Sélection des paramètres du sol à estimer

Article 1 : "Global sensitivity analysis for choosing the main soil parameters of a crop model to be determined for simulating agro-environmental variables"

Nous rappelons ici l'objectif poursuivi et la démarche mise en œuvre dans cet article, ainsi que les principaux résultats et leur intérêt dans notre démarche globale.

3.1. Objectif

Nous avons vu dans le Chapitre 1 les problèmes posés par l'estimation d'un grand nombre de paramètres du modèle STICS ainsi que les voies possibles pour réduire le nombre de paramètres à estimer. L'enjeu de ce chapitre est de sélectionner un sous-groupe de paramètres du sol, parmi les 75 existants, qui puisse être estimé à partir d'observations du couvert végétal. L'article qui en constitue le corps cherche à répondre à cette question dans un double contexte :

- celui d'un utilisateur qui souhaite savoir quels sont les paramètres du sol qui ont le plus d'influence sur les variables de sortie d'intérêt et sur lesquels il devra investir en priorité pour les mesurer,
- celui d'un utilisateur qui se pose les mêmes questions mais qui dispose d'un ensemble d'observations lui permettant d'estimer, au lieu de mesurer, les paramètres en utilisant le modèle en mode inverse.

3.2. Méthodes

Nous proposons d'atteindre cet objectif en différentes étapes successives :

1. choix d'un modèle simplifié,
2. réduction des problèmes d'identifiabilité par fixation de valeurs de paramètres,
3. sélection des paramètres importants par analyse de sensibilité.

Les étapes (2) et (3) ont été présentées au Chapitre 1.2. Nous ferons toutefois un rapide rappel ici de ces trois étapes, avant de présenter l'étape (3) qui sera développée dans l'article.

3.2.1. Choix d'un modèle simplifié

La simplification de la représentation du sol et de son fonctionnement que nous avons adopté concerne :

- la prise en compte des processus simulés : nous avons choisi des options de simulation qui permettent de ne pas prendre en compte des processus relativement complexes tels que la circulation de l'eau et des solutés dans la macroporosité du sol, les fissures ou les cailloux ou bien le transfert ascendant de l'eau par capillarité, ou encore les processus de nitrification. Ce choix permet évidemment de ne pas considérer l'ensemble des paramètres sol impliqués dans la description de ces processus,
- une description simplifiée du sol : nous considérons un sol à deux couches, dont la couche de surface est d'une épaisseur fixée à 30 cm, qui est une valeur courante dans les sols agricoles classiquement travaillés.

Ces choix définissent le domaine de validité du modèle et des résultats trouvés en terme d'estimation des paramètres du sol. Toutefois, ils sont cohérents avec les sols des sites de Chambry et de Bruyères, sites sur lesquels est appliquée la méthodologie d'estimation des paramètres du sol. La non prise en compte des cailloux – qui existent dans ces sols – et de leurs propriétés, comme celle des différents horizons pédologiques réellement présents sur les sites, revient à estimer les caractéristiques d'un sol « équivalent » dont on s'est assuré qu'il permettait de décrire correctement les transferts d'eau et la minéralisation de la matière organique sur les sols considérés. Notons que des situations où les processus négligés ici seraient prépondérants obligeraient à reconsidérer ces processus et les paramètres correspondants, ou à accepter l'erreur commise sur l'estimation des paramètres.

Cette première étape permet de réduire le nombre de paramètres du sol de 75 à 18. Ces paramètres concernent ceux déjà présentés dans le Chapitre 2.4.1 : *argi*, *Norg*, *calc*, *albedo*, *q0*, *epc(2)*, *DA(1)*, *DA(2)*, *HCC(1)*, *HCC(2)*, *HMIN(1)*, *HMIN(2)*, *Hinit(1)*, *Hinit(2)*, *NO3init(1)* et *NO3init(2)*, où le chiffre entre parenthèse représente la couche de sol concernée. Deux autres paramètres sont également considérés à ce stade : *ruisolnu* (fraction d'eau qui ruisselle sur sol nu) et *profhum* (profondeur de sol concernée par les processus d'humification).

Par ailleurs, deux relations entre les conditions initiales (*Hinit* et *NO3init*) des deux couches ont été ajoutées au modèle afin de diminuer le nombre de paramètres. Ces relations ont été déterminées sur la base de données ayant servi à la calibration des paramètres liés aux caractéristiques du blé (voir Annexe) et sont les suivantes :

$$\begin{cases} Hinit(1) = Hinit(2) \\ NO3init(1) = \frac{2}{3} NO3init(2) \end{cases} \tag{3-1}$$

A ce niveau de la sélection, le nombre de paramètres atteint le nombre de 16.

3.2.2. Réduction des problèmes d'identifiabilité

La méthode proposée par Makowski (2006a), visant à analyser les équations du modèle STICS afin d'éviter les problèmes d'identifiabilité en fixant certains paramètres (voir Chapitre 1.2.2), a ensuite été appliquée aux 16 paramètres issus de l'étape précédente. L'analyse des équations du modèle faisant intervenir les paramètres sol nous a permis de cibler deux paramètres: *profhum*, la profondeur de sol concernée par les processus d'humification, et *HMIN*, l'humidité du sol au point de flétrissement. En effet, le paramètre *profhum* intervient toujours dans les équations du modèle à travers un produit avec le paramètre *Norg* (voir l'Equation (1-1) du Chapitre 1.1.2). Nous proposons alors de fixer la valeur de *profhum* à une valeur nominale, à savoir 30 cm, qui correspond à une profondeur classique de sol labouré. Seule la variation de *Norg* permettra de rendre compte de la variation de la quantité de matière organique active *NHUM*. Pour le paramètre *HMIN* des deux couches de sol, nous avons vu dans l'Equation (1-2) du Chapitre 1.1.2 qu'il peut agir par différence avec le paramètre *HCC,* pour exprimer la réserve d'eau utile du sol. Plus généralement, il arrive fréquemment que ce paramètre agisse en différence avec *HCC* dans le modèle STICS. Nous avons donc décidé de ne pas estimer *HMIN* pour les deux couches, en le fixant à une valeur nominale, propre à la parcelle considérée. Cette deuxième étape permet, en fixant *profhum* et *HMIN* des deux couches à des valeurs nominales, de diminuer le nombre de paramètres du sol à estimer de 16 à 13.

3.2.3. Sélection des principaux paramètres par analyse de sensibilité

La dernière étape consiste à effectuer une analyse de sensibilité globale des variables observables de STICS à ces 13 paramètres du sol, afin de distinguer les paramètres qui n'ont aucun effet sur les variables observables (à fixer à une valeur nominale) des paramètres qui ont un effet significatif (à estimer par inversion). L'issue de cette étape permet alors de déterminer le sous-groupe de paramètres du sol à estimer. La méthode d'analyse de sensibilité globale Extended FAST a été appliquée aux 13 paramètres du sol sur un ensemble de variables de sortie d'intérêt agroenvironnemental (indice foliaire, azote absorbé par la plante à des stades clés, rendement et qualité de la récolte et azote minéral du sol à la récolte).

Pour ce faire, nous considérons huit différentes configurations agropédoclimatiques sur lesquelles nous analyserons la sensibilité des variables aux paramètres. Ces configurations sont composées de :

- deux cultures annuelles différentes (blé d'hiver et betterave à sucre),
- deux climats contrastés caractérisés comme sec et humide (parmi ceux présenté au Chapitre 2.4.3),
- deux gammes de profondeurs de sol (de 30 à 100 cm pour les sols peu profonds et de 80 à 160 cm pour les sols profonds).

La méthode permet de calculer non seulement les indices de sensibilité globaux qui permettent de mesurer l'importance du paramètre sur la variation de la variable de sortie, mais aussi le coefficient de variation qui permet de déterminer l'importance relative de la variation des paramètres du sol sur celle de la variable de sortie. Ces métriques sont ensuite utilisées pour décider, selon deux optiques différentes, du sous-groupe de paramètres à considérer. La première optique est celle de la minimisation du coût de mesure des paramètres du sol et la seconde est celle de l'estimation des paramètres par inversion du modèle.

