}^{\infty}\left(A_j^2+B_j^2\right). \tag{2}$$

where $E(Y)$ and $Var(Y)$ is the expected value and variance of the output Y, s is a scalar variable varied over the range $-\infty < s < +\infty$; A_j and B_j are the Fourier coefficients over the domain of integer frequencies $j \in \{-\infty,\ldots,-1,0,1,\ldots,+\infty\}$, the expressions for which are as follows:

$$A_j = \frac{1}{2\pi}\int_{-\pi}^{\pi} f(s)Cos(js)\mathrm{d}s, \tag{3}$$

$$B_j = \frac{1}{2\pi}\int_{-\pi}^{\pi} f(s)Sin(js)\mathrm{d}s \tag{4}$$

$$\widehat{Var}_i(Y) = 2\sum_{j=1}^{\infty}\left(A_{jw_i}^2 + B_{jw_i}^2\right), \tag{5}$$

$$\widehat{Var}(Y) = 2\sum_{j=1}^{\infty}\left(A_j^2 + B_j^2\right), \tag{6}$$

$$S_i = \widehat{Var}_i(Y)/\widehat{Var}(Y), \tag{7}$$

$$ST_i = 1 - \frac{\widehat{Var}_{(-i)}(Y)}{\widehat{Var}(Y)}, \tag{8}$$

$$C = nN_s = nN_r(2M\omega_{\max}+1). \tag{9}$$

where $\widehat{Var}_i(Y)$ is the estimated conditional variance of the ith factor, $\widehat{Var}_{(-i)}(Y)$ is the estimated conditional variance except for the ith factor, S_i is the main sensitivity index of the ith factor, ST_i is the total sensitivity index of the ith factor, n denotes the number of parameters, N_s is the sample size, N_r is the search curve number of the resampling scheme, M is the interference factor (set to 4), $\omega_{\max}$ is the largest among the set of ω_i frequencies, and C is the number of model evaluations needed to complete a numerical experiment of SA. A higher frequency is set for the analyzed factor, and a lower frequency is set for other parameters. According to the discussion on the frequency and search curve by Saltelli et al. (1999) and selected numerical experiments, the frequency of the parameter of interest and other parameters as well as the search curve numbers are determined according to the relationships among ω_i, N_r and M.

2.4. Sensitivity analysis numerical experiment

Four numerical experiment schemes of the parameter SA in the WOFOST model are designed and described in detail in the following section.

2.4.1. The impacts of sample size on the convergence of the sensitivity measures

During the parameter SA process, sampling is a highly important step for exploring the interest domain, and the sample size determines the number of model evaluations. The high number of model evaluations needed to perform the parameter sensitivity analysis restricts the method's use; as a consequence, the relationship between the sample size and the convergence of the sensitivity measurement is of the utmost importance.

Therefore, to assess the influence of sample size on the convergence of the sensitivity indices, the evolution of the sensitivity index values is investigated in this paper for all parameters with increasing sample size. For this research, we design nine cases for the sample size, i.e., the frequency assigned to the factor of interest, which is set to 8, 16, 32, 64, 128, 256, 512, 1024 or 2048. Therefore, the sample size is equal to 65, 129, 257, 513, 1025, 2049, 4097, 8193, and 16,385, respectively, to observe the convergence of the sensitivity index.

In addition, we investigate the robustness of the EFAST algorithm by repeating the experiment times for each of the nine sample sizes. In this work, the number of repetitions is taken as 10. Next, the mathematic mean and the standard deviation of these repetitions are calculated. In this analysis, $a \pm 10\%$ perturbation of the specific corn parameter values described in the parameter file was chosen as the parameter variation range for the requirements of the EFAST algorithm.

2.4.2. The impacts of parameter variation ranges on sensitivity analysis

Two sets of parameter variation ranges derived from the references and documentation are used to set the upper and lower limits of the crop parameters, as presented in Table 2. One set is determined by the ±10% perturbation of the specific corn parameter values described in the parameter file. The other set is based on the Ceglar's collection (Ceglar et al., 2011), which is derived from observations, references, and statistical data of corn crops. No further information on these parameters is available, and therefore, a uniform distribution is temporarily assumed in this experiment. Moreover, the major objective of the crop growth models is the estimation of yield and is therefore considered to be the target output for assessing the impact of parameter variation range on the parameter SA.

In addition, a more detailed numerical experiment is performed on the first parameter variation range. The parameter variation range is separately set to those cases, which are the ±10%, ±20%, ±30%, ±40% and ±50% perturbations of the default corn parameter values. In fact, these cases proportionally magnify the lower and upper limits of the first parameter variation range, and with the boundary condition amplified, the parameter space is also enlarged.

2.4.3. The temporal characteristics of parameter sensitivity

The main eco-physiological processes of the crop vary in every growth stage. For example, in the early growth stage, vegetative growth is dominant, whereas reproductive growth is dominant after anthesis. The dominant biological process differs throughout the entire growth period, which results in differences among the dominant parameters. Therefore, it is necessary to analyze the temporal characteristics of each of the parameter sensitivities.

The yield remains the main concern for crop growth models. The storage organ biomass is the basis of yield formation and is thus selected as the target output of the temporal characteristic analysis of the parameter sensitivity. Because the storage organ becomes relevant after anthesis, the simulation is discussed beginning from the 210th day. In this numerical experiment, the ±20% perturbation of the default corn parameter values are set as the upper and lower limits of the parameter variation, and the main sensitivity index is adopted as the evaluation criterion.

2.4.4. Parameter sensitivity analysis for various output variables

Crop growth models are able to simulate many physiological processes and can export various state variables, including the dry biomass of each plant organ, transpiration rate, leaf area index, growth respiration and maintenance respiration. These variables are also important to the modeling of users and policy makers. For example, research on biomass is closely related to that of carbon cycles. Therefore, analyzing the roles of the parameters for other state variables is quite meaningful.

The WOFOST model, a light-use efficiency model, is based on the relationship among the photosynthetic active radiation, leaf area index and light use efficiency. Therefore, the simulations of the leaf expansion and dry mass accumulation, including the total aboveground biomass (TAGP), leaf area index (LAI), and weight of storage organ (WSO), carry important meaning and must be addressed. In addition, the transpiration coefficient (TRC), which represents the water use efficiency, is also set in the analyzed output variables. Moreover, the parameter sensitivities in the three important development periods (emergence, anthesis and maturity), are chosen to simultaneously reflect the respective temporal characteristics of the SA.

3. Results and discussion

3.1. The impacts of sample size on the convergence of the sensitivity measures

The goal of parameter SA is to explore the entire input space with a reasonable sample size and identify the sensitive parameters. A key element of SA is the sampling of input parameters for the

Table 2
Upper and lower limits of the parameters in the WOFOST model.

