Crop Monitoring as an
E-agricutural tool in
Developping Countries

SENSITIVITY ANALYSIS REPORT

Reference: *E-AGRI_D32.1_Sensitivity analysis report _1.0, E-AGRI_D34.1*

Author(s): Roberto Confalonieri, Simone Bregaglio, Giovanni Cappelli, Caterina Francone, Marta Carpani, Marco Acutis, Wang Zhiming

Version: 1.0
Date: 21/03/2012

DOCUMENT CONTROL

Signatures

Author(s) : Roberto Confalonieri
Simone Bregaglio
Giovanni Cappelli
Caterina Francone
Marta Carpani
Marco Acutis
Wang Zhiming

Reviewer(s) :

Approver(s) :

Issuing authority :

Change record

Release	Date	Pages	Description	Editor(s)/Reviewer(s)
1.0	21/03/2012			

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ACRONYMS & GLOSSARY

CROP MODEL: a series of equations and/or algorithms, mainly implemented in a computer program, that reproduce the growth and development of crops. Data on weather, soil, and crop management are processed to predict information like, e.g., crop yield, maturity date, efficiency of fertilizers and other elements of crop production. Algorithms implemented in crop models are based on the existing knowledge on physiological, physical and ecological information on the way crops interact with environment.

SENSITIVITY ANALYSIS: the study of how the variability in the outputs of mathematical models can be attributed to the uncertainty in the values of the inputs or of the parameters of the models.

WARM: a model for the simulation of rice growth and development. It include modules for the simulation of the floodwater effect on the vertical thermal profile, rice blast disease, paddy soil hydrology, and the spikelet sterility due to abiotic factors.

WOFOST: a model for the simulation of crop growth and development based on the concept of gross photosynthesis. It is the main model used by the Joint Research Centre of the European Commission for crop monitoring and yield forecasting.

CROPSYST: a generic crop simulator based on the concept of net photosynthesis, estimated on a daily basis as driven by potentially transpired water and absorbed photosynthetically active radiation.

MORRIS METHOD: a sensitivity analysis method based on the assumption that model outputs are at least once differentiable with respect to inputs, and on an efficient sampling design, derived from independent sampling strategies for the exploration of the parameter hyperspace.

SOBOL’ METHOD: a sensitivity analysis method that allows the simultaneous exploration of the parameter hyperspace via Monte Carlo or quasi Monte Carlo sampling. The relevance of parameters or parameter interactions is quantified as percentage contribution to the total variance, computed using a distribution of model responses.

EXECUTIVE SUMMARY

The adoption of biophysical simulation models for crop yield forecasting in large areas requires their correct parameterization, aimed at increasing their degree of adeherence to the real system, and thus at providing reliable monitoring and yield estimates. To allow crop models reproducing properly the behaviour of the cultivated varieties in a region, a parameter set for each of them should be defined, and detailed information on where they are grown should be available and periodically updated. Since this is not feasible, modellers are used to group varieties according to their morphological and physiological features and to define a parameter set for each of the group.

The preliminary step for the development of a parameter set for each of these groups of varieties was an extensive, spatially distributed, sensitivity analysis (SA) experiment, carried out on the three crop growth models that will be used for crop yield forecasting, WARM, WOFOST, and CropSyst. This study, performed by using two advanced SA techniques (Morris and Sobol'), allowed to identify – for each models and for the conditions experienced by rice in Jiangsu – the parameters with the highest influence on the accumulation of aboveground biomass at maturity. For WARM they are (i) maximum radiation use efficiency, (ii) optimum temperature for growth, (iii) partitioning to laves at emergence, (iv) extinction coefficient for solar radiation, and (v) Specific Leaf Area at tillering. For WOFOST they are (i) efficiency of photosynthates conversion into storage organs, (ii) fraction of total biomass partitioned to roots at maturity, (iii) fraction of total biomass partitioned to roots at emergence, (iv) efficiency of photosynthates conversion into leaves, and (v) efficiency of photosynthates conversion into root. Lastly, for CropSyst they are (i) maximum radiation use efficiency, (ii) optimum mean daily temperature for growth, (iii) initial Leaf Area Index, biomass-transpiration coefficient, and (v) extinction coefficient for solar radiation (k).

These parameters are those on which the effort during the calibration activities will be concentrated, thus allowing to define the parameters sets that will be used to simulate rice in Jiangsu.