Lorsque l'on se place dans le contexte de minimisation du coût de mesure des paramètres du sol, il est nécessaire de considérer à la fois les indices de sensibilité des paramètres et le coefficient de variation de la variable. Les variables peuvent alors être classées en deux groupes :

1. les variables ayant un petit coefficient de variation : dans ce cas les paramètres ne requièrent pas une mesure précise car ils n'ont pas un grand effet sur la simulation des variables de sortie,
2. les variables ayant un grand coefficient de variation : dans ce cas seuls les paramètres ayant un indice de sensibilité total significatif pour la variable de sortie doivent être mesurés avec précision.

Lorsqu'on se place dans le contexte d'estimation de paramètres par inversion du modèle, il n'est pas nécessaire de considérer le coefficient de variation des variables de sortie. En effet, même si une variable de sortie donnée a un faible coefficient de variation, l'estimation des paramètres du sol peut être possible à condition que l'indice de sensibilité total ne soit pas négligeable. Dans ce cas, le coût d'estimation n'en est pas accru, contrairement à l'optique mesure.

3.3. Résultats

Dans l'optique de la mesure des paramètres du sol, les résultats présentés dans l'article montrent que le nombre de variables nécessitant un effort de mesure des paramètres du sol pour être simulées correctement dépend fortement de la configuration agropédoclimatique dans laquelle elles doivent être simulées. Par exemple, lorsque la betterave est simulée, le nombre de variable nécessitant un effort de mesure est plus important que lorsque le blé est simulé. Il en est de même concernant le climat : lorsque le climat est sec, ce nombre est plus important que lorsque le climat est humide. Pour les variables nécessitant un effort de mesure des paramètres du sol, le nombre de paramètres à mesurer varie entre 1 et 8 selon la variable et la configuration. Dans le cas contraire où les variables ne nécessitent pas un effort de mesure, le nombre de paramètres à mesurer est nul.

Pour notre objectif d'estimation par inversion de STICS, la sélection du sous-groupe de paramètres à estimer avec des observations du couvert végétal sera donc faite à partir des indices de sensibilité totaux concernant les variables observables *LAI* et *QN* aux stades *AMF*, *LAX* et *FLO* pour le blé, *AMF* et *Summer* pour la betterave, ainsi que *Yld* à la récolte. La règle de décision permettant de retenir ou non un paramètre pour son estimation est la suivante :

$$\begin{cases} \exists(k,c) / ST\left(y_{obs}^{k,c},\theta_i\right) > 0.1 \Rightarrow \theta_i = \hat{\theta}_i \\ ST\left(y_{obs}^{k,c},\theta_i\right) < 0.1, \forall(k,c) \Rightarrow \theta_i = \theta_i^{nom} \end{cases} \tag{3-2}$$

où $y_{obs}^{k,c}$ est la variable observable *k*, $k=1,\cdots,7$ pour le blé et $k=1,\cdots,5$ pour la betterave, simulée dans la configuration agropédoclimatique *c*, $c=1,\cdots,8$, θ_i, $i=1,\cdots,13$, est un paramètre du sol proposé, $ST\left(y_{obs}^{k,c},\theta_i\right)$ est l'indice de sensibilité total de la variable $y_{obs}^{k,c}$ au paramètre θ_i, θ_i^{nom} est la valeur nominale de θ_i et $\hat{\theta}_i$ est l'estimation de θ_i. Ainsi, si l'indice de sensibilité total est supérieur au seuil de 10% pour au moins une variable observable *k* simulée dans une configuration *c* donnée, alors le paramètre en question sera retenu pour être estimé par inversion ; sinon il sera fixé à une valeur nominale.

Le Tableau 3-1 dresse la liste des 7 paramètres du sol ainsi retenus pour l'estimation : *argi*, *Norg*, *epc(2)*, *HCC(1)*, *HCC(2)*, *Hinit* et *NO3init*. Il existe une forte variabilité entre les valeurs des indices de sensibilité totaux, ce qui signifie que l'observation de chaque variable apporte une quantité d'information très différente selon le paramètre considéré (voir Chapitre 1-3). Dans le chapitre suivant, il sera question de montrer la relation qui existe entre les indices de sensibilité globaux et la quantité d'information fournie par les observations sur les paramètres.

a)	Blé						
	LAI_{AMF}	QN_{AMF}	LAI_{LAX}	QN_{LAX}	LAI_{FLO}	QN_{FLO}	*Yld*
argi	0.09	**0.10**	0.07	**0.12**	0.03	**0.10**	0.02
Norg	0.09	**0.20**	**0.11**	**0.21**	0.04	**0.17**	0.02
epc(2)	**0.11**	**0.36**	**0.68**	**0.57**	**0.79**	**0.66**	**0.55**
HCC(1)	**0.22**	**0.20**	**0.37**	**0.32**	**0.45**	**0.24**	**0.49**
HCC(2)	0.07	0.03	**0.13**	0.06	**0.20**	**0.10**	**0.27**
Hinit	**0.93**	**0.90**	0.04	0.04	0.04	0.04	**0.20**
NO3init	0.09	**0.12**	0.06	**0.11**	0.03	0.08	0.01

b)	Betterave				
	LAI_{AMF}	QN_{AMF}	LAI_{Summer}	QN_{Summer}	*Yld*
argi	0.01	0.01	0.04	0.05	0.05
Norg	0.02	0.02	0.04	0.06	0.05
epc(2)	**0.18**	**0.20**	**0.57**	**0.42**	**0.49**
HCC(1)	**0.96**	**0.95**	**0.43**	**0.65**	**0.46**
HCC(2)	0.02	0.02	**0.40**	**0.15**	**0.27**
Hinit	0.02	0.04	**0.54**	**0.35**	**0.48**
NO3init	0.02	0.03	**0.10**	0.09	0.06

Tableau 3-1. Valeur maximale de l'indice de sensibilité total des paramètres sélectionnés, calculée sur l'ensemble des configurations et pour chaque variable d'intérêt a) du blé et b) de la betterave. En gras les valeurs supérieures à 10%.

3.4. Article 1 : "Global sensitivity analysis for choosing the main soil parameters of a crop model to be determined for simulating agro-environmental variables"

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Global sensitivity analysis for choosing the main soil parameters of a crop model to be determined for simulating agro-environmental variables.

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Abstract

The use of a crop model like STICS for appropriate management decision support requires a good knowledge of all the parameters of the model. Among them, the soil parameters are difficult to know at each point of interest and different costly techniques may be used to measure them. It is therefore important to know which soil parameters need to be determined. It can be stated that those which affect significantly the output variable deserve an accurate determination while those which slightly affect the model output variable do not. This paper demonstrates how a global sensitivity analysis method based on variance decomposition can be applied on soil parameters in order to divide them in the two categories. The Extended FAST method applied to the crop model STICS and a set of 13 soil parameters first allows to calculate the part of variance explained by each soil parameter (giving global sensitivity indices of the soil parameters) and the coefficient of variation of the output variables (measuring the effect of the parameter uncertainty on each variable). These metrics are therefore used for deciding on the importance of the parameter value measurement. Different output variables (Leaf Area Index and chlorophyll content) are evaluated at different stages of interest while others (crop yield, grain protein content, soil mineral nitrogen) are evaluated at harvest. The analysis is applied on two different annual crops (wheat and sugar beet), two contrasted weather and two types of soil depth. When the uncertainty of the output generated by the soil parameters is large (coefficient of variation > 1/3), only the parameters having a significant global sensitivity indices (higher than 10%) are retained. The results show that the number of soil parameters which deserve an accurate determination for simulating correctly the outputs can be significantly reduced (can reach 4) by the use of this relevant method for appropriate management decision support.

Keywords: Global sensitivity analysis, uncertainty, soil parameters, crop model STICS, management decision support, agro-environmental variables.