Parameter names	Definition	±10% perturbation of default corn parameter value		Parameter variation range provided by Ceglar et al.	
		Minimum	Maximum	Minimum	Maximum
LAIEM	Leaf area index at emergence (ha ha^{-1})	0.0435	0.0532	0.04	0.09
RGRLAI	Maximum relative increase in LAI (ha ha^{-1} d^{-1})	0.0265	0.0323	0.02	0.04
$SLATB_{00}$	Specific leaf area (DVS = 0) (ha kg^{-1})	0.0023	0.0029	0.0022	0.0035
$SLATB_{0.78}$	Specific leaf area (DVS = 0.78) (ha kg^{-1})	0.0011	0.0013	0.0010	0.0018
$SLATB_{2.0}$	Specific leaf area (DVS = 2.0)	0.0011	0.0013	0.0010	0.0018
SPAN	Life span of leaves growing at 35 °C (d)	29.70	36.30	30	35
TBASE	Lower threshold temperature for aging of leaves (°C)	9.00	11.00	8	10
$KDIFFTB_{0.0}$	Extinction coefficient for diffuse visible light (DVS = 0)	0.54	0.66	0.44	0.65
$KDIFFTB_{2.0}$	Extinction coefficient for diffuse visible light (DVS = 2.0)	0.54	0.66	0.44	0.65
$EFFTB_{00}$	Light-use efficiency of single leaf (kg/ha h j/m^2 s) (T = 0 °C)	0.405	0.495	0.45	0.55
$EFFTB_{40}$	Light-use efficiency of single leaf (kg/ha h j/m^2 s) (T = 40 °C)	0.405	0.495	0.45	0.55
$AMAXTB_{0.0}$	Maximum leaf CO_2 assimilation rate (DVS = 0)	63.00	77.00	65	72
$AMAXTB_{1.5}$	Maximum leaf CO_2 assimilation rate (DVS = 1.5)	56.70	69.30	55	65
$AMAXTB_{1.75}$	Maximum leaf CO_2 assimilation rate (DVS = 1.75)	44.10	53.90	40	50
$AMAXTB_{2.0}$	Maximum leaf CO_2 assimilation rate (DVS = 2.0)	18.90	23.10	15	25
$TMPFTB_{9}$	Reduction factor of AMAX (T = 9 °C)	0.045	0.055	0.05	0.225
$TMPFTB_{16}$	Reduction factor of AMAX (T = 16 °C)	0.72	0.88	0.48	0.80
$TMPFTB_{18}$	Reduction factor of AMAX (T = 18 °C)	0.85	1.00	0.55	0.94
$TMPFTB_{20}$	Reduction factor of AMAX (T = 20 °C)	0.90	1.00	0.63	1.00
CVL	Efficiency of conversion into leaves	0.61	0.75	0.68	0.72
CVO	Efficiency of conversion into storage organ	0.60	0.74	0.73	0.76
CVR	Efficiency of conversion into roots	0.62	0.76	0.65	0.69
CVS	Efficiency of conversion into stems	0.59	0.72	0.65	0.72
Q_{10}	Relative increase in respiration rate per 10 °C temperature increase	1.80	2.20	1.50	2.00
RML	Relative maintenance respiration rate of leaves (kg(CH_2O) kg^{-1} d^{-1})	0.027	0.033	0.003	0.011
RMO	Relative maintenance respiration rate of storage organ (kg(CH_2O) kg^{-1} d^{-1})	0.009	0.011	0.005	0.010
RMR	Relative maintenance respiration rate of roots (kg(CH_2O) kg^{-1} d^{-1})	0.014	0.017	0.006	0.010
RMS	Relative maintenance respiration rate of stems (kg(CH_2O kg^{-1} d^{-1}))	0.014	0.017	0.006	0.015
$RFSETB_{1.75}$	Reduction factor for senescence (DVS = 1.75)	0.23	0.68	0.70	0.80
$RFSETB_{2.0}$	Reduction factor for senescence (DVS = 2.0)	0.28	0.83	0.20	0.30
$FRTB_{0.0}$	Fraction of total dry matter to roots (DVS = 0)	0.36	0.44	0.35	0.40
$FRTB_{0.4}$	Fraction of total dry matter to roots (DVS = 0.4)	0.24	0.30	0.25	0.30
$FRTB_{0.6}$	Fraction of total dry matter to roots (DVS = 0.6)	0.17	0.21	0.19	0.23
$FRTB_{0.9}$	Fraction of total dry matter to roots (DVS = 0.9)	0.05	0.07	0.06	0.10
$FLTB_{0.0}$	Fraction of aboveground dry matter to leaves (DVS = 0)	0.56	0.68	0.55	0.65
$FLTB_{0.33}$	Fraction of aboveground dry matter to leaves (DVS = 0.33)	0.56	0.68	0.55	0.63
$FLTB_{0.88}$	Fraction of aboveground dry matter to leaves (DVS = 0.88)	0.14	0.17	0.10	0.20
$FLTB_{0.95}$	Fraction of aboveground dry matter to leaves (DVS = 0.95)	0.14	0.17	0.10	0.20
$FLTB_{1.1}$	Fraction of aboveground dry matter to leaves (DVS = 1.1)	0.09	0.11	0.05	0.10
$FOTB_{1.1}$	Fraction of aboveground dry matter to storage organ (DVS = 1.1)	0.45	0.55	0.45	0.55
$FOTB_{1.2}$	Fraction of aboveground dry matter to storage organ (DVS = 1.2)	0.90	1.00	0.90	1.00
PERDL	Maximum relative death rate of leaves due to water stress	0.03	0.03	0.01	0.03
$RDRSTB_{1.5001}$	Relative death rate of stems (DVS = 1.5001) (kg kg^{-1} d^{-1})	0.018	0.022	0.005	0.020
$RDRSTB_{2.0}$	Relative death rate of stems (DVS = 2.0) (kg kg^{-1} d^{-1})	0.018	0.022	0.005	0.020
RDI	Initial rooting depth (cm)	9.00	11.00	7.00	10.00
RRI	Maximum daily increase in rooting depth (cm d^{-1})	1.98	2.42	1.50	3.00
RDMCR	Maximum rooting depth (cm)	90.00	110.00	80.00	130.00

Note: DVS denotes the phenological development stage.

simulation, and the sample size determines the computational cost of the analysis.

The parameter rankings for all parameters with an increasing sample size are presented in Table 1. From this table, we find the sample size affects the parameter importance ranking. However, this influence is small. As shown in Table 1, the rankings for most parameters remain quite stable for a smaller sample size. The sensitive parameters still rank at the top after an increase in sample size. For example, the most sensitive parameter (SPAN) ranks first in all cases, and the non-sensitive parameters still rank lower. The variation in the parameter rankings is small with the increase in sample size. Therefore, if the objective of the parameter SA is solely to calculate a parameter ranking prior to calibration of the parameters, then the EFAST analysis can be applied with a sample size of 129 to yield a reliable ranking result (as described in Table 3).

In addition, the evolution of the sensitivity index with the increasing sample size is shown in Fig. 1. In this work, we choose only three types of parameters: the most important, the medium important and the non-important. According to the importance ranking of the parameters listed in Table 1, the SPAN, $FOTB_{1.1}$ and $RDRSTB_{1.5001}$ were separately chosen as the cases with the most importance, medium importance and no importance.

From this figure, the sample size is the main determining factor for the convergence of the main sensitivity indices for the yield

Table 3
Influence of sample size on the parameter importance ranking of the WOFOST model.

Parameter names	Sample size								
	65	129	257	513	1025	2049	4098	8193	16,385
LAIEM	47	47	47	45	45	45	45	45	45
RGRLAI	36	36	35	35	35	35	35	35	35
$SLATB_{00}$	27	29	28	28	28	28	28	28	28
$SLATB_{0.78}$	5	5	5	5	5	5	5	5	5
$SLATB_{2.0}$	34	34	34	32	32	32	32	32	32
SPAN	1	1	1	1	1	1	1	1	1
TBASE	3	3	3	3	3	3	3	3	3
$KDIFFTB_{0.0}$	17	18	19	19	19	19	19	19	19
$KDIFFTB_{2.0}$	8	9	10	8	8	8	8	8	8
$EFFTB_{00}$	6	6	6	6	6	6	6	6	6
$EFFTB_{40}$	4	4	4	4	4	4	4	4	4
$AMAXTB_{0.0}$	23	24	24	25	25	25	25	25	25
$AMAXTB_{1.5}$	13	14	14	14	14	14	14	14	14
$AMAXTB_{1.75}$	16	13	12	12	12	13	13	13	13
$AMAXTB_{2.0}$	26	26	26	26	26	26	26	26	26
$TMPFTB_{9}$	44	45	45	47	47	47	47	47	47
$TMPFTB_{16}$	39	38	38	38	38	38	38	38	38
$TMPFTB_{18}$	35	33	33	34	34	34	34	34	34
$TMPFTB_{20}$	18	16	18	18	17	18	18	18	18
CVL	22	20	20	20	20	20	20	20	20
CVO	2	2	2	2	2	2	2	2	2
CVR	21	22	23	23	23	23	23	23	23
CVS	33	35	37	37	37	37	37	37	37
Q_{10}	9	7	7	7	7	7	7	7	7
RML	15	12	13	13	13	12	12	12	12
RMO	20	21	21	21	21	21	21	21	21
RMR	19	19	17	17	18	17	17	17	17
RMS	10	8	8	10	9	10	9	10	10
$RFSETB_{1.75}$	14	15	15	15	15	15	15	15	15
$RFSETB_{2.0}$	31	31	31	31	31	31	31	31	31
$FRTB_{0.0}$	29	27	27	27	27	27	27	27	27
$FRTB_{0.4}$	37	37	36	36	36	36	36	36	36
$FRTB_{0.6}$	32	32	32	33	33	33	33	33	33
$FRTB_{0.9}$	42	41	42	42	42	42	42	42	42
$FLTB_{0.0}$	25	23	22	22	22	22	22	22	22
$FLTB_{0.33}$	11	11	11	11	11	11	11	11	11
$FLTB_{0.88}$	12	17	16	16	16	16	16	16	16
$FLTB_{0.95}$	28	28	29	29	29	29	29	29	29
$FLTB_{1.1}$	30	30	30	30	30	30	30	30	30
$FOTB_{1.1}$	24	25	25	24	24	24	24	24	24
$FOTB_{1.2}$	7	10	9	9	10	9	10	9	9
PERDL	45	44	44	44	44	44	44	44	44
$RDRSTB_{1.5001}$	46	46	46	46	46	46	46	46	46
$RDRSTB_{2.0}$	41	39	39	39	39	39	39	39	39
RDI	40	43	43	43	43	43	43	43	43
RRI	38	42	41	40	40	40	40	40	40
RDMCR	43	40	40	41	41	41	41	41	41