1. Introduction

In the last years, different typologies of systems for crop yield forecasts have been proposed, differing for the techniques adopted, for the spatial scale considered, and for the sources of information used (Rojas et al., 2005). They range from simple systems based on extensive field surveys to complex systems able to work at continental scale and to integrate different sources of information. Some of the most simple ones are based on empirical relationships between remotely sensed vegetation indices and historical series of yield data (e.g., Mkhabela et al., 2005). Other approaches are based on biophysical simulation models, where species-specific (e.g., Bannayan and Crout, 1999; Bezuidenhout and Singles, 2007) or generic (e.g., Soler et a., 2007) crop simulators are used. The most sophisticated crop monitoring and forecasting systems are based on the combined use of data simulated by crop models and information derived from remote sensing (e.g., Genovese et al, 2001).

For the systems that are partly or entirely based on crop models, a correct parameterization of the models themselves is crucial to get a satisfactory adherence of the simulated system to the real one, and thus to provide reliable monitoring and yield estimates.

When crop models have to be used on large areas for reproducing the behaviour of all the varieties grown in that region, a specific parameter set for each of the variety should ideally be defined, and detailed information on where each variety is grown should be available and periodically updated. This is of course not feasible, and modellers are used to define a single parameter set where morphological and physiological features averaged for all the varieties grown in the area are codified. A way to increase the reliability of large-area simulations is (i) to define groups of varieties with similar morphological and physiological features, (ii) to specify a set of parameters for each groups, (iii) to perform simulations – where possible – using a parameters set in the sub-areas where the corresponding varieties are grown.

Parameters sets can be defined by using observations, in case parameters have a morphological or physiological meaning (i.e., they can be measured/estimated via growth chamber or field experiments). If parameters are not measurable or if observations are not available, or when models have a high number of parameters, their values are usually defined by performing calibrations aimed at lowering the differences between observed and simulated state variables. In this case, it is important to identify the parameters with the highest relevance on synthetic model outputs, therefore, those on which to concentrate the efforts during the calibration. The identification of the most relevant model parameters is carried out using advanced Monte Carlo based sensitivity analysis techniques (e.g., Asseng et al., 2002; Saltelli et al., 2005) that, in case model behaviour has to be analyzed for large areas, should be

- multi-year (to avoid getting results affected by seasonal-specific conditions) and
- spatially distributed (to properly account for the spatial heterogeneity of the conditions explored).

1.1. Sensitivity analysis of biophysical models

Sensitivity analysis (SA) is a fundamental tool for supporting mathematical models development and use (Tarantola and Saltelli, 2003) because of its capability of explaining the variability in the outputs of the models themselves (Cariboni et al., 2007), via the quantification of the role of uncertain factors (i.e., parameters or driving variables).

In recent years, SA has been increasingly used as a tool to understand models behaviour and to support their development, also through reduction or simplification processes aiming at avoiding redundancies in model structure and/or over-parametrizations (Tarantola and Saltelli, 2003; Jakeman et al., 2006). This is particularly important when interactions among different factors affect model outputs (Ratto et al., 2001), since other techniques like conventional multivariate statistics (principal component analysis to analyse interactions) proved to be only partially adequate (Spear et al., 1994). In this context, SA was recently recommended as a tool to be iteratively used during the process of model development (Ravetz, 1997; Refsgaard et al., 2005; Jakeman et al., 2006), in order to assure coherence in mathematical formalizations, to avoid over-parameterizations by driving simplification processes (Ratto et al., 2001; Tarantola and Saltelli, 2003), and to support the development of balanced models (Confalonieri, 2010). These features favoured the introduction of SA in different typologies of documents defining guidelines for model development (e.g., European Commission, 2005; Jakeman et al., 2006). All these findings lead to consider SA as a prerequisite for model use and calibration (Ratto et al., 2001).

1.1.1. Sensitivity analysis techniques

It is possible to distinguish between two major groups of SA methods (Saltelli et al., 1999): local and global. Local methods examine the local response of the output(s) by varying parameters one at a time while keeping the others constant. Global methods examine the global response (averaged over the variation of all the parameters) of model output(s) while exploring the parameters hyperspace. Local methods, easier to implement, can only inspect one point at a time, and the SA results for a specific parameter depend on the central values of the others.