1. Introduction

Dynamic crop models are very useful to predict the behavior of crops in their environment and are widely used in a lot of agro-environmental work such as crop monitoring, yield prediction or decision making for cultural practices (Batchelor et al., 2002; Gabrielle et al., 2002; Houlès et al., 2004). These models usually have many parameters and their spatial application for agro-environmental predictions is difficult without a good knowledge of these parameters (Launay and Guérif, 2003; Tremblay and Wallach, 2004).

The crop models parameters can be divided in three groups: those related to the agricultural techniques, those related to the genotype of the crop and those related to the soil properties. Generally, agricultural techniques are quite easy to know as they are those used by the farmer. Crop parameters can be determined from literature, or estimated from experimental work or calibrated on a large database (Flenet et al., 2003; Hadria et al., 2007; Singh et al., 2008). The knowledge of the soil parameters is an important issue because the spatial variability of the crop model simulations depends for a large part on the soil parameter values (Guérif and Duke, 1998) and predictions obtained with the model are not reliable when inaccurate parameter values are used. This knowledge may be especially difficult to acquire because parameter values can greatly vary in space (Irmak et al., 2001; Ferreyra et al., 2006). The use of existing soil maps and associated pedotransfer functions can be considered where accurate soil map are available (Nemes et al., 2009); but in many cases, the spatial accuracy of the map is too limited for accurate applications such as for example precision agriculture (King et al., 1994). In those cases, these parameters should be determined in another way. Measurements can be made directly with soil sampling analysis at different locations of the study area or indirectly by using electrical geophysical measurements (Samouelian et al., 2005; Bourennane et al., 2007). Whatever the technique of measurement used, it is submitted to practical limitations and to time and financial constraints. Another way of gathering quite accurate values on soil parameters consists in estimating them through an inverse modeling approach using a crop model and observations on the crop state variables (Braga and Jones, 2004; Ferreyra et al., 2006; Varella et al., 2009). However, the soil parameters may not have the same contribution to the performance of the crop model and do not require the same precision of determination for a given objective: some of them deserve an accurate determination while the others can be fixed at nominal values (Bouman, 1994; St'astna and Zalud, 1999). Considering this aspect, the practical limitations of soil parameter measurements, as well as time and financial constraints should be reduced by considering only a subset of the crop model soil parameters depending on the objective and configuration of the study.

The combination of uncertainty analysis and sensitivity analysis techniques should help in identifying these key parameters. The objective of sensitivity analysis is to study how the variation of selected outputs of a model can be apportioned to different sources of variation (Saltelli et al., 2000a). In particular, sensitivity analysis methods can be used to rank uncertain input factors with respect to their effects on the model output variables by calculating quantitative or qualitative indices. Nevertheless, the fact that some factors are detected as important for a given output variable on the basis of sensitivity analysis results is not sufficient to decide that the uncertainties on these factors should be reduced. Indeed, if the variation of the considered output variable induced by the uncertainties on the factors is low then the results of sensitivity analysis on this output variable should not be taken into account. The description and quantification of these variations is the objective of uncertainty analysis.

Some authors (Bouman, 1994; Aggarwal, 1995; Blasone et al., 2008; Lawless et al., 2008; Tolson and Shoemaker, 2008; van der Keur et al., 2008) used uncertainty analysis techniques to quantify the uncertainties of a selection of crop models output variables generated by uncertainties on some selections of input parameters. Others authors (Campolongo and Saltelli, 1997; Saltelli et al., 2000b; Gomez-Delgado and Tarantola, 2006; Makowski et al., 2006b; Pathak et al., 2007) used global sensitivity analysis to evaluate the contribution of the parameters to the variance of the model output variables. Unfortunately, few studies concerning crop models consider both uncertainty analysis and sensitivity analysis, and, to our knowledge, not at all used the combination of these techniques to identify soil parameters that need particular accuracy for simulating a set of given output variables of interest in spite of the financial and practical interests of such a study.

In this study, we propose to use a variance-based sensitivity analysis method in order to rank the soil parameters relatively to their importance on some selected outputs of the crop model STICS (Brisson et al., 2002) and to select those which deserve an accurate determining by considering also the coefficient of variation of the outputs, that is the variation of the outputs compared to their magnitude. We considered 13 soil parameters and their effects on 5 dynamic output variables of the STICS crop model, at different phenological stages, which are involved in decision making for crop management. Two different crops (winter wheat and sugar beet) growing on different seasons are considered in order to illustrate the impact of soil properties on crop growth. Each crop considered is simulated under different pedological conditions and weather.

2. Methods

2.1 The STICS model

The STICS model (Brisson et al., 2008) is a nonlinear dynamic crop model simulating various crops. For a given crop, STICS takes into account the weather, the type of soil and the cropping techniques used, and simulates the carbon, water and nitrogen balances of the crop-soil system on a daily time-scale. In this study, winter wheat and sugar beet crops are simulated. The crop is essentially characterized by its above-ground biomass carbon and nitrogen, and leaf area index. The soil is considered as a series of layers where the transfer of water and nitrate is described by a reservoir-type analogy. The main outputs are agronomic variables (yield, grain protein content for wheat) as well as environmental variables (water and nitrate leaching).

The STICS model includes more than 200 parameters. The global sensitivity analysis described in this study only concerns the soil parameters. The values of the parameters related to the crop have been determined either from literature, from experimental works conducted on specific processes included in the model (e.g. mineralization rate, critical nitrogen dilution curve etc.) or from a calibration based on a large experimental database (Houlès, 2004 for the wheat crop; Launay et al., 2009 for the sugar beet crop). Cropping techniques and soil parameters ranges are described in Section 2.5.

2.2 The soil parameters

Among the available options for simulating the soil system, the simplest was chosen in this study, by considering only the transfers in the microporosity and ignoring those in the macroporosity, the cracks, pebbles, and processes like capillary rise and nitrification. We then considered the soil as a succession of two horizontal layers, the top layer having a thickness fixed at 30 cm. Based on the measurements made on the site considered for this study (see Section 2.5) for several years, we added relations between the initial contents of water *Hinit* and mineral nitrogen *NO3init* of the two soil layers in order to limit the number of parameters that should be varied:

$$\begin{aligned} Hinit &= Hinit_{first\_layer} = Hinit_{second\_layer} \\ NO3init &= NO3init_{first\_layer} = \frac{2}{3} NO3init_{second\_layer} \end{aligned} \qquad (1)$$

Finally, the different hypotheses made on the soil description lead to consider a set of 13 soil parameters, defined in Table 1. They refer to permanent characteristics and initial conditions. Among the permanent characteristics, clay and organic nitrogen content of the top layer are involved mainly in organic matter decomposition processes. Water content at field capacity of both layers affects the water (and nitrogen) movements and storage in the soil reservoir and the thickness of the second layer defines the volume of the reservoir. The initial conditions correspond to the water and nitrogen content, *Hinit* and *NO3init*, at the beginning of the simulation, in this case the sowing date.

Parameter	Definition	Range	Unit	Label
argi	Clay content of the 1rst layer	14-37	%	*ar*
Norg	Organic nitrogen content of the 1rst layer	0.049-0.131	%	*N*
calc	Limestone content of the 1rst layer	0-28	%	*c*
albedo	Albedo of the bare dry soil	0.13-0.31	–	*al*
q_0	Threshold of daily evapotranspiration	7.5-14.5	mm	*q*
ruisolnu	Fraction of drip rainfall on a bare soil	0-0.065	–	*r*
epc(2)	Thickness of the 2nd layer	0-70 or 50-130*	cm	*e*
DA(1)	Bulk density (1rst layer)	1.22-1.42	–	*D1*
DA(2)	Bulk density (2nd layer)	1.39-1.59	–	*D2*
HCC(1)	Water content at field capacity (1rst layer)	14-30	$g\ g^{-1}$	*H1*
HCC(2)	Water content at field capacity (2nd layer)	14-30	$g\ g^{-1}$	*H2*
Hinit	Initial water content (both layers)	4-29	% of weight	*h*
NO3init	Initial mineral nitrogen content (1rst layer)	4-21.5 or 12-55**	$kg\ N\ ha^{-1}$	*n*

* the first range determine a shallow soil and the second determine a deep soil.