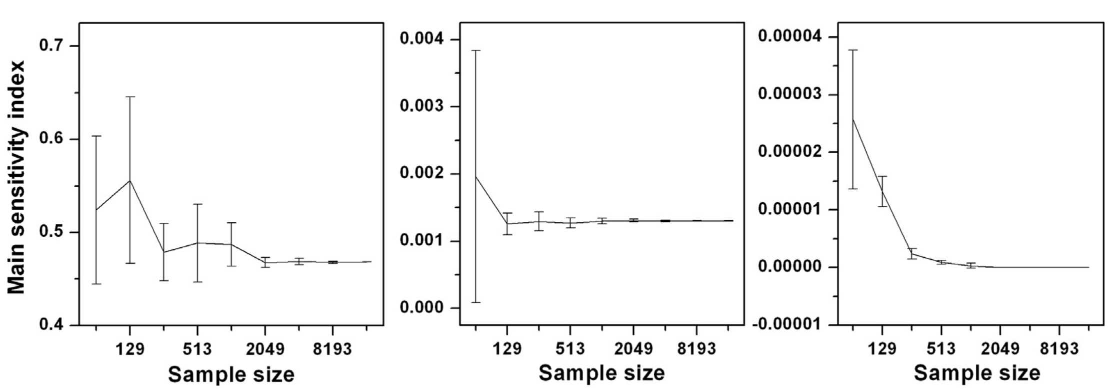

Fig. 1. Evolution of the sensitivity index of parameters SPAN, $FOTB_{1.1}$, and $RDRSTB_{1.5001}$ with increasing sample size.

simulations with the WOFOST model. In general, it appears from the plots that a sample size of greater than 1025 is required to reach the final converged value for the most parameters. The sample size of 2049 yields the most stable sensitivity indices. When sample size is small, i.e., only 65, the sensitivity index shows strong variations and cannot reach a stable convergence result for the three parameters. For most parameters, fewer than 65 samples are not sufficient to reach a stable value. This situation can be noted for the sensitivity index value of SPAN, $FOTB_{1.1}$, and $RDRSTB_{1.5001}$. In addition, the error grows gradually smaller as the sample size increases.

For the parameter with the highest sensitivity, such as SPAN, the final stable sensitivity index value is attained rather slowly, and greater fluctuations are observed. The sensitivity is able to obtain convergence for this type of parameter under the condition of large sample size. However, those insensitive parameters are more prone to the minor fluctuations that can appear with increasing sample size. For those insensitive parameters, the sensitivity analysis can quickly obtain convergence.

3.2. Impacts of parameter variation range on the parameter sensitivity analysis

According to the above numerical experiments on sample size, the frequency of the interest parameter was set to 128 in this and the following sections. The impacts of the parameter variation range on the parameter SA are shown in Fig. 2. When adopting different parameter variation ranges, the sensitive parameters vary as well. For the first parameter variation range, four parameters had the highest sensitivities to yield, i.e., the life span of leaves growing at 35 °C (SPAN), the efficiency of conversion into a storage organ (CVO), the lower threshold temperature for aging of leaves (TBASE), and the light use efficiency of a single leaf (T = 40 °C)($EFFTB_{40}$). Their main sensitivity indices all exceeded 0.05, and their total effects reached 85%, with SPAN showing a 47% effect on the yield variance. SPAN had twice as much influence on the total variance than the second-ranked parameter. However, for this case, certain parameters did not show any influence on the final yield. For the second parameter variation range, four parameters, i.e., the relative maintenance respiration rate of stems (RMS), the SPAN, the specific leaf area (DVS = 0.78)($SLATB_{0.78}$), and the extinction coefficient for diffuse visible light (DVS = 2.0)($KDIFFTB_{2.0}$), were identified as those showing the most important effects on yield, with a total effect of 74%. The reduction factor of the AMAX (DVS = 2.0)($TMPFTB_{2.0}$) and $EFFTB_{40}$ were also noted as sensitive parameters. The conclusions of the second parameter set were same as those in Ceglar's studies.

In general, regardless of the parameter space, the parameter SPAN is identified by the EFAST method as the parameter with the higher influence on the yield simulation. The parameters are related to specific biological processes. The important biological processes for yield formation differ together with the variation of the parameter range. For example, in the first variation range, only carbon assimilation and dry matter conversion dominate the highest parameter ranks, whereas in the second variation range, maintenance respiration plays the most critical role. The above results show that the parameter variation range was the main influence factor on its sensitivity.

In both cases, the most sensitive parameters were those of the leaf expansion and crop respiration processes. Because the leaf (one of the most important organs) is able to intercept light and absorb energy to form the basis of yield formation, the parameters that address the leaf expansion processes are highly important. The respiration parameters are defined as the dry mass consumption ratio relating to the plant respiration and indirectly influencing the accumulation of biomass and its conversion to yield. Therefore, the respiration parameters are also highly important, especially for the stem maintenance respiration rate, which ranks at the top due to the high matter consumption induced by a high stem dry weight.

In addition, several parameters cause markedly different output variations in the two cases, and many parameters do not impact the yield, as they have main sensitivity indices less than 0.001. These parameters are primarily related to the stem death and root properties. The research region is located in an irrigation agriculture zone, where irrigation water is able to meet the requirements