Different global SA techniques have been developed in the last years. Among the methods most used, it is possible to identify three main classes: screening methods, regression-based methods, variance-based methods. The most used screening method is the one proposed by Morris (1991), particularly effective in identifying a sub-set of important parameters in models (i) with a high number of parameters and (ii) with high computational requirements (Richter et al., 2009), maybe because of very small time step, or when many SA experiments must be carried out. This method is based on the computation of a certain number of incremental ratios (elementary effects) for each factor and on averaging them to estimate the overall factor importance on model output(s) (Campolongo et al., 2007). The second class includes the regression methods, which are based on the computation of standard or partial regression coefficients, quantifying the effects of changes in the parameters values. Within this class, different methods can be used to generate the sample of parameter combinations needed to obtain the evaluation of model sensitivity, and therefore to calculate the regression coefficients: Latin Hypercube Sampling (LHS), Random and Quasi-Random LpTau are some of the most used worldwide. The last class of SA approaches, the variance-based methods, includes the Fourier Amplitude Sensitivity Test (FAST) (Cukier et al., 1978), its evolution Extended FAST (E-FAST; Saltelli et al., 1999), and the method of Sobol' (Sobol', 1993). All the methods belonging to this class compute total sensitivity indices for first and higher orders effects and are quite demanding in terms of computational time because of the high number of model simulations needed for each model factor under evaluation. FAST and E-FAST use transformation functions to sample the parameters space stochastically, whereas Sobol' does not use transformation functions, thus having lower computational efficiency. Results obtained using Sobol' often serve as benchmark for testing other SA methods (e.g., Saltelli and Sobol', 1995).

1.1.2. Sensitivity analysis of agrometeorological models

Advanced SA techniques are increasingly used in the field of agrometeorological modelling. Van Griensven et al. (2006) applied a novel sampling strategy to identify the most relevant parameters in the SWAT catchment model for water flow, concluding that hydrologic parameters had the greatest impact on water quality. In the context of crop growth modelling, Richter et al. (2010) used the Morris method to identify the parameters of a complex crop model with the highest impact on Durum wheat yield formation at two locations, identifying the parameters involved with development and early light interception as the most relevant. Confalonieri et al. (2010a) applied the Morris and Sobol' methods to a model for rice growth and development, comparing the SA results obtained for five European countries and, within each country, for three years characterized by different degree of continentality. Confalonieri (2011) quantified the impact of weather variables on the crop model CropSyst (spring barley in Norther Italy was simulated) by coupling a standard SA method (i.e., Morris) and a weather generator.

1.2. Contents of the deliverable

In this report, we report the methodology and the results of multi-year, spatially distributed sensitivity analyses of the models WARM, WOFOST and CropSyst for rice simulation in Jiangsu.

The methodology used is presented in section 2.1 “Multi-year, spatially distributed sensitivity analysis of the models WARM, WOFOST and CropSyst for rice simulation in Jiangsu”.
Results and discussion are in section 3.1 “Sensitivity analysis of the models WARM, WOFOST and CropSyst for rice simulation in Jiangsu”.

2. Materials and methods

2.1. Multi-year, spatially distributed sensitivity analysis of the models WARM, WOFOST and CropSyst for rice simulation in Jiangsu

2.1.1. The crop models

The simulators on which SAs were performed are WARM (Confalonieri et al., 2009a,b), WOFOST (Van Keulen and Wolf, 1986), and CropSyst (Stöckle et al., 2003) and. WARM (Water Accounting Rice Model) is a model specific for rice simulations, and it is used by the European Commission for rice yield forecasts. WOFOST is also used by the European Commission, within the MARS Crop Yield Forecasting System (http://mars.jrc.it/) for the simulation of the main herbaceous crops grown in Europe. CropSyst has been used in many studies worldwide for evaluating the impact of management and climatic scenarios for a variety of crops (e.g., Tubiello et al., 2000; Monzon et al., 2006). The models differ for the approaches used to reproduce the different processes related to crop growth and development, for the amount of data needed for their use, and for their behaviour, being characterized by different degrees of complexity, robustness and balance (Confalonieri et al., 2009; Confalonieri et al., 2010b; Confalonieri, 2010).
The three models simulate crop development as a function of thermal time accumulated, with options to account for photoperiod. CropSyst has an option to account also for vernalization, and WARM accounts for the floodwater effects influencing air temperature using the micrometeorological model TRIS (Confalonieri et al., 2005).
WARM simulates net photosynthesis using a RUE approach, with RUE varying to account for thermal limitation to photosynthesis, saturation of the enzymatic chains, senescence. Photosynthates are daily partitioned to leaves, stems and panicles. LAI is computed multiplying the leaves biomass by the specific leaf area, with the latter varying according to the development stage. Development stages are standardized by converting growing degrees days into a numerical code, in turn used to synchronise the simulation of different processes. Effects of diseases and abiotic damages on crop growth are simulated.
Concerning daily biomass accumulation, CropSyst is based on the Tanner and Sinclair (1983) relationship between aboveground biomass (AGB), potential transpiration, vapour pressure deficit (VPD) and a VPD-corrected transpiration use efficiency (TUE_{VPD}). The instability of the Tanner and Sinclair equation for low values of VPD leads to the adoption of a temperature-limited radiation use efficiency (RUE) approach when these conditions occur. CropSyst simulates leaf area development as a function of AGB, a constant specific