** the first range concern the wheat (cultivated after beet) and the second concern the beet (cultivated after a bare soil).

Table 1. Definition of the 13 soil parameters and their ranges of variation.

2.3 Model outputs

In this study, the STICS output variables we are mostly interested in are:

(i) the amount of nitrogen absorbed by the plant (*QN*) and the leaf area index (*LAI*) at two (for sugar beet) or three (for wheat) different key stages during the season which are important variables for making a diagnosis on crop growth,

(ii) the yield, and the mineral nitrogen content in the soil at harvest (for both crops) plus the grain protein content (for wheat), which are of particular interest for decision making, especially for monitoring nitrogen fertilization (Houlès et al., 2004).

The different stages of interest and the corresponding variables of interest are displayed for each crop on Table 2. For the wheat, the three key stages concern the maximum leaf growth rate – beginning of stream elongation – (*AMF*), the maximum leaf area – or booting – (*LAX*) and the flowering (*FLO*). For the sugar beet, the two key stages concern the maximum leaf growth rate (*AMF*) and the maximum leaf area (*Summer*).

Crop simulated	Variable of interest	Stage of interest	Signification of the stage
Wheat	*LAI* and *QN*	*AMF*	Stage of maximum leaf growth rate (beginning of steam elongation)
		LAX	Stage of maximum leaf area (booting)
		FLO	Flowering
	Yld, Prot and *Nit*	*Harvest*	Harvest
Sugar beet	*LAI* and *QN*	*AMF*	Stage of maximum leaf growth rate
		Summer	Day where maximum leaf area is achieved in most cases
	Yld and *Nit*	*Harvest*	Harvest

Table 2. Definition of the variables and the stages of interest.

2.4 Sensitivity and uncertainty analysis

Among the available methods of sensitivity analysis, variance-based methods are well adapted for non-linear models that need less than 1 minute for a simulation (Cariboni et al., 2004). These methods are widely used in different contexts (Campolongo and Saltelli, 1997; Saltelli et al., 2000b; Gomez-Delgado and Tarantola, 2006; Makowski et al., 2006b; Pathak et al., 2007). Their principle is to evaluate the contribution of the given uncertain factors to the variance of the model output variables selected. We will describe in this section the sensitivity indices that can be computed with these methods and the EFAST variance-based method we have used in this study to compute these indices. Uncertainty analysis is performed here by computing the coefficient of variation of the output variables considered from the simulations realized for the sensitivity analysis.

Sensitivity indices and coefficient of variation

We note further *Y* an output variable of STICS. *Y* will represent in turn *LAI* and *QN* computed at the different phenological stages and the variables computed at harvest. The total variance of *Y*, $V(Y)$, is partitioned as follows (Chan et al., 2001):

$$V(Y) = \sum_{i=1}^{13} V_i + \sum_{1 \le i < j \le 13} V_{ij} + \cdots + V_{1,2,\cdots,13}, \quad (2)$$

where $V(Y)$ is the total variance of the output variable *Y* induced by the 13 soil parameters θ, $V_i = V[E(Y|\theta_i)]$ measures the main effect of the parameter θ_i,

$i = 1, \cdots, 13$, and the other terms measure the interaction effects. Decomposition (2) is used to derive two types of sensitivity indices defined by:

$$S_i = \frac{V_i}{V(Y)}, \tag{3}$$

$$ST_i = \frac{V(Y) - V_{-i}}{V(Y)}, \tag{4}$$

where V_{-i} is the sum of all the variance terms that do not include the index i.

S_i is the first-order sensitivity index of the ith parameter. It computes the fraction of *Y* variance explained by the uncertainty of parameter θ_i and represents the main effect of this parameter on the output variable *Y*. ST_i is the total sensitivity index of the ith parameter and is the sum of all effects (first and higher order) involving the parameter θ_i. S_i and ST_i are both in the range (0, 1), low values indicating negligible effects, and values close to 1 huge effects. ST_i takes into account both S_i and the interactions between the ith parameter and the 12 other parameters, interactions which can therefore be assessed by the difference between ST_i and S_i. The interaction terms of a set of parameters represent the fraction of V(*Y*) induced by these parameters but that is not explained by the sum of their main effects. The two sensitivity indices S_i and ST_i are equal if the effect of the ith parameter on the model output is independent of the values of the other parameters: in this case, there is no interaction between this parameter and the others and the model is said to be additive with respect to θ_i. Selecting the parameters that have a negligible effect and that can thus be fixed to nominal values is called factor fixing in the literature (Ratto et al., 2007). Total effects must be considered in this case. Indeed, a factor that has a small main effect but a medium to high total effect cannot be considered as negligible: its effect depends on the value of other uncertain factors and can be important in some cases.

The coefficient of variation of the output variable *Y* can be calculated by:

$$CV(Y) = \frac{\sqrt{V(Y)}}{\bar{Y}} = \frac{\sigma(Y)}{\bar{Y}} \tag{5}$$

where, $\sigma(Y)$ is the standard deviation of the output variable *Y* and $\bar{Y}$ is the mean of *Y* induced by the 13 soil parameters θ.

Extended FAST

Sobol's method and Fourier Amplitude Sensitivity Test (FAST) are two of the most widely used methods to compute S_i and ST_i (Chan et al., 2000). We have chosen here to use the extended FAST (EFAST) method, which has been proved, in several studies (Saltelli and Bolado, 1998; Saltelli et al., 1999; Makowski et al., 2006b), to be more efficient in terms of number of model evaluations than Sobol's method. The main difficulty in evaluating the first-order and total sensitivity indices is that they require the computation of high dimensional integrals. The EFAST algorithm performs a judicious deterministic sampling to explore the parameter space which makes it possible to reduce these integrals to one-dimensional ones using Fourier decompositions. The reader interested in a detailed description of EFAST can refer to (Saltelli et al., 1999).

We have implemented the EFAST method in the Matlab® software, as well as a specific tool for computing and easily handling numerous STICS simulations. The uncertainties considered for the soil parameters are described in the next section. A preliminary study of the convergence of the sensitivity indices allowed us to set the number of simulations per parameter to 5000, leading to a total number of model runs of 13×5000=65000 to compute the main and total effects for all output variables and parameters considered here. One run of the STICS model takes about 1s with a Pentium 4, 2.9 GHz processor.

2.5 Data

In this study, we have considered two crops: winter wheat and sugar beet. This allows us illustrating the difference of sensitivities of different crops to the soil properties. For the same reason, each crop is simulated for two different weathers and two different types of soil depth. The weather data were obtained from the meteorological station of Roupy (49.48°N, 3.11°E). The first set of data is chosen to characterize a dry weather (1975-1976) and the second set is chosen to characterize a wet weather (1990-1991). Table 3 shows the amount of rainfall calculated for each season and weather data set. The wheat crop simulated in this study is sown on October 30th while the sugar beet crop is sown on March 30th. The amount of fertilizer provided on wheat varies between 200 kg (shallow soil) and 240 kg (deep soil), while the amount provided on sugar beet varies between 150 kg (shallow soil) and 200 kg (deep soil).

	Spring	Summer	Autumn	Winter
Dry weather	343.4	167.8	222.4	218.8
Wet weather	361.4	247.9	239.4	316.4

Table 3. Amount of rainfall (in mm) calculated for each season and weather.