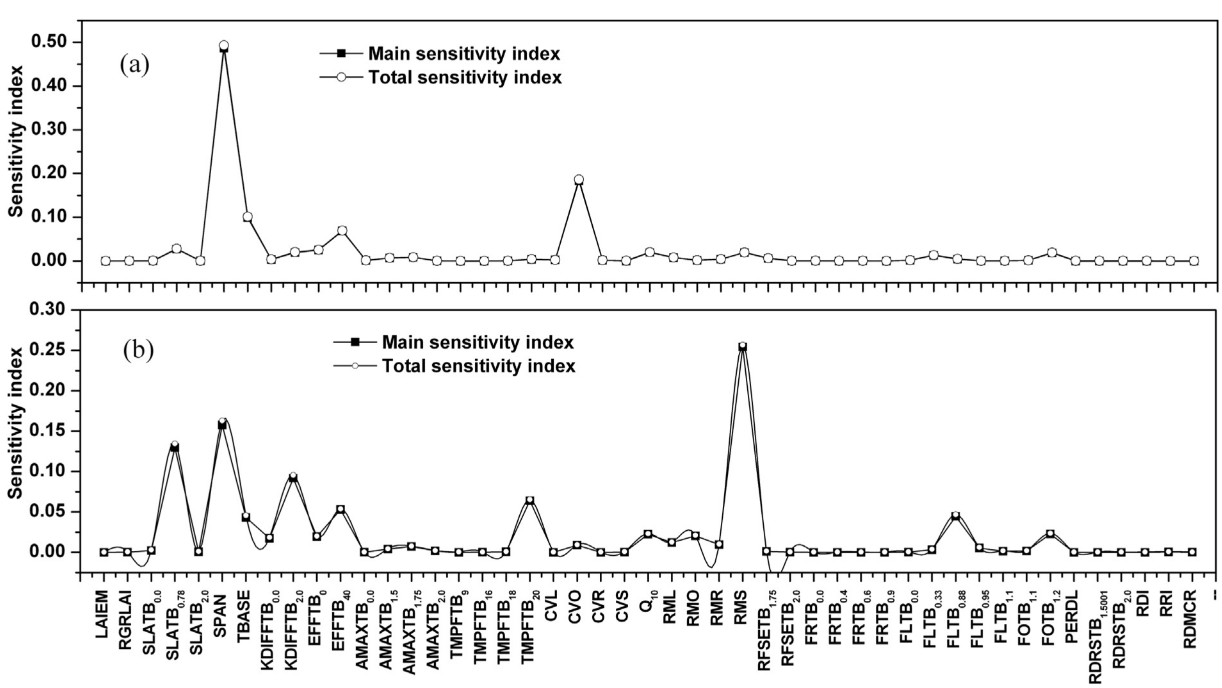

Fig. 2. Effects of the different parameter variation ranges on the parameter SA: (a) ±10% perturbation of the corn parameter, (b) provided by Ceglar et al.

of crops such that the root parameters have little effect, suggesting that the sensitivity of certain parameters may be related to the environment. Furthermore, for the final yield, the partition parameters as well as the photosynthesis parameters and their limit factors are also insensitive to the final yield in these two cases.

According to Fig. 3, when the parameter range is proportionally amplified from ±10% to ±50% perturbation, although the parameter space enlarges, the sensitivity rankings do not change and remain the same as that of the ±10% perturbations. The most sensitive parameters are still SPAN, CVO, TBASE, and $EFFTB_{40}$. Compared with the above results for the two types of parameter variation range, although certain parameter spaces are also magnified (such as the $SLATB_{0.78}$, the parameter space of which varies from [0.0011,0.0013] to [0.0010, 0.0018]) according to documentation by Ceglar, it is clear that the parameter sensitivity ranking has changed. This result suggests that parameter sensitivity is mainly related to the combination and configuration among the parameters, not only to the parameter values.

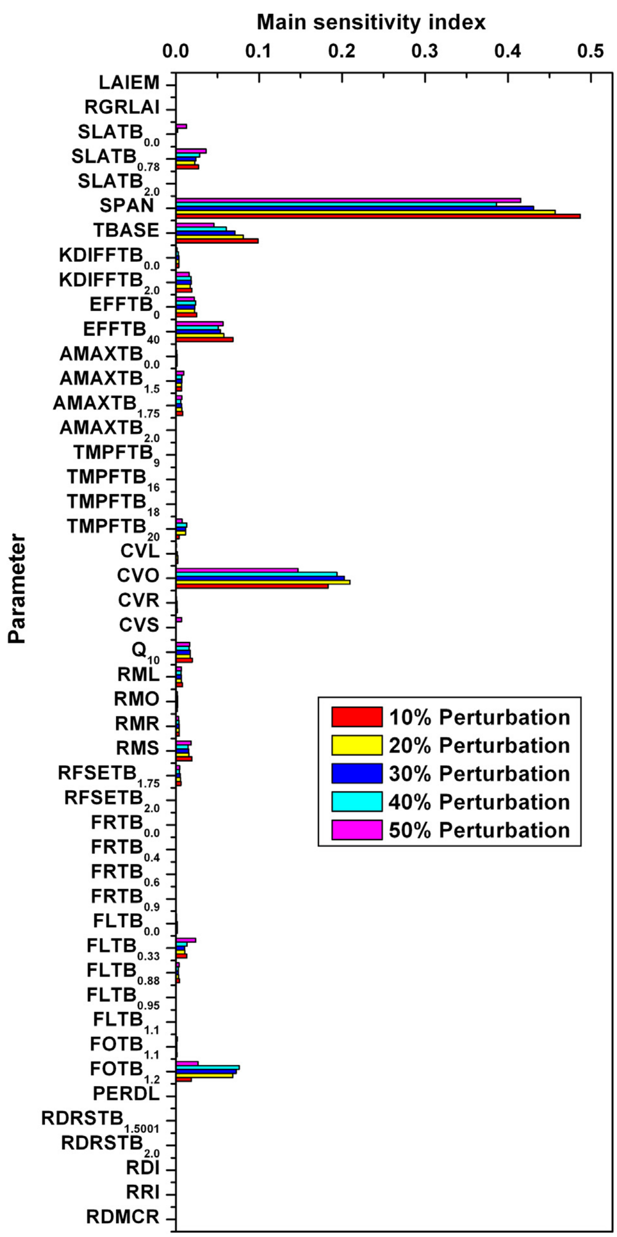

Fig. 3. Proportional influence of default corn parameter amplification on the SA.

3.3. Temporal characteristics of parameter sensitivity

The temporal characteristics of the parameter sensitivity are shown in Fig. 4. According to this figure, several parameters that are sensitive to grain biomass exist throughout the entire development stage, i.e., $SLABT_{0.78}$, SPAN, TBASE, $KDIFFTB_{2.0}$, $EFFTB_0$, $EFFTB_{40}$, $AMAXTB_{1.5}$, CVO, Q_{10}, RML, RMS, $FLTB_{0.33}$, $FOTB_{1.1}$, and $FOTB_{1.2}$. It is clear that their sensitivity indices are higher than those of the other parameters during the reproduction period. In addition, at a certain stage, these parameters play key roles and have much higher sensitivity indices. However, certain parameters perform only small roles in grain biomass after anthesis, such as TMPFTB, RFSETB, FRTB, RDRSTB, RDI, and RRI.

Twelve sensitive parameters, each with a main sensitivity index exceeding 0.05, are chosen to better understand the temporal trends of the parameter sensitivity (Fig. 5). The temporal evolution of the parameter sensitivity is shown in the diagram. Similarly, SPAN, $EFFTB_{40}$, CVO, and $FOTB_{1.2}$ play important roles in the yield throughout the entire growth period, whereas the other eight parameters have influence only during certain growth stages. In this model, SPAN, $KDIFFTB_{2.0}$, $EFFTB_{40}$, and $AMAXTB_{1.5}$ are related to the process of carbon assimilation, illustrating that carbon assimilation is the core of the WOFOST model and plays an important role up to the maturity stage. The related process is the key factor that determines the final yield. At the reproduction growth stage, the life span of leaves growing at 35 °C and the efficiency of conversion into the storage organs are both highly important. If the SPAN and CVO values are high, then the yield will increase. In addition, the fraction of aboveground dry matter to leaves at the jointing stage also plays a role in the final yield, which suggests that this growth stage is quite important. During the jointing growth stage, more crop individuals and leaves grow rapidly, and additional carbohydrates are allocated to the leaves, which is beneficial for intercepting additional light and forming the final dry matter. Thus, sufficient amounts of fertilizer and irrigation are necessary in the jointing stage, and the fraction of aboveground dry matter shunted to the storage organs shortly after anthesis is also highly important.

During crop growth, certain parameters are more sensitive, such as SPAN. The importance of SPAN becomes increasingly distinct, especially in the growth stage just before maturity. For other parameters, such as CVO, the sensitivity decreases. This behavior suggests that at the upcoming maturity stage, the leaf life is more important because it is able to efficiently provide nutrient matter. Because the accumulation of leaf biomass is the base of yield formation and may continuously provide nutrient matter to the storage organ even at the maturity stage, maintaining additional vegetative organs is necessary for a higher yield.