leaf area and an empirical coefficient, without the simulation of dynamic AGB partitioning to the different plant organs.
WOFOST is the most sophisticated in reproducing the biophysical processes involved with crop growth, calculating gross photosynthesis, growth (during photosynthates partitioning to plant organs) and maintenance respirations. Partitioning of assimilates is thus driven by growth respiration, development-specific partitioning factors and efficiencies of assimilates conversion into the different organs. Leaf area expansion is calculated as a function of temperature for leaf area index (LAI) lower than one, and derived from specific leaf area and development stage elsewhere. WOFOST has a three-layer canopy representation, with a spherical leaf angle distribution and LAI split among the layers using a Gaussian integration. Leaves death is simulated by the two models as driven by senescence, with WOFOST reproducing this process also as a function of leaves self-shading.
Excluding the simulation of the processes involved with crop development, WOFOST is the model with the highest number of parameters to be specified/calibrated to define the morphological and physiological features of a variety (from about 40 to more than 100, according to the information available for parameters that change their values according to development stage or temperature). CropSyst has 12 parameters directly involved with the simulation of biomass accumulation and leaf area expansion. WARM is the most parsimonious, with five parameters involved with net photosintesis and six with aboveground biomass partitioning and leaf area index.
The models are fully described in the seminal literature.

2.1.2. The sensitivity analysis methods

The high number of SA executions to be performed and the high number of parameters of the WOFOST model (see section 2.1.3) suggested to adopt a two steps procedure (e.g., Confalonieri et al., 2010a). The parameters of the two models were thus first screened using the parsimonious Morris method (Morris, 1991) and, then, the variance-based method of Sobol' (Sobol', 1993), considered a reference in SA but the most computationally expensive, was applied to the parameters with a not-negligible relevance according to Morris.
In spite of its low model executions requirement, the Morris method proved its effectiveness in ranking parameters according to their relevance in different studies where it was compared with other methods (e.g., Campolongo et al. 2007, Confalonieri et al., 2010c; Yang, 2011). In particular, Yang (2011) demonstrated that, although the method is not able to quantify the amount of variance each parameter is responsible for, it provides a good approximation of relative importance of each parameter, also in term of interaction characterization.
The Morris method can be regarded as global, since the final measure is obtained by averaging local (elementary) effects (Kucherenko et al., 2009). It is based on the assumption that model outputs are at least once differentiable with respect to inputs, and

on a particular design of the SA experiment, derived from independent sampling strategies for the exploration of the parameter hyperspace. The first assumption allows to determine which parameters can be considered to have effects on outputs that are (i) negligible, (ii) linear and additive or (iii) non-linear or involved in interactions with other parameters.
Assuming k as the total number of model parameters, X = (x_1,…, x_k) is the parameter vector. Each parameter x_i, after being scaled in the interval [0, 1], may takes on values in the set {0, 1/(p-1), 2/(p-1),…,1}, where p is the number of levels. The parameter space Ω is then defined as a k-dimensional p-level unit hypercube. Assuming Δ as 1/[2(p-1)] and y(X) as a model output, an elementary effect of the i-th factor is therefore calculated as:

$$R_i(X,\Delta) = \frac{y(x_1,\ldots,x_{i-1},x_i+\Delta,x_{i+1},\ldots,x_k) - y(X)}{\Delta}$$

The finite distribution of R_i is obtained by randomly sampling X in Ω and is composed by a total of p^{k-l}[p - Δ(p - 1)] elements for each x_i. Mean (μ_i) and standard deviation (σ_i) of each distribution of R_i are the sensitivity measures. μ_i represents the overall influence (total effect: strength, hereafter) of the parameter x_i, while standard deviation (spread) identifies – for high values – nonlinearities in model response or interactions with other parameters.
Morris suggested a random sampling design to estimate μ and σ over a smaller number of elementary effects. The method selects r different trajectories of (k+1) points, each differing from the previous because of Δ applied each time to a single parameter. This design is notably an improvement with respect to varying one-factor at a time (OAT), both because each parameter step does not revert to the baseline point and because r is usually major than one, leading to widely explore Ω (Saltelli, 2010). In this way, the total number of model evaluations is then lowered to r(k+1), in turns decidedly lowering the computational time. After this sampling phase, parameters are transformed from the unit hypercube to their physical values.
In this study, the evolution of the Morris method proposed by Campolongo et al. (2007) was used. This approach allows to (i) select the r trajectories in such a way to maximise their dispersion in the input space Ω, and (ii) get the values of μ_i^* (instead of μ_i), which is the estimate of the mean of the distribution of the absolute values of the elementary effects R_i:

$$\mu_i^* = \frac{\sum_{i=1}^{r} |R_i|}{r}$$

The use of μ_i^* solves the problems due to effects of opposite signs which occurs when the model is non-monotonic.
The method of Sobol' allows the simultaneous exploration of the parameter hyperspace via Monte Carlo or quasi Monte Carlo sampling. According to Sobol', the variance of the model output is decomposed into terms of increasing dimension, called partial variances, that represent the contribution of each single input (but even pairs, triplets, etc.) to the overall uncertainty of the model output. The relevance of parameters or parameter

interactions is quantified as percentage contribution to the total variance, computed using a distribution of model responses (Tang et al., 2007). For independent parameters, the Sobol' variance decomposition can be written as:

$$V(y)=\sum_{i} V_i + \sum_{i<j} V_{ij} + \sum_{i<j<k} V_{ijk} + \ldots + V_{12\ldots k}$$

where V_i is the amount of variance of the model output y due to the ith parameter, V_{ij} is the amount of y variance explained by the interaction of the ith and jth parameters, V_{ijk} is the proportion of y variance due to the interaction of the ith, jth and kth parameters, k is the number of parameters, defining the k-dimensional hyperspace. This variance decomposition is used to derive sensitivity indices of different order as $S_i = \frac{V_i}{V}$, $S_{ij} = \frac{V_{ij}}{V}$, etc., with the total order effect for a parameter, St_i, equal to the sum of S_i, S_{ij}, … up to the k^th order of analysis. In this study, the value of St for each parameter was calculated according to Homma and Saltelli (1996) and Saltelli (2002), to reduce the computational cost of the analysis.

2.1.3. Sensitivity analysis experiments

Information on weather data were retrieve from the ECMWF (European Centre for Medium-Range Weather Forecasts) ERA-Interim database (1989-2010) (http://www.ecmwf.int/research/era/do/get/era-interim), whereas sowing information were derived from the SAGE Center for Sustainability and the Global Environment database (SAGE, http://www.sage.wisc.edu/index.html).

For all the SAs, aboveground biomass at physiological maturity (AGB_{mat}) was considered as the model output to investigate. AGB_{mat} was selected as it is a synthetic representation of the culmination of numerous biophysical processes. AGB_{mat} is also a product of all crop parameters, acting in conjunction with each other.

For both the SA methods, the generation of the samples of possible combinations of crop parameters was carried out using the SimLab dynamic link library (SimLab, 2011), as well as the computation of the sensitivity indices from simulation results.

For this study, only crop parameters directly involved in crop growth (photosynthesis, partitioning of assimilates, leaf area evolution, senescence) were used.

Both SA methods require knowing the probability distributions of the various parameters in order to compute the sensitivity measures of interest (Morris μ* and Sobol St in this study). A set of values was therefore associated to each parameter, as derived from literature (Tables 1, 2 and 3). Means and standard deviations were calculated for each parameter, after the application of the Shapiro-Wilk test guaranteed on the normality of the distributions. Specific sampling designs (according to the Morris and Sobol' methods) were applied to generate the samples of combinations in the parameters hyperspace and simulations were carried out using both the models for each sample point. To avoid getting results affected by seasonal-specific effects, 5-year simulations were run and their results

averaged. The model outputs (averaged) were then provided to the sensitivity procedures to calculate the sensitivity measures.
To avoid sampling values in the tails of the normal distribution, the domain of each parameter was limited by truncations at the 10th and 90th percentiles. This allowed avoiding uncoherent parameters values.
For WOFOST, the number of couples [development stage, value] and [average daily air temperature, value] for which SA was performed was reduced (i) to focus on the most relevant ones and (ii) to avoid inconsistencies which can occur when sample values are generated during SA (e.g., partitioning coefficients to storage organs decreasing with development stage).
The total number of models runs was 9,668,970.

Table 1: Crop parameters of WARM and statistical settings used for sensitivity analysis – rice.

Parameter	Unit	Mean	Standard deviation	Source[a]
Maximum radiation use efficiency (RUE)	g MJ^{-1}	3	0.5	1
Extinction coefficient for solar radiation (k)	-	0.5	0.04	1
Base temperature for growth (Tbase)	°C	12	0.6	2
Optimum temperature for growth (Topt)	°C	28	2	2
Maximum temperature for growth (Tmax)	°C	42	2	3
Initial specific leaf area (SLAini)	m^2 kg^{-1}	27	2	4
Specific leaf area at tillering (SLAtill)	m^2 kg^{-1}	18	3	6, 7, 8
Partition coefficient to leaf at early stages (RipL0)	kg kg^{-1}	0.7	0.1	6, 8
Leaf duration (LeafDur)	°C-d	700	80	9
Maximum panicle height (Hmax)	cm	100	20	3