The range of parameter values considered in this study correspond to the soil description of the precision agriculture experimental site in northern France near Laon, Picardie (Chambry 49.35°N, 3.37°E) (Guérif *et al.*, 2001). In this study, the uncertainties of these 13 soil parameters are observed in the literature (for parameters related to albedo, evapotranspiration or drip rainfall) or measured in the experimental site (for the other parameters), and their ranges of variation are displayed on Tab. 1. Concerning the parameter *NO3init* two ranges of variation are considered, depending on the crop cultivated just before the one considered: in this study, the wheat is cultivated after sugar beet and the sugar beet is cultivated after a bare soil. The different previous crops used determine the quantity of nitrogen *NO3init* at the beginning of the corresponding crop season. The two different types of soil depth are defined by their ranges of variation (Tab. 1) and correspond to a shallow soil and a deep soil. The uncertainties considered in the global sensitivity analysis for the soil parameters are assumed independent and follow uniform distributions. The ranges of variation of the distributions are given in Tab. 1.

3. Results and discussion

Only the main results of the study are presented here for the sake of clarity. These results concern: (i) wheat crop simulated with dry, then wet weather and a shallow soil and (ii) sugar beet crop simulated with dry, then wet weather and deep soil.

3.1 Global sensitivity analysis

Figure 1 shows the sensitivity indices calculated for the 13 soil parameters and for each output variable of the wheat crop simulated with a dry weather and a shallow soil. For the early stage the initial water content is dominant because in the considered weather, the rainfall is light in autumn when the wheat is sown (see Tab. 3): at the stage *AMF* (Fig. 1a), *Hinit* is the only parameter contributing (for more than 90%) to the output variance for both variables *LAI* and *QN*. In the later stages, the effects of parameters evolve with the soil volume explored by the roots (first layer, then second one) up to the flowering stage where the root development is maximum: at the stage *LAX* (Fig. 1b) and *FLO* (Fig. 1c), the effect of *Hinit* disappears and that of *HCC(1)* and *epc(2)* increase, with a dominant position of *epc(2)*. At harvest (Fig. 1d), the variables are much sensitive to *epc(2)* followed by *HCC(1)*, *HCC(2)* and *Hinit* for the three variables and *albedo* for the variable protein of the grain. In those conditions of dry weather and shallow soil, the parameters related to water availability (*epc(2)*, *HCC(1)*, *HCC(2)* and *Hinit*) are the main parameters contributing to the variance of the outputs. Those concerned by the turnover of organic nitrogen in the soil are not concerned, because the water stress is the dominant limiting factor and also because the mineralization processes are reduced by dry conditions.

When considering wet conditions (Figure 2), the water stress is not so much a limiting factor: maximum *LAI* is equal to 3.61 in average, whereas it is equal to 2.57 in dry conditions (see Table 4). The roots grow more rapidly at the beginning of the season and the size of the soil reservoir (via the parameter *epc(2)*) is important since the *AMF* stage: the depth of roots is equal to 55.84 in average (3 months after the sowing), whereas it is equal to 45.62 in dry conditions (see Tab. 4). Moreover, in these conditions, the mineralization of the soil organic matter is increased and the effects of the concerned parameters *argi* and *Norg* do so: the cumulative mineral nitrogen arising from humus is equal to 23.95 in average (at stage *LAX*), whereas it is equal to 18.09 in dry conditions (see Tab. 4). This does not seem to influence the effects of the different parameters on LAI at stage AMF since they are very similar to these obtained with the dry weather. On the contrary, the sensitivities of the variable *QN* to the different parameters are very different from the ones obtained with a dry weather: there is no contribution of *Hinit* but *epc(2)*, *HCC(1)* and parameters involved in the mineralization process (*argi*, *Norg* and *NO3init*) significantly contributes to the variance of this variable. This is also the case for both *LAI* and *QN* on later stages, with an increasing dominancy of *epc(2)*. At harvest (Fig 2d), the variables are sensitive to the parameters *epc(2)*, *HCC(1)* and *HCC(2)* with still a slight sensitivity to *argi* and *Norg* for the soil mineral nitrogen content. The main difference between these results and those presented in Fig.1 lies in the sensitivity to parameters involved in the mineralization process (especially *argi* and *Norg*).

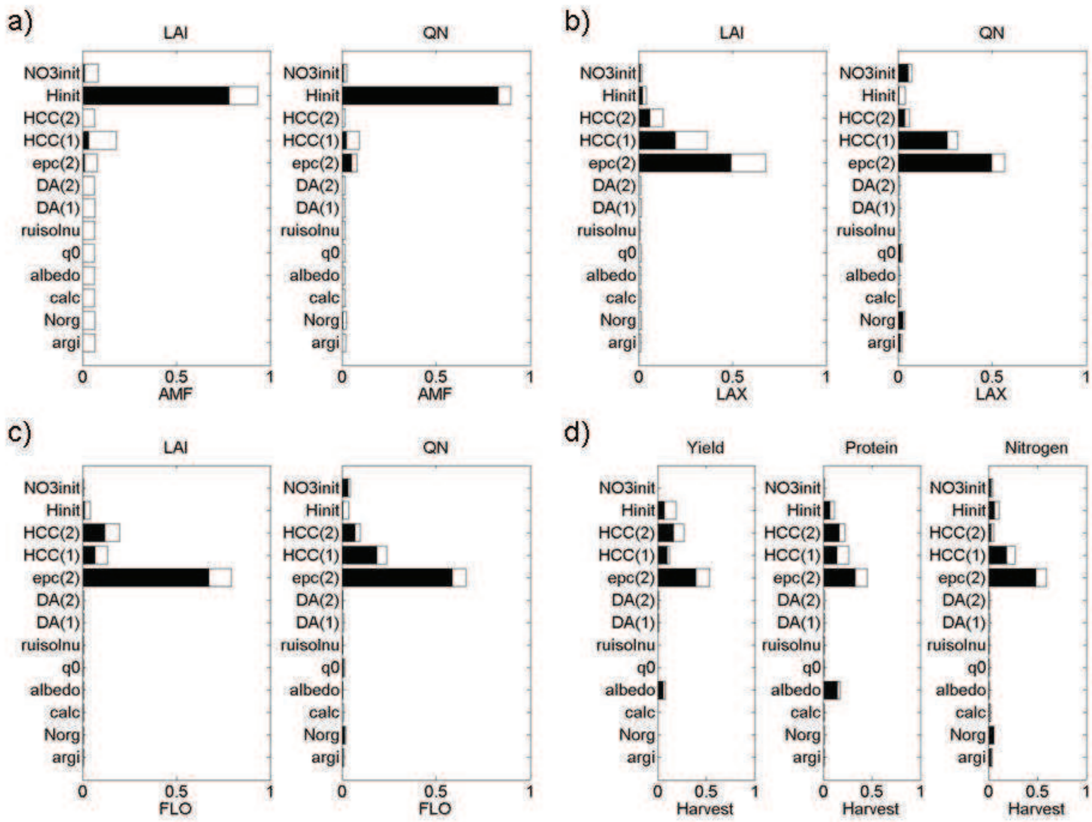

Figure 1. Sensitivity indices of the 13 soil parameters for each model output of the wheat crop simulated with a dry weather and a shallow soil. The outputs a) correspond to *LAI* and *QN* at stage *AMF*, b) correspond to *LAI* and *QN* at stage *LAX*, c) correspond to *LAI* and *QN* at stage *FLO* and d) correspond to *Yld*, *Prot* and *Nit* at *Harvest*. First-order indices are in black and interactions in white.