Previous studies have shown that certain parameters may have zero effects on the final yield and are thus considered insignificant, and even their related parameterization processes are in question. However, from the analysis shown in the present study, it may be observed that certain parameters play roles in certain growth stages but may have no effect on the final yield. An example is the fraction of aboveground dry matter directed to the storage organs, FOTB. If we only consider the final yield to be the output variable, its importance is not distinct. However, from the results of this study, it may be said that FOTB is valuable for storage organ accumulation. This analysis will aid in correctly understanding the model structure and the roles of each parameter. The results suggest that when performing SA on a dynamic model, it is necessary to perform research throughout the entire time series.

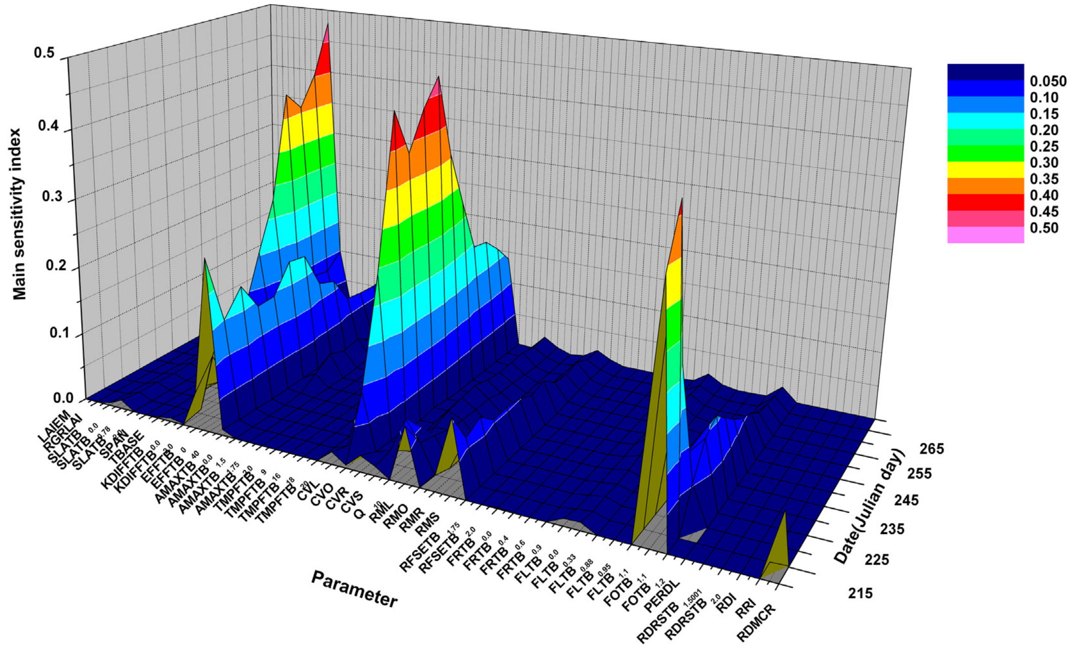

Fig. 4. Temporal attributes of the parameter sensitivity.

3.4. Parameter sensitivity for various state variables

The effects of the parameter on four state variables were assessed, and the results are shown in Fig. 6. It may be observed that the sensitive parameters for the four state variable outputs were completely different. Because grain biomass does not come into being until the anthesis stage, no parameter has an effect on the WSO in the emergence stage. During this earlier stage, $SLATB_{0.0}$, $FLTB_{0.0}$, and $FRTB_{0.0}$ are sensitive to LAI, whereas SPAN and CVO are the most sensitive for TAGP, and $EFFTB_0$, $EFFTB_{40}$, $KDIFFTB_{0.0}$, $KDIFFTB_{2.0}$, and CVO have important effects on TRC. After the anthesis stage, the sensitive parameters of TRC are same as in the previous stage, but the sensitive parameters of LAI, WSO, and TAGP at the reproductive stage are distinctly different from those at the vegetation stage. At the anthesis stage, $KDIFFTB_{0.0}$ and $KDIFFTB_{2.0}$ for LAI, $EFFTB_{40}$ and CVS for TAGP, and $EFFTB_{40}$ and $FOTB_{1.1}$ for WSO are more sensitive, as are SPAN for LAI, SPAN, and $EFFTB_{40}$ for TAGP, and SPAN and CVO for WSO at the maturity stage. Similar to the conclusion drawn in the previous section, during the last growth period, SPAN is a highly sensitive parameter for all processes directly related to crop growth, and the accurate estimation of this parameter is therefore critical for precise crop growth monitoring and yield prediction.

In addition, because carbon assimilation and water evapotranspiration combine the most eco-physiological processes and factors, additional parameters play important roles in the total biomass and transpiration coefficient.

From the dynamic evolution of parameter sensitivity, it may be found that, with the exception of TRC with non-variable parameter sensitivity, the sensitive parameters from emergence to maturity of other outputs are variable, which proves that the temporal properties of parameter sensitivity are highly important.

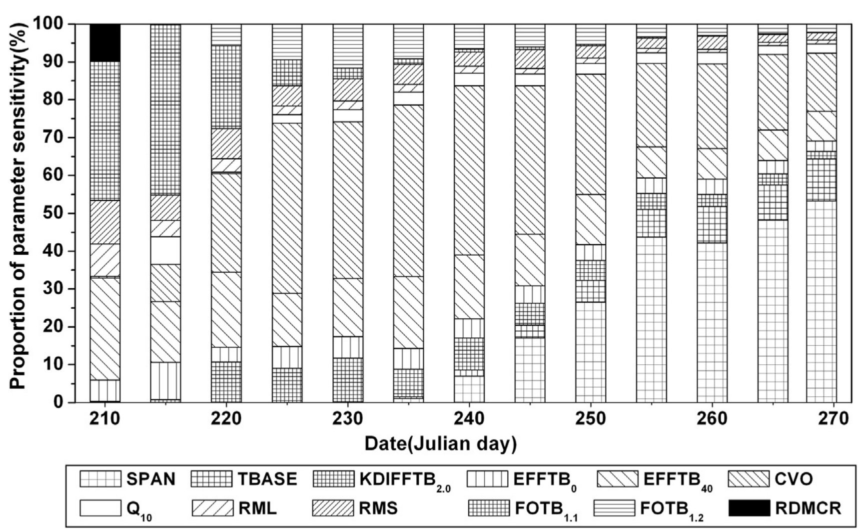

Fig. 5. Temporal characteristics of the parameter sensitivity for the twelve main parameters.