[a] 1: Boschetti et al. (2006); 2: Confalonieri et al. (2009b) 3: Local experience; 4: Boschetti (unpublished data); 5: Boschetti et al. (2006); 6: Kropft et al. (1994); 7: Van Diepen et al. (1988); 8: Confalonieri (unpublished data); 9: Confalonieri and Bocchi (2005);

Table 2: Crop parameters of WOFOST and statistical settings used for sensitivity analysis - rice

Parameter	Unit	Mean	Standard deviation	Source[c]
Leaf area index at emergence (LAIEM)	$m^2\ m^{-2}$	0.01	0.005	1, 2
Relative leaf area growth rate (RGRLAI)	°C d^{-1}	0.00855	0.000482	3
Specific leaf area at DVS[a] = 35 (SLA35)	ha kg^{-1}	0.0035	0.000525	4
Specific leaf area at DVS[a] = 45 (SLA45)	ha kg^{-1}	0.00262	0.0002128	4
Specific leaf area at DVS[a] = 65 (SLA65)	ha kg^{-1}	0.0023	0.000276	4
Life span of leaves growing at 35°C (SPAN)	D	35	3.5	5
Base temperature for leaves aging (Tbase)	°C	9	1.5	5
Extinction coefficient for diffuse visible light at DVS = 0 (KDIF000)	-	0.436	0.1	3, 4, 6
Extinction coefficient for diffuse visible light at DVS = 100 (KDIF100)	-	0.625	0.02	3, 6
Light use efficiency at Tavg[b] = 10°C (EFFTB10)	kg ha^{-1} h^{-1} J^{-1}	0.55	0.04	5, 7
Light use efficiency at Tavg = 30°C (EFFTB30)	kg ha^{-1} h^{-1} J^{-1}	0.35	0.04	5, 7
Maximum CO_2 assimilation rate at DVS = 000 (AMAXTB000)	kg ha^{-1} h^{-1}	40.24	10.2	8
Maximum CO_2 assimilation rate at DVS = 200 (AMAX200)	kg ha^{-1} h^{-1}	40.24	10.2	3, 5, 7
AMAX reduction factor at Tavg = 14°C (TMPFTB14)	°C	0.2	0.08	3, 5, 7
AMAX reduction factor at Tavg = 23°C (TMPFTB23)	°C	0.8	0.02	3, 5, 7
Correction factor for traspiration rate (CFET)	-	1	0.08	3, 5, 7
Efficiency of conversion into leaves (CVL)	kg kg^{-1}	0.5	0.14	3, 5, 7
Efficiency of conversion into	kg kg^{-1}	0.5	0.14	3, 5, 7

storage organs (CVO)				
Efficiency of conversion into roots (CVR)	kg kg^{-1}	0.5	0.14	3, 5, 7
Efficiency of conversion into stems (CVS)	kg kg^{-1}	0.5	0.14	3, 5, 7
Relative increase in respiration rate per 10°C of temperature increase (Q10)	-	1.8	0.1	3, 5, 7
Relative maintenance respiration rate for leaves (RML)	kg CH_2O kg^{-1} d^{-1}	0.028	0.0005	3, 5, 7
Relative maintenance respiration rate for storage organs (RMO)	kg CH_2O kg^{-1} d^{-1}	0.01	0.003	3, 5, 7
Relative maintenance respiration rate for roots (RMR)	kg CH_2O kg^{-1} d^{-1}	0.012	0.0011	3, 5, 7
Relative maintenance respiration rate for stems (RMS)	kg CH_2O kg^{-1} d^{-1}	0.018	0.001	3, 5, 7
Fraction of total biomass to roots at DVS = 0 (FRTB000)	kg kg^{-1}	0.45	0.058	3, 5, 7
Fraction of total biomass to roots at DVS = 100 (FRTB100)	kg kg^{-1}	0.25	0.042	3, 5, 7
Fraction of aboveground dry matter to leaves at DVS = 0 (FLTB000)	kg kg^{-1}	0.7	0.083	3, 5, 7
Fraction of aboveground dry matter to leaves at DVS = 50 (FLTB050)	kg kg^{-1}	0.45	0.16	3, 5, 7
Fraction of aboveground dry matter to storage organs at DVS = 82 (FOTB082)	kg kg^{-1}	0.2	0.043	3, 5, 7
Fraction of aboveground dry matter to storage organs at DVS = 100 (FLTB100)	kg kg^{-1}	0.65	0.083	3, 5, 7
Specific stem area at DVS = 30 (SSA030)	ha kg^{-1}	0.000919	0.000269	3
Specific stem area at DVS = 120 (SSA120)	ha kg^{-1}	0.000216	0.00005	3
Specific stem area at DVS = 150 (SSA150)	ha kg^{-1}	0.000335	0.000009	3

[a] Development stage code (unitless; 0: emergence, 100: flowering, 200: physiological maturity)

[b] Average air daily temperature (°C)
[c] 1: Boschetti (unpublished data); 2: Stroppiana et al. (2006); 3: Casanova et al. (2000); 4: Dingkuhn et al. (1999); 5: Kropff et al. (1994); 6: Boschetti et al. (2006); 7: Van Diepen et al. (1988); 8: Ziska and Teramura (1992).