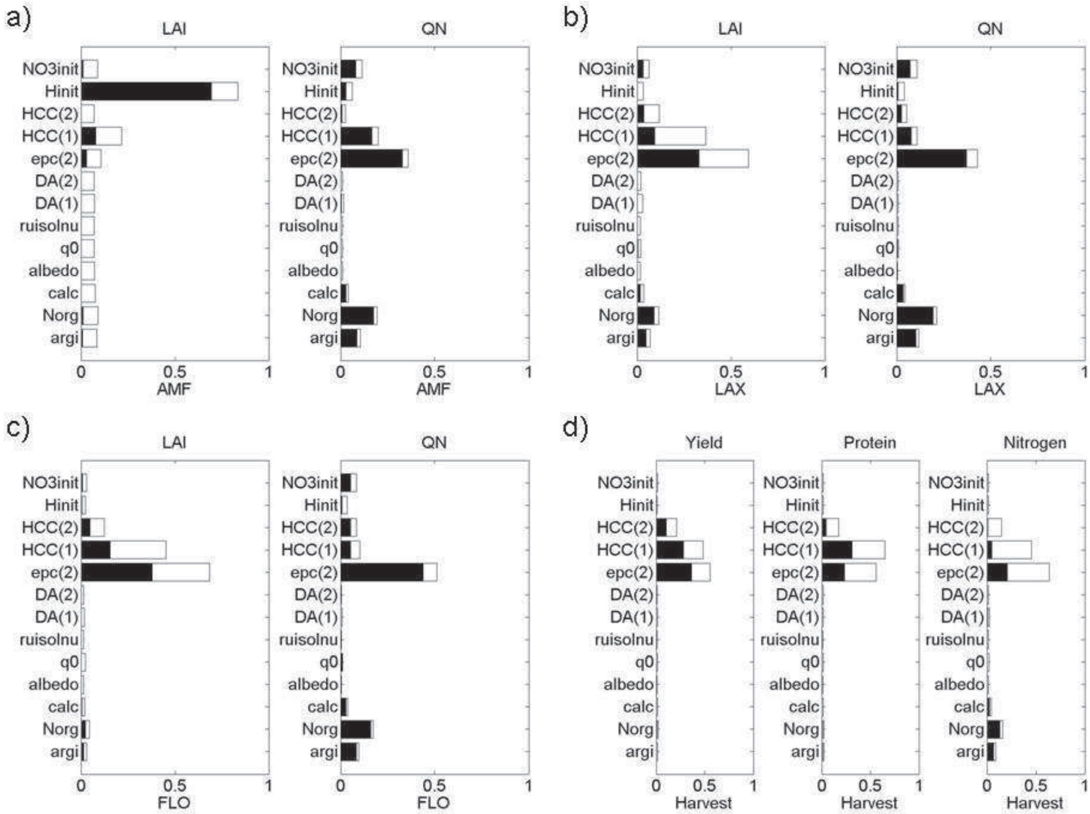

Figure 2. Sensitivity indices of the 13 soil parameters for each model output of the wheat crop simulated with a wet weather and a shallow soil. The outputs a) correspond to *LAI* and *QN* at stage *AMF*, b) correspond to *LAI* and *QN* at stage *LAX*, c) correspond to *LAI* and *QN* at stage *FLO* and d) correspond to *Yld*, *Prot* and *Nit* at *Harvest*. First-order indices are in black and interactions in white.

Configuration of simulation	Maximum *LAI*			*Qminh*			*Zrac*		
	min	mean	max	min	mean	max	min	mean	max
W C1 -	0.78	2.57	3.73	7.19	18.09	40.51	30.1	45.62	56.52
W C2 -	2.51	3.61	5.08	9.8	23.95	48.85	30.1	55.84	69.91
SB C1 +	0	1.42	4.61	0	24.91	83.38	12.06	77.58	129.61
SB C2 +	0.19	4	6.06	19.19	50.19	121.45	71.08	85.55	102.58

Table 4. Ranges of some output variables uncertainties generated by the uncertainties on the soil parameters. The output concerns the value of maximum *LAI*, the cumulative mineral nitrogen arising from humus *Qminh* (calculated at the stage *LAX* or *Summer*) and the depth of roots *Zrac* (calculated 3 months after the sowing date). The results are calculated for the four configurations of simulation: wheat crop, dry weather and shallow soil (*W C1* -), wheat crop, wet weather and shallow soil (*W C2* -), sugar beet crop, dry weather and deep soil (*SB C1* +) and sugar beet crop, wet weather and deep soil (*SB C2* +).

Figure 3 shows the sensitivity indices calculated for the 13 soil parameters and for each output variable of the sugar beet crop simulated with a deep soil and a dry weather. In this case, the crop grows mainly in summer where it experiences a severe water stress, leading to a value of maximum *LAI* equal to 1.42 in average (see Tab. 4). The depth of the second layer (parameter *epc(2)*) does not have any importance here. This is also the case for wheat crop with a deep soil (results not shown here). Indeed, as the root growth is no longer limited by the thickness of soil (the depth of roots is equal to 77.58 in average), the output variables are no longer sensitive to the parameter *epc(2)* when the soil is deep. Moreover, the outputs are not at all sensitive to the initial water content *Hinit* because the amount of rainfall is quite important in spring, when the sugar beet is sown (see Tab. 3). The soil water reserve is therefore the main limiting factor and it depends only on *HCC(1)* for the early stage *AMF*: it contributes for 95 % of the total output variance of *LAI* and *QN*. For the *Summer* stage (Fig. 3b), which correspond to the maximum of water stress index, *LAI* is mainly sensitive to parameters linked to water availability of both soil layers (*HCC(1)*and *HCC(2)*) with an increase of the sensitivity to *Hinit*. *QN* is more sensitive to characteristics of the top layer (*HCC(1)* and *Hinit*) where is concentrated the organic nitrogen, as it influences the fate of available nitrogen coming from mineralization. The same tendencies are noticed for the output variables at harvest, *Yield* being more linked to *LAI* and soil mineral nitrogen to *QN*. Many interactions are visible between all these parameters. It is also noticeable that, as in the case of wheat, the output variables have very low sensitivity to the parameters concerned with nitrogen turnover in the soil, due to the dry weather and limited mineralization. The main differences of these results with respect to those presented for the wheat crop (Fig. 1 and 2) is: (i) that *HCC(1)* contributes a lot to the variance of the output variables during all the crop season, (ii) that *Hinit* as no contribution to the variance of the output variables at the beginning of the sugar beet season and (iii) that *epc(2)* does not affect the output variables when the soil is deep.

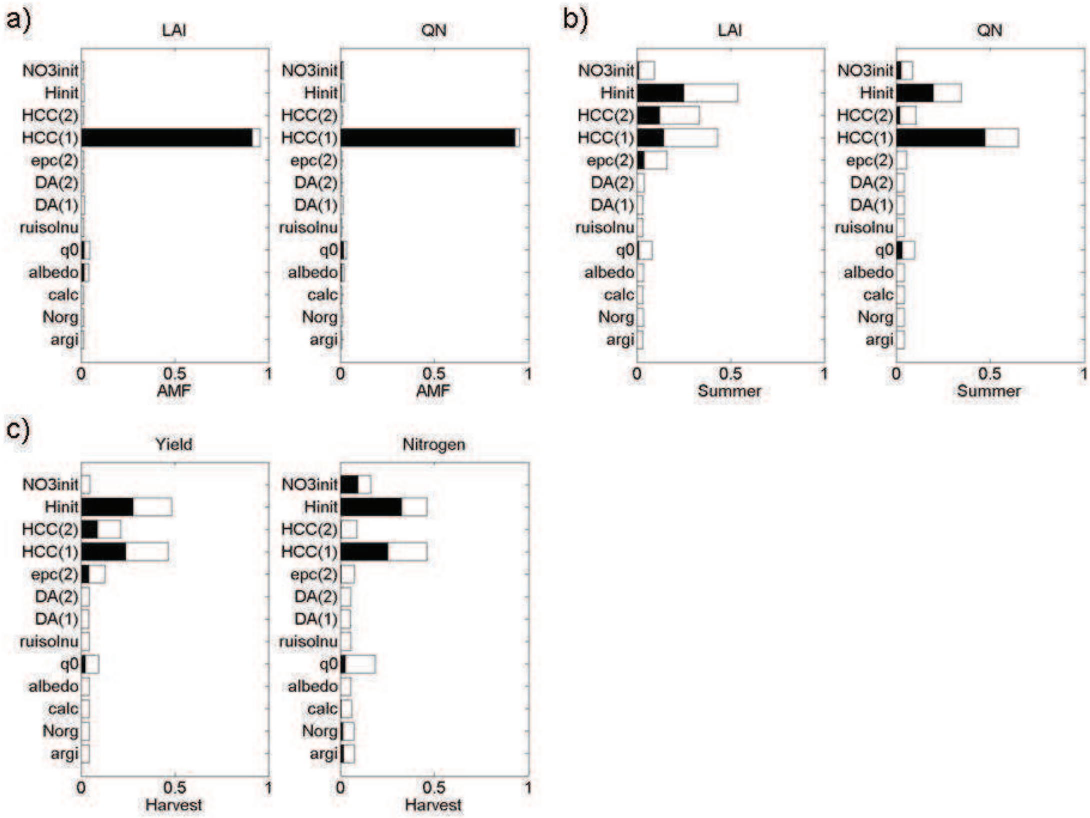

Figure 3. Sensitivity indices of the 13 soil parameters for each model output of the sugar beet crop simulated with a dry weather and a deep soil. The outputs a) correspond to *LAI* and *QN* at stage *AMF*, b) correspond to *LAI* and *QN* at *Summer* and c) correspond to *Yld* and *Nit* at *Harvest*. First-order indices are in black and interactions in white.