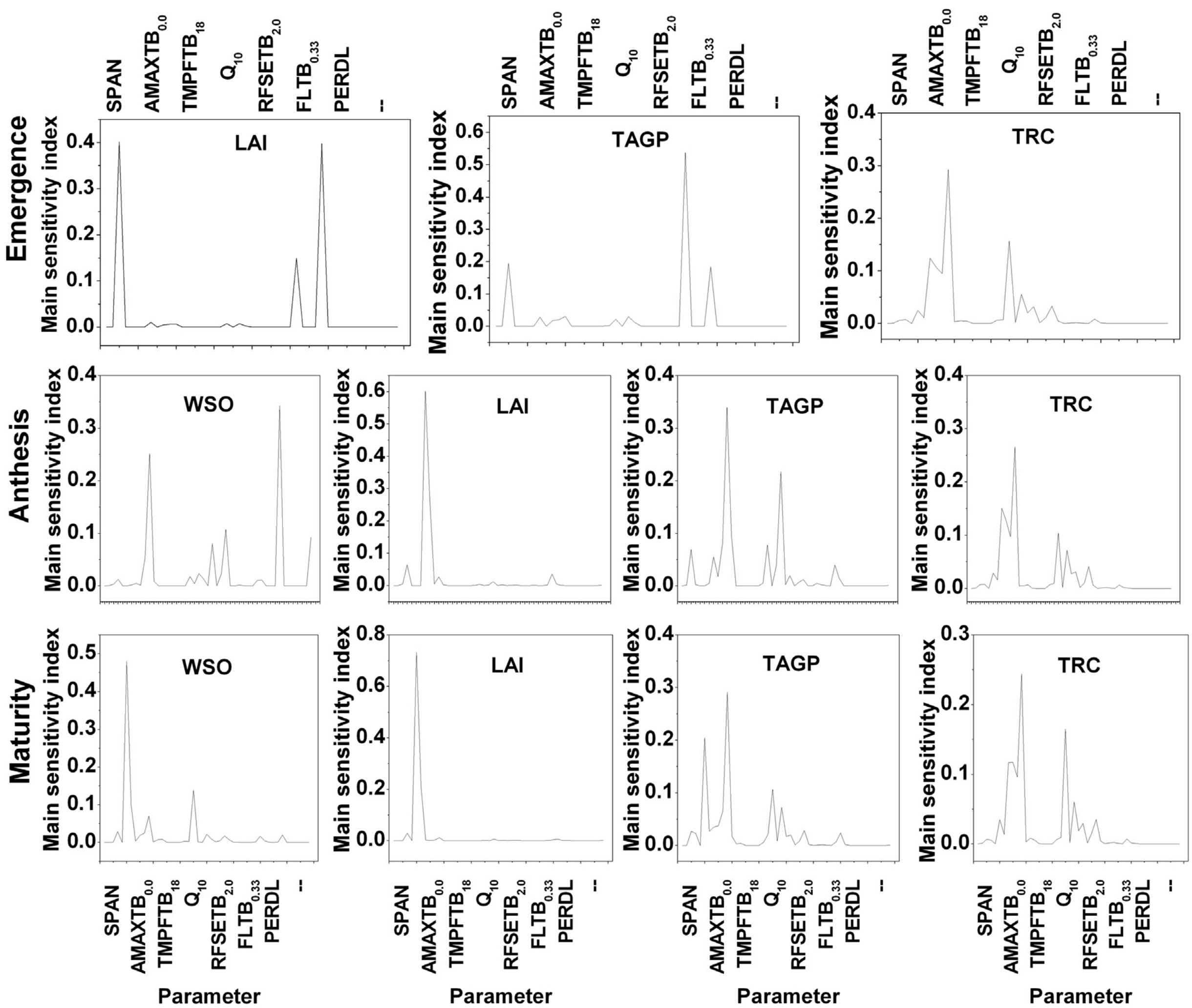

Fig. 6. Parameter sensitivity analysis of the weight of storage organ (WSO), leaf area index (LAI), total aboveground biomass (TAGP), and transpiration coefficient (TRC) as the target outputs in the growth stages of emergence, anthesis, and maturity.

4. Conclusion

Crop growth models have been widely applied in the fields of crop-growth monitoring, yield estimating and agricultural policy-making. However, numerous parameters and their difficult acquisition restrict their applications. Parameter SA is a basic tool for model understanding and application. Based on the results of the parameter SA, the sensitive parameters are first calibrated, and a set of parameters applicable to the local environment is subsequently obtained. The EFAST algorithm provides a simple, quick and global method for the assessment of parameter sensitivity across the entire feasible parameter space.

However, when implementing the EFAST method, attention has rarely focused on the effects of the parameter variation range on the SA. With the exception of parameters with distinct physical meanings that possess clear parameter attributes, most parameter properties are difficult to acquire and may only be obtained indirectly or estimated from references, observations or statistical files. For these reasons, the parameter SA results are quite uncertain. A default parameter range is often adopted, especially for crop growth models, which is improper from the perspective of crop properties. In addition, little attention has focused on the evolution of the sensitivity index with increasing sample size, which is important for the parameter SA to achieve a stable sensitivity ranking with a proper sample size. In addition, a larger sampling size indicates higher computation consumption, especially for complex ecological models. Therefore, before performing the sensitivity analysis, determining the necessary sampling size is essential, which is helpful for high-efficiency parameter sensitivity analysis.

In this paper, taking the WOFOST crop growth models as an example, several issues related to parameter SA application are discussed, such as sampling size, parameter variation range, temporal characteristics of SA and multi-variable output. The results show that sampling size has little influence on the parameter importance ranking; however, it distinctly affects the convergence of the sensitivity measures. For most parameters, if the sampling size is above 1025, a stable sensitivity analysis result can be obtained. For certain parameters, the sensitivity analysis can produce stable results with a small sample size, and the non-sensitive parameters converge rather quickly.

In addition, the parameter variation range has a clear influence on the parameter sensitivity, including the individual parameters and parameter interactions. However, when the upper and lower limits of the parameter range are proportionally magnified, there is little impact on the parameter sensitivity rankings. These observations suggest the importance of confirming the correct parameter boundary conditions before conducting the parameter SA. At the same time, the results also show that certain parameters are highly important, whereas others have little influence. It was found that the leaf expansion, light interception, assimilation and phenological parameters play key roles in the WOFOST model.

The temporal characteristics of the parameter SA are also studied. The results show that certain parameters have little influence on the final output but play key roles at other growth stages, and the importance of other parameters gradually increase. Lamboni et al. (2009) also emphasized that when performing SA on a dynamic model, it is most practical to consider the output throughout the entire time series. Therefore, when improving or simplifying the model structure, the dynamic characteristics of parameter sensitivity must be considered. For example, when not considering the temporal properties of parameters, certain parameterization processes for the dry mass partition are clearly redundant, which suggests that this process may be simplified (Richter et al., 2010). Steduto et al. (2009) proposed that the partition coefficients among different plant organs may be neglected and that the harvest index may substitute for the relationship between yield and biomass. A similar example is found in the crop growth models of Aquacrop (Steduto et al., 2009). However, due to the temporal characteristics of parameter SA, the partition coefficients of different plant organs also play key roles at certain growth stages. Therefore, the time-dependent characteristics are an important feature of the parameter SA.

In addition, although the crop yield is the main output of the crop growth models, in this study, the energy and mass transmission processes between the crops and the eco-environment are also simulated and yield many significant outputs, particularly the state variables related to the carbon cycle, e.g., GPP, LAI, biomass, and transpiration rate. Sensitivity analyses of different state variables are performed, and the results indicate that for different model outputs, the sensitive parameters also differ. This result suggests that when simplifying or improving models, the various roles of the models and parameters must be considered, and this observation aids in further understanding the model structure and how to more efficiently apply the crop growth models. Campbell et al. (2006) proposed a new approach for a dynamic model with multivariable and temporal characteristics known as the multivariate global SA. This concept will be tested in future research and will also further aid in understanding parameter sensitivity.

Finally, it may be said that in the WOFOST model, only a few parameters play important roles in the final yield output, which is risky for the model robustness, although it may reflect the true nature of the system (Confalonieri et al., 2010c). If these key parameters are set to incorrect values, the model yield prediction output will be uncertain; improving the model structure and increasing its stability are thus the next objectives in research on parameter SA. The perspective of SA further proves that SA will lead to a better comprehension of model behavior, which is directly related to a more informed operational application of crop growth models.

Acknowledgments

This work is financially supported by the NSFC (National Natural Science Foundation of China) Fund for Distinguished Young Scholars (grant 40925004), the CAS Action-plan for West Development "Eco-hydrological remote sensing algorithm development and application experiments in the Heihe River basin" (No. KZCX2-XB3-15), the NSFC project (grant 41101422), and the National Key Basic Research Program of China (2013CB430206). The authors thank Professor Iwan Supit from Wageningen University in the Netherlands for the use of his WOFOST model and the WATER project for the ground observation data set provided. The authors also thank the many instructors and students at the Cold and Arid Regions Environmental and Engineering Research Institute, CAS, who provided tuition and assistance with data management and the algorithm implementation. Finally, the authors thank the anonymous reviewers for their helpful comments.