Table 3: Crop parameters of CropSyst and statistical settings used for sensitivity analysis - rice

Parameter	Unit	Mean	Standard deviation	Source[a]
Biomass-transpiration coefficient (BTR)	kPa kg m^{-3}	5	1	1
Radiation use efficiency (RUE)	g MJ^{-1}	3	0.5	2
Specific leaf area (SLA)	m^2 kg^{-1}	27	2	2
Stem/leaf partition coefficient (SLP)	-	2	0.8	6
Leaf duration (LeafDur)	°C-d	700	80	1
Extinction coefficient for solar radiation (k)	-	0.5	0.04	2
Base temperature (Tbase)	°C	12	0.6	1
Optimum temperature (Topt)	°C	28	2	1
Initial leaf area index (LAIini)	m^2 m^{-2}	0.01	0.005	4, 5
Full canopy coefficient (Kc)	-	1.05	0.15	7
Maximum leaf area index (LAImax)	m^2 m^{-2}	7	0.5	4,5
Actual to potential transpiration ratio to limit leaf growth (ActPotTrLeaf)	-	0.8	0.1	3
Actual to potential transpiration ratio to limit root growth (ActPotTrRoot)	-	0.5	0.1	3
Maximum water uptake (MaxWupt)	mm d^{-1}	10	1	1

1: Confalonieri and Bocchi (2005); 2: Boschetti et al. (2006); 3: Confalonieri (unpublished data); 4: Boschetti (unpublished data); 5: Stroppiana et al. (2006); 6: Confalonieri et al. (2009c); 7: Allen et al. (1998).

3. Results and Discussion

3.1. Sensitivity analysis of the models WARM, WOFOST and CropSyst for rice simulation in Jiangsu

3.1.1. Results obtained with the Morris method

Results of the SAs carried out on the WARM model using the Morris method are shown from Figure 1 to Figure 6.
The first three maps – describing the spatial distribution of Morris μ* for the most relevant parameters – do not show any pattern (i.e., a single parameter is present for each rank position). The parameter ranked first was maximum radiation use efficiency (RUE; Figure 1), followed by optimum temperature for growth (Topt; Figure 2), and partitioning to leaves at emergence (RipL0; Figure 3). The importance ot these three parameters was already observed in a previous study in Europe (Confalonieri et al., 2010a), although the ranking of the remaining factors was different, reflecting the peculiarities of the explored conditions.

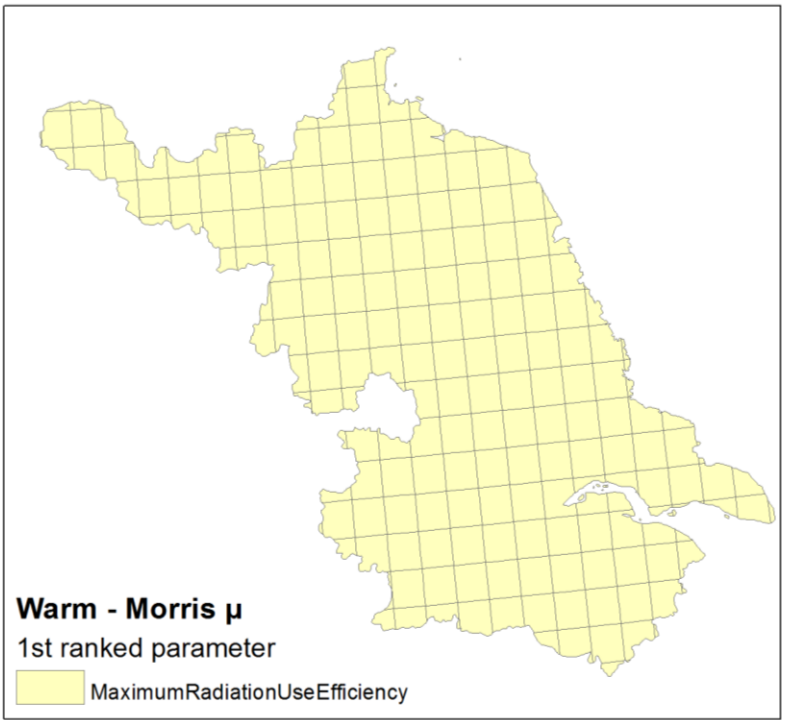

*Figure 1: WARM parameters ranked first according to the values achieved for Morris μ**