When considering wet conditions (Figure 4), the sugar beet crop growth is less affected by the water stress: maximum *LAI* is equal to 4 in average, whereas is equal to 1.42 in dry conditions (see Tab. 4). The soil water reserve of the second layer is not a limiting factor in deep soil and wet conditions for both stages *AMF* and *Summer* because the soil reservoir has a large size and the water stress is low. Thus, *LAI* and *QN* are only sensitive to the soil water reserve of the first layer which only depends on *HCC(1)* (it does not depend on *Hinit* because of the high amount of rainfall in spring). Nevertheless, the soil water reserve of the second layer becomes a limiting factor at the end of the sugar beet crop season, when the roots are deep, involving a significant sensitivity of the output *Yld* to the parameters *HCC(1)*, *HCC(2)* and *epc(2)*. Moreover, the mineralization of the soil organic matter slightly increases in wet conditions and so do the effects of the concerned parameters on *QN* at *Summer* and *Nit* at *yield*: the cumulative mineral nitrogen arising from humus is equal to 50.19 in average, whereas is equal to 24.91 in dry conditions (see Tab. 4). The main difference between these results and those presented in Fig. 3, lies in the lower sensitivity of the soil water reserve parameters of the second layer at the two first stages of interest.

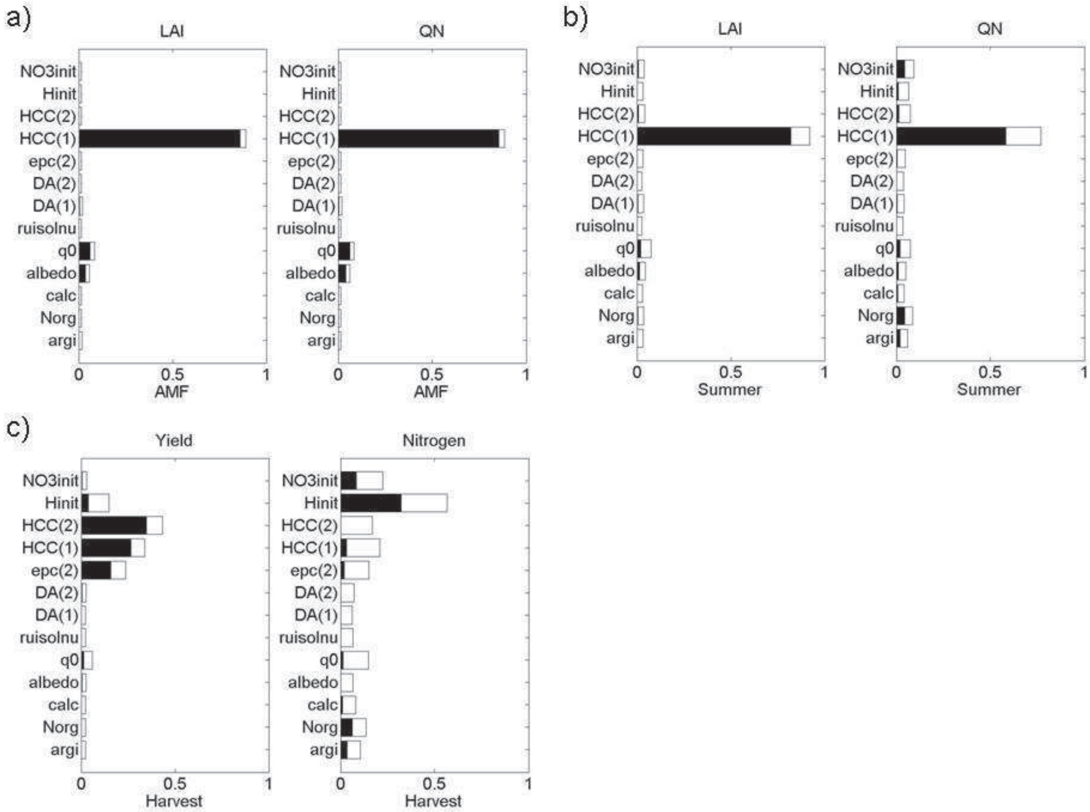

Figure 4. Sensitivity indices of the 13 soil parameters for each model output of the sugar beet crop simulated with a wet weather and a deep soil. The outputs a) correspond to *LAI* and *QN* at stage *AMF*, b) correspond to *LAI* and *QN* at *Summer* and c) correspond to *Yld* and *Nit* at *Harvest*. First-order indices are in black and interactions in white.

3.2 Total effect and coefficient of variation

For each configuration of simulation presented above, Figure 5 shows the coefficient of variation *CV* of each output variable and the corresponding total effect *ST* of each parameter. The horizontal dashed line is situated at an arbitrary minimum value *ST*=10% and the vertical dashed line is situated at another arbitrary minimum value *CV*=1/3. The threshold of 10% for *ST* has been proposed by Makowski (2006b) for screening the significant sensitivity values. When wheat crop is simulated with a dry weather and a shallow soil (see Fig. 5a), three output variables have a coefficient of variation higher than 1/3: *Prot* (*CV*=0.37), *Yld* (*CV*=0.54) and *LAI* at the stage *FLO* (*CV*=0.62). For these outputs, only 5 soil parameters have a *ST* higher than 10%: *epc(2)*, *HCC(1)*, *HCC(2)*, *Hinit* and *albedo*. This means that for simulating correctly these output variables of the wheat crop when the weather is dry and the soil depth is shallow, only *epc(2)*, *HCC(1)*, *HCC(2)*, *Hinit* and *albedo* have to be determined accurately (assuming the arbitrary threshold *ST*=10% and *CV*=1/3) and the other parameters can be fixed at a nominal value. When wheat crop is simulated with a wet weather and a shallow soil (Fig. 5b), only the variable *Nit* has a coefficient of variation slightly higher than 1/3 (*CV*=0.38). The corresponding parameters having a *ST* higher than 10% are *epc(2)*, *HCC(1)*, *HCC(2)* and *Norg*, meaning that these parameters are important to be determined accurately for simulating correctly the wheat crop in this case. The first main difference between the results presented in Fig. 5a and Fig. 5b is that only one output variable has a *CV* higher than 1/3 when the weather is wet, instead of three when the weather is dry. The second main difference is that the parameters *albedo* and *Hinit*, which contribute for a significant part of the output variance when the weather is dry, are replaced by the parameter *Norg*, which is involved in the mineralization process and contribute for a significant part of the variance of the outputs when the weather is wet.