References

Annoni, P., Bruggemann, R., Saltelli, A., 2011. Partial order investigation of multiple indicator systems using variance-based sensitivity analysis. Environmental Modelling & Software 26, 950–958.
Asseng, S., Jamieson, P.D., Kimball, B., Pinter, P., Sayre, K., Bowden, J.W., Howden, S.M., 2004. Simulated wheat growth affected by rising temperature, increased water deficit and elevated atmospheric CO_2. Field Crops Research 85, 85–102.
Batchelor, W.D., Basso, B., Paz, J.O., 2002. Examples of strategies to analyze spatial and temporal yield variability using crop models. European Journal of Agronomy 18, 141–158.
Benedetti, L., Claeys, F., Nopens, I., Vanrolleghem, P.A., 2011. Assessing the convergence of LHS Monte Carlo simulations of wastewater treatment models. Water Science and Technology 63 (10), 2219–2224.
Benson, J., Ziehn, T., Dixon, N.S., Tomlin, A.S., 2008. Global sensitivity analysis of a 3D street canyon model—part II: application and physical insight using sensitivity analysis. Atmospheric Environment 42, 1874–1891.
Borgonovo, E., Castaings, W., Tarantola, S., 2012. Emulators in moment independent sensitivity analysis: an application to environmental modelling. Environmental Modelling & Software 34, 105–115.
Bouman, B.A.M., van Laar, H.H., 2006. Description and evaluation of the rice growth model ORYZA2000 under nitrogen-limited conditions. Agricultural Systems 87, 249–273.
Campbell, K., Mckay, M.D., Williams, B.J., 2006. Sensitivity analysis when model outputs are functions. Reliability Engineering & System Safety 91, 1468–1472.
Campolongoa, F., Cariboni, J., Saltellia, A., 2007. An effective screening design for sensitivity analysis of large models. Environmental Modelling & Software 22 (10), 1509–1518.
Cariboni, J., Gatelli, D., Liska, R., Saltelli, A., 2007. The role of sensitivity analysis in ecological modelling. Ecological Modelling 203, 167–182.
Castaings, W., Borgonovo, E., Morris, M.D., Tarantola, S., 2012. Sampling strategies in density-based sensitivity analysis. Environmental Modelling & Software 38, 13–26.
Ceglar, A., Crepinsek, Z., Kajfez-Bogataj, L., Pogacar, T., 2011. The simulation of phenological development in dynamic crop model: the Bayesian comparison of different methods. Agricultural and Forest Meteorology 151, 101–115.
Chan, K., Saltelli, A., Tarantola, S., 1997. Sensitivity analysis of model output: variance-based methods make the difference. In: Proceedings of the 1997 Winter Simulation Conference, Atlanta, Georgia.
Chu-Agor, M.L., Munoz-Carpena, R., Kiker, G., Emanuelesson, A., Linkov, I., 2011. Exploring vulnerability of coastal habitats to sea level rise through global sensitivity and uncertainty analyses. Environmental Modelling & Software 26, 593–604.
Ciric, C., Ciffroy, P., Charles, S., 2012. Use of sensitivity analysis to identify influential and non-influential parameters within an aquatic ecosystem model. Ecological Modelling 246, 119–130.
Confalonieri, R., Acutis, M., Bellocchi, G., Cerrani, I., Tarantola, S., Donatelli, M., Genovese, G., 2006. Exploratory sensitivity analysis of Cropsyst, WARM and WOFOST: a case study with rice biomass simulations. Italian Journal of Agrometeorology 3, 17–25.
Confalonieri, R., Bellocchi, G., Bregaglio, S., Donatelli, M., Acutis, M., 2010a. Comparison of sensitivity analysis techniques: a case study with the rice model WARM. Ecological Modelling 221, 1897–1906.
Confalonieri, R., Bellocchi, G., Tarantola, S., Acutis, M., Donatelli, M., Genovese, G., 2010b. Sensitivity analysis of the rice model WARM in Europe: exploring the effects of different locations, climates and methods of analysis on model sensitivity to crop parameters. Environmental Modelling & Software 25, 479–488.
Confalonieri, R., Bregaglio, S., Acutis, M., 2010c. A proposal of an indicator for quantifying model robustness based on the relationship between variability of errors and of explored conditions. Ecological Modelling 221, 960–964.
Cukier, R.I., Levine, H.B., Shuler, K.E., 1978. Nonlinear sensitivity analysis of multiparameter model systems. Journal of Computational Physics 26, 1–42.
DeJongea, K.C., Ascough, J.C., Ahmadi, M., Andalesc, A.A., Arabi, M., 2012. Global sensitivity and uncertainty analysis of a dynamic agroecosystem model under different irrigation treatments. Ecological Modelling 231, 113–125.
Donatelli, M., van Ittersum, M.K., Bindi, M., Porter, J.R., 2002. Modelling cropping systems-highlights of the symposium and preface to the special issues. European Journal of Agronomy 18, 1–11.
Feyereisen, G.W., Sands, G.R., Wilson, B.N., Strock, J.S., Porter, P.M., 2006. Plant growth component of a simple rye growth model. Transactions of the ASABE 49, 1569–1578.
Foscarini, F., Bellocchi, G., Confalonieri, R., Savini, C., Van den Eede, G., 2010. Sensitivity analysis in fuzzy systems: integration of SimLab and DANA. Environmental Modelling & Software 25, 1256–1260.