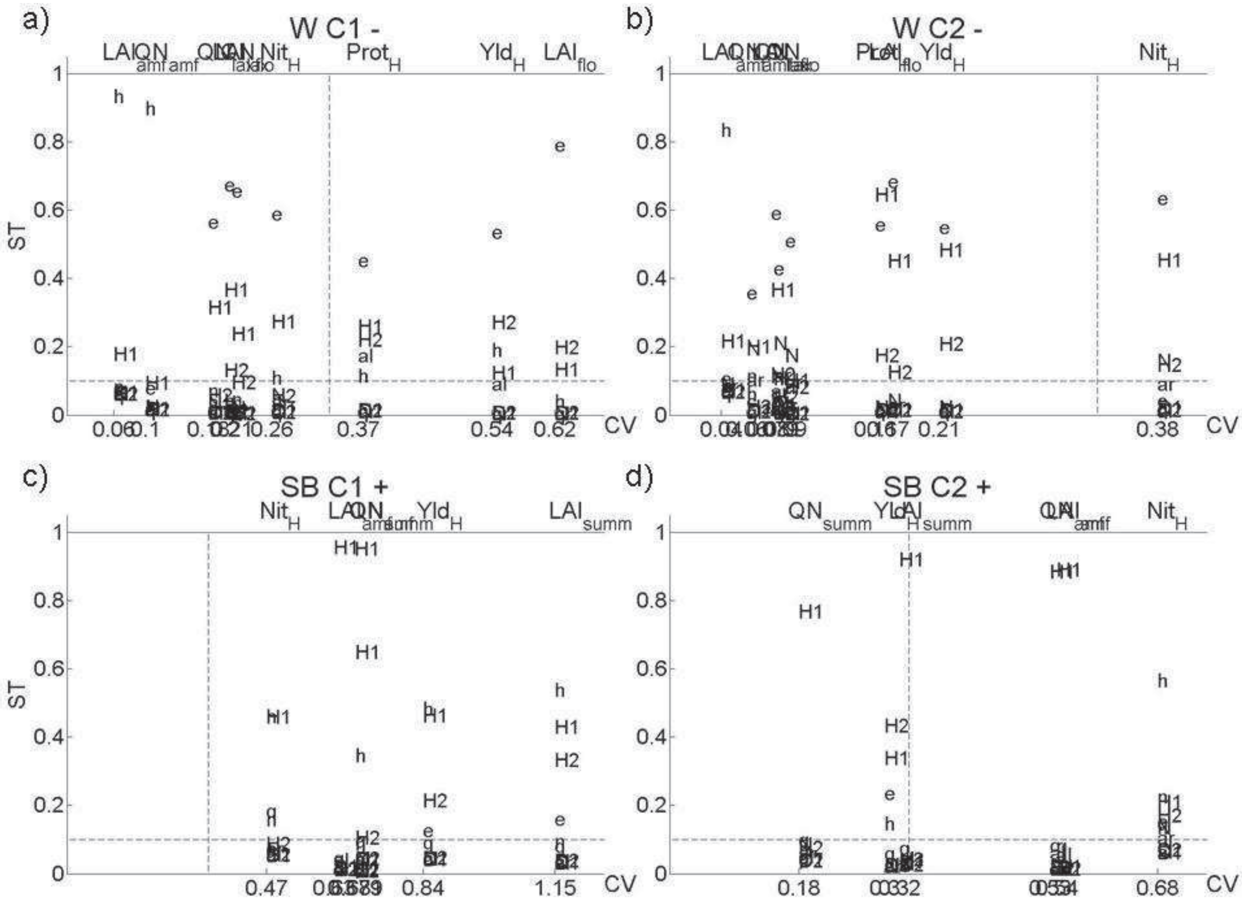

Figure 5. Coefficient of variation *CV* of each output variables and the corresponding total effects *ST* of the 13 soil parameters. The horizontal dashed line is situated at *ST*=10% and the vertical dashed line is situated at *CV*=1/3. The outputs are simulated for a) wheat crop, dry weather and shallow soil, b) wheat crop, wet weather and shallow soil, c) sugar beet crop, dry weather and deep soil and d) sugar beet crop, wet weather and deep soil. Label *C1* correspond to the dry weather and *C2* to the wet one, *W* correspond to the wheat crop and *SB* to sugar beet, - correspond to a shallow soil and + to a deep one. Parameter labels are presented in Table 1.

Considering the results presented in Fig. 5a and Fig. 5b, the parameter *Hinit*, which contributes for a large part to the variance of the output variables *LAI* and *QN* at the stage *AMF* of the wheat crop (see Section 3.1), does not need in fact an accurate determination for simulating correctly these output variables. Its *ST* values are higher than 0.8 for these outputs but the *CV* values of these outputs are lower than 0.1. If only the results provided by sensitivity analysis are used, *Hinit* would have been considered as an important parameter to be determined, but considering also the coefficient of variation allows stating that this parameter is not as important as previously thought. The parameter *epc(2)*, which contributes for a large part to the variance of all the output variables during all the wheat crop season (see Section 3.1), proves to be the most important parameter to be determined accurately for simulating the wheat crop when the type of soil depth is shallow.

The Fig. 5c shows the results when the sugar beet crop is simulated with a dry weather and a deep soil. It reveals that all the output variables have a coefficient of variation higher than 1/3 meaning that the uncertainties on the soil parameters generate a large uncertainty one the considered variables. Among those parameters, five need to be measured accurately: *epc(2)*, *HCC(1)*, *HCC(2)*, *Hinit* and *q0*. The main difference between the results presented in Fig. 5a and Fig. 5c is that the entire output variables are strongly affected by the measurement of the soil parameters when the sugar beet is simulated. When sugar beet is simulated with a deep soil and a wet weather (Fig. 5d), only the output variables *LAI* and *QN* at the stage *AMF* and *Nit* have a *CV* higher than 1/3 (resp. *CV*=0.54, 0.53 and 0.68). For *LAI* and *QN* at the stage *AMF*, the only parameter having a *ST* higher than 10% is *HCC(1)*. For *Nit*, a lot of parameters exceeds this threshold: *argi*, *Norg*, *q0*, *epc(2)*, *HCC(1)*, *HCC(2)*, *Hinit* and *NO3init*. It is thus necessary to determine accurately a lot of parameters for simulating correctly the output *Nit*, while it is necessary to determine only one parameter for simulating correctly *LAI* and *QN* at the stage *AMF*. The main difference between these results and those presented in Fig. 5c is that, excepted for the output *Nit*, at most one parameter has to be accurately known for simulating correctly the sugar beet crop in deep soil and wet conditions. The parameter *HCC(1)*, which contributes for a large part to the variance of all the output variables during all the sugar beet crop season (see Section 3.1), proves to be the most important parameter to be measured accurately for simulating the sugar beet crop when the soil is deep.

4. Conclusion

Global sensitivity analysis is an interesting tool for ranking parameters with respect to their contribution to the variance of the output variables of a model. However, the only use of sensitivity indices proves to be unsatisfactory for deciding which parameters should be accurately measured in a given configuration. Only the combination of uncertainty and sensitivity analysis is relevant to reach this goal. Unfortunately too few studies consider simultaneously these two aspects. We propose in this study a simple and easy to use method that combines these two methods in order to select the parameters that needs particular accuracy for simulating a set of variables of interest with an acceptable precision. The method has three steps: (i) compute the global sensitivity indices for each uncertain parameter (ii) compute the coefficient of variation of the outputs of interest from the set of simulations performed at step (i) and (iii) select the parameters to be accurately measured for simulating correctly these outputs by setting thresholds on sensitivity indices and coefficients of variation. Of course the results of this method are strongly linked to the uncertainties hypothesized for the parameters and special attention must be paid to this aspect. Coefficients of variation and sensitivity indices thresholds should be adapted to each case depending on the level of measurements constraints and of the accuracy wishes for model output simulations.

We apply this method to the crop model STICS for selecting soil parameters that need to be measured at a field scale. Practically this needs the knowledge of the conditions under which the crop grows (weather, type of soil depth, agricultural techniques …) and it has been shown here that the results depend on these conditions. Concerning non-permanent soil parameters such as initial conditions, the application of the method needs thus to be based on future scenarios. However, this application shows that the number of STICS soil parameters to be measured accurately for simulating correctly the output variables considered here for wheat and sugar beet crops (given the parameters uncertainties used and in the configurations studied) can be significantly reduced by the use of this method. This is of particular interest given the time and financial cost of soil measurements.

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