Fraedrich, D., Goldberg, A., 2000. A methodological framework for the validation of predictive simulations. European Journal of Operational Research 124 (1), 55–62.
Francos, A., Elorza, F.J., Bouraui, F., Bidoglio, G., Galbiati, L., 2003. Sensitivity analysis of distributed environmental simulation models: understanding the model behaviour in hydrological studies at the catchment scale. Reliability Engineering & System Safety 79, 205–218.
Fieberg, J., Jenkins, K.J., 2005. Assessing uncertainty in ecological systems using global sensitivity analyses: a case example of simulated wolf reintroduction effects on elk. Ecological Modelling 187, 259–280.
Ginot, V., Gaba, S., Beaudouin, R., Aries, F., Monod, H., 2006. Combined use of local and ANOVA-based global sensitivity analysed for the investigation of a stochastic dynamic model: application to the case study of an individual-based model of a fish population. Ecological Modelling 193, 479–491.
Guerif, M., Duke, C.L., 2000. Adjustment procedures of a crop model to the site specific characteristics of soil and crop using remote sensing data assimilation. Agriculture, Ecosystems and Environment 81, 57–59.
Guerif, M., Houles, V., Makowski, D., Lauvernet, C., 2006. Data assimilation and parameter estimation for precision agriculture using the crop model STICS. In: Wallach, D., Makowski, D., Jones, J.W. (Eds.), Working with Dynamic Crop Models. Elsevier.
Helton, J.C., Davis, F.J., Johnson, J.D., 2005. A comparison of uncertainty and sensitivity analysis results obtained with random and Latin hypercube sampling. Reliability Engineering & System Safety 89, 305–330.
Hirabayashi, S., Kroll, C.N., Nowak, D.J., 2011. Component-based development and sensitivity analyses of an air pollutant dry deposition model. Environmental Modelling & Software 26, 804–816.
Houles, V., Mary, B., Guérif, M., Makowski, D., Juste, E., 2004. Evaluation of the crop model STICS to recommend nitrogen fertilization rates according to agro-environmental criteria. Agronomie 24, 1–9.
Hsiao, T.C., Heng, L., Steduto, P., Rojas-Lara, B., Raes, D., Fereres, E., 2009. Aquacrop-The FAO crop model to simulate yield response to water: parameterization and testing for maize. Agronomy Journal 101 (3), 448–459.
Lamboni, M., Makowski, D., Lehuger, S., Gabrielle, B., Monod, H., 2009. Multivariate global sensitivity analysis for dynamic crop models. Field Crops Research 113, 312–320.
Li, X., Koike, T., Pathmathevan, M., 2004. A very fast simulated re-annealing(VFSA) approach for land data assimilation. Computers & Geosciences 30, 239–248.
Li, X., Li, X.W., Li, Z.Y., Ma, M.G., Wang, J., Xiao, Q., Liu, Q., Che, T., Chen, E.X., Yan, G.J., Hu, Z.Y., Zhang, L.X., Chu, R.Z., Su, P.X., Liu, Q.H., Liu, S.M., Wang, J.D., Niu, Z., Chen, Y., Jin, R., Wang, W.Z., Ran, Y.H., Xin, X.Z., Ren, H.Z., 2009. Watershed allied telemetry experimental research. Journal of Geophysical Research 114, D22103. http://dx.doi.org/10.1029/2008JD011590.
Li, X., Li, X.W., Roth, K., Menenti, M., Wagner, W., 2011. Preface "Observing and modeling the catchment scale water cycle". Hydrology and Earth System Sciences 15, 597–601.
Luquet, D., Dingkuhn, M., Kim, H., Tambour, L., Clement-Vidal, A., 2006. EcoMeristem, a model of morphogenesis and competition among sinks in rice. 1. Concept, validation and sensitivity analysis. Functional Plant Biology 33, 309–323.
Makler-Pick, V., Gal, G., Gorfine, M., Hipsey, M.R., Carmel, Y., 2011. Sensitivity analysis for complex ecological models – a new approach. Environmental Modelling & Software 26, 124–134.
Makowski, D., Naud, C., Jeuffroy, M.H., Barbottin, A., Monod, H., 2006. Global sensitivity analysis for calculating the contribution of genetic parameters to the variance of crop model prediction. Reliability Engineering & System Safety 91, 1142–1147.
Manache, G., Melching, C.S., 2008. Identification of reliable regression- and correlation-based sensitivity measures for importance ranking of water-quality model parameters. Environmental Modelling & Software 23, 549–562.
Mckay, M.D., Beckman, R.J., Conover, W.J., 1979. A comparison of three methods for selecting values of input variables in the analysis of output from a computer code. Technometrics 21 (2), 239–245.
Miao, Z.W., Lathrop, R.G., Xu, M., La Puma, I.P., Clark, K.L., Homb, J., Skowronski, N., van Tuyl, S., 2011. Simulation and sensitivity analysis of carbon storage and fluxes in the New Jersey Pinelands. Environmental Modelling & Software 26, 1112–1122.
Morris, M.D., 1991. Factorial sampling plans for preliminary computational experiments. Technometrics 33, 161–174.
Nossent, J., Elsen, P., Bauwens, W., 2011. Sobol's sensitivity analysis of a complex environment model. Environmental Modelling & Software 26, 1515–1525.
Pandya, N., Gabas, N., Marsden, E., 2012. Sensitivity analysis of Phast's atmospheric dispersion model for three toxic materials (nitric oxide, ammonia, chlorine). Journal of Loss Prevention in the Process Industries 25, 20–32.
Post, J., Hattermann, F.F., Krysanova, V., Suckow, F., 2008. Parameter and input data uncertainty estimation for the assessment of long-term soil organic carbon dynamics. Environmental Modelling & Software 23, 125–138.
Ratto, M., Castelletti, A., Pagano, A., 2012. Emulation techniques for the reduction and sensitivity analysis of complex environmental models. Environmental Modelling & Software 34, 1–4.
Reusser, D.E., Buytaert, W., Zehe, E., 2011. Temporal dynamics of model parameter sensitivity for computationally expensive models with the Fourier amplitude sensitivity test. Water Resources Research 47, W07551. http://dx.doi.org/10.1029/2010WR009947.
Richter, G.M., Acutis, M., Trevisiol, P., Latiri, K., Confalonieri, R., 2010. Sensitivity analysis for a complex crop model applied to Durum wheat in the Mediterranean. European Journal of Agronomy 32, 127–136.
Saltelli, A., Tarantola, S., Chan, K.P.S., 1999. A quantitative model-independent method for global sensitivity analysis of model output. Technometrics 41, 39–56.
Saltelli, A., Ratto, M., Andres, T., Campolongo, F., Cariboni, J., Gatelli, D., Saisana, M., Tarantola, S., 2008. Global Sensitivity Analysis. The Primer, John Wiley and Sons.
Saltelli, A., Campolongo, F., Cariboni, J., 2009. Screening important inputs in models with strong interaction properties. Reliability Engineering & System Safety 94 (7), 1149–1155.
Saltelli, A., Annoni, P., Azzini, I., Campolongo, F., Ratto, M., Tarantola, S., 2010. Variance based sensitivity analysis of model output. Design and estimator for the total sensitivity index. Computer Physics Communications 181, 259–270.
Sieber, A., Uhlenbrook, S., 2005. Sensitivity analyses of a distributed catchment model to verify the model structure. Journal of Hydrology 310, 216–235.
SimLab ver. 3.2.6, 2009. Development Framework for Uncertainty and Sensitivity Analysis. Joint Research Centre of the European Commission, Econometrics and Applied Statistics, Ispra, Italy. http://simlab.jrc.ec.europa.eu.
Sobol, I.M., 1993. Sensitivity estimates for nonlinear mathematical models. Math Modeling & Computational Experiment 14, 407–414.
Steduto, P., Hsiao, T.C., Raes, D., Fereres, E., 2009. AquaCrop—the FAO crop model to simulate yield response to water: I. concepts and underlying principles. Agronomy Journal 101, 426–437.
Su, Y.H., Zhu, G.F., Miao, Z.W., Feng, Q., Chang, Z.Q., 2009. Estimation of parameters of a biochemically based model of photo-synthesis using a genetic algorithm. Plant, Cell & Environment 32, 1710–1723.
Sun, X.Y., Newham, L.T.H., Croke, B.F.W., Norton, J.P., 2012. Three complementary methods for sensitivity analysis of a water quality model. Environmental Modelling & Software 37, 19–29.
Supit, I., Hooijer, A.A., van Diepen, C.A., 1994. System Description of the WOFOST 6.0 Crop Simulation Model Implemented in CGMS. In: Theory and Algorithms, vol. 1. EUR 15956, Office for Official Publications of the European Communities, Luxembourg, p. 4.
Tarantola, S., Becker, W., Zeitz, D., 2012. A comparison of two sampling methods for global sensitivity analysis. Computer Physics Communications 183 (5), 1061–1072.
Van Griensven, A., Meixner, T., Grunwald, S., Bishop, T., Diluzio, M., Srinivasan, R., 2006. A global sensitivity analysis tool for the parameters of multi-variable catchment models. Journal of Hydrology 324, 10–23.
Van Keulen, H., Penning de Vries, F.W.T., Drees, E.M., 1982. A summary model for crop growth. In: Penning de Vries, F.W.T., van Laar, H.H. (Eds.), Simulation of Plant Growth and Crop Production, Simulation Monographs. Pudoc, Wageningen, The Netherlands, pp. 87–98.
Van Keulen, H., Wolf, J., 1986. Modelling of Agricultural Production: Weather Soils and Crops. In: Simulation Monographs. Pudoc, Wageningen, The Netherlands, p. 479.
Vardit, M.P., Gideon, G., Malka, G., Matthew, R.H., Yohay, C., 2011. Sensitivity analysis for complex ecological models – a new approach. Environmental Modelling & Software 26, 124–134.
Varella, H., Guerif, M., Buis, S., 2010. Global sensitivity analysis measures the quality of parameter estimation: the case of soil parameters and a crop model. Environmental Modelling & Software 25, 310–319.
Villa-Vialaneix, N., Follador, M., Ratto, M., Leip, A., 2012. A comparison of eight metamodeling techniques for the simulation of N_2O fluxes and N leaching from corn crops. Environmental Modelling & Software 34, 51–66.
Wang, X.., Potter, S.R., Williams, J.R., Atwood, J.D., Pitts, T., 2006. Sensitivity analysis of APEX for national assessment. Transactions of the ASABE 49 (3), 679–688.
Yen, B.C., Cheng, S.T., Melching, C.S., 1986. In: Yen, B.C. (Ed.), First Order Reliability Analysis: Stochastic and Risk Analysis in Hydraulic Engineering. Water Resources Publications, Littleton, Colorado, pp. 1–36.
Yang, J., 2011. Convergence and uncertainty analyses in Monte-Carlo based sensitivity analysis. Environmental Modelling & Software 26, 444–457.
Yang, R., Liu, W.J., 2010. Nitrate contamination of groundwater in an agroecosystem in Zhangye Oasis, Northwest China. Environment Earth Science 61, 123–129.
Zhu, G.F., Li, X., Su, Y.H., Lu, L., Huang, C.L., 2011. Seasonal fluctuations and temperature dependence in photosynthetic parameters and stomatal conductance at the leaf scale of *Populus euphratica* Oliv. Tree Physiology 31 (2), 178–195.