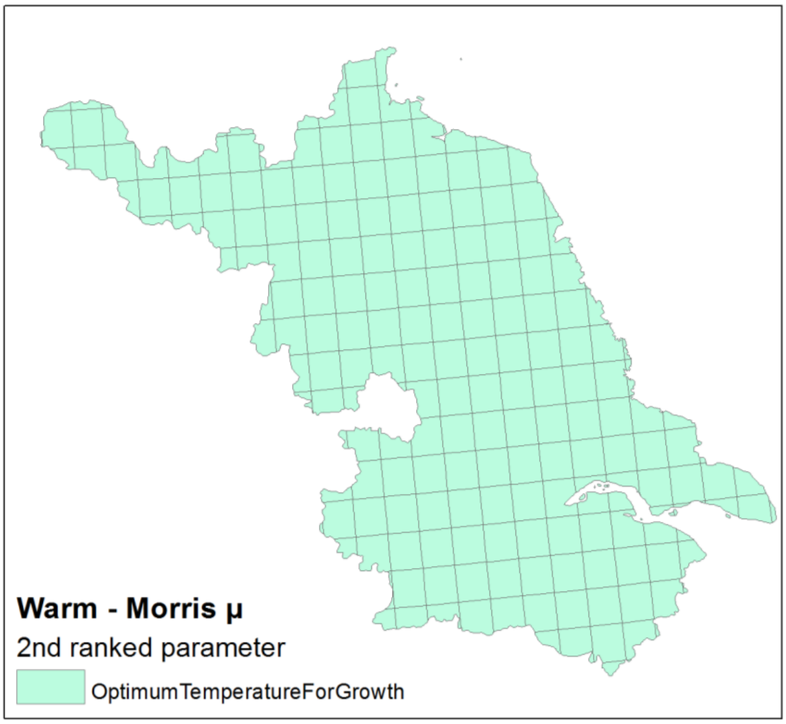

*Figure 2: WARM parameters ranked second according to the values achieved for Morris μ**

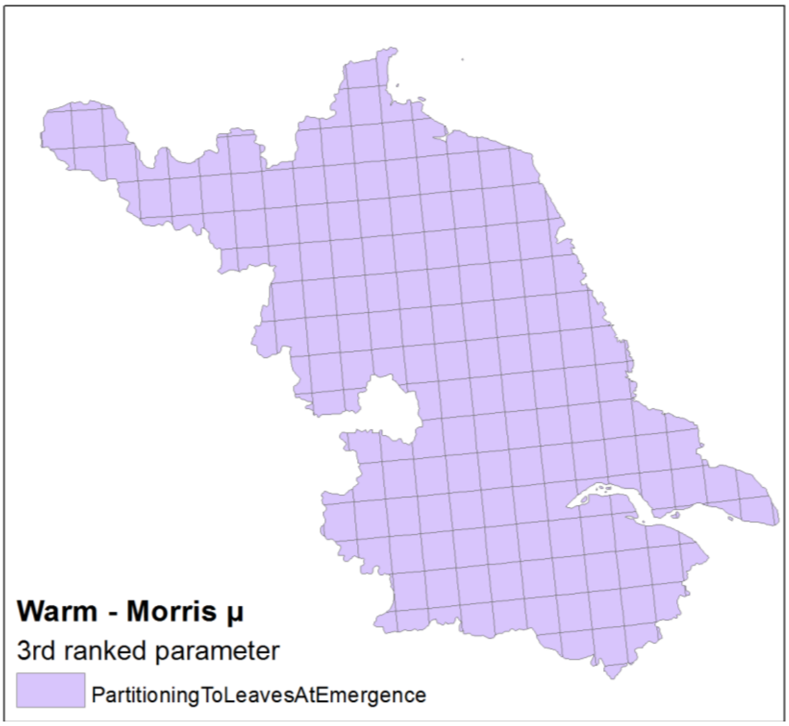

*Figure 3: WARM parameters ranked third according to the values achieved for Morris μ**

RUE and extinction coefficient for solar radiation (k) achieved the highest values for Morris σ (Figure 4). High values for this index are explained by a high degree of non-linearity of the processes involving the parameters, and/or by interactions with other factors. Although k was not ranked among the three most relevant parameters according to μ*, it is one of the main factors involved with light interception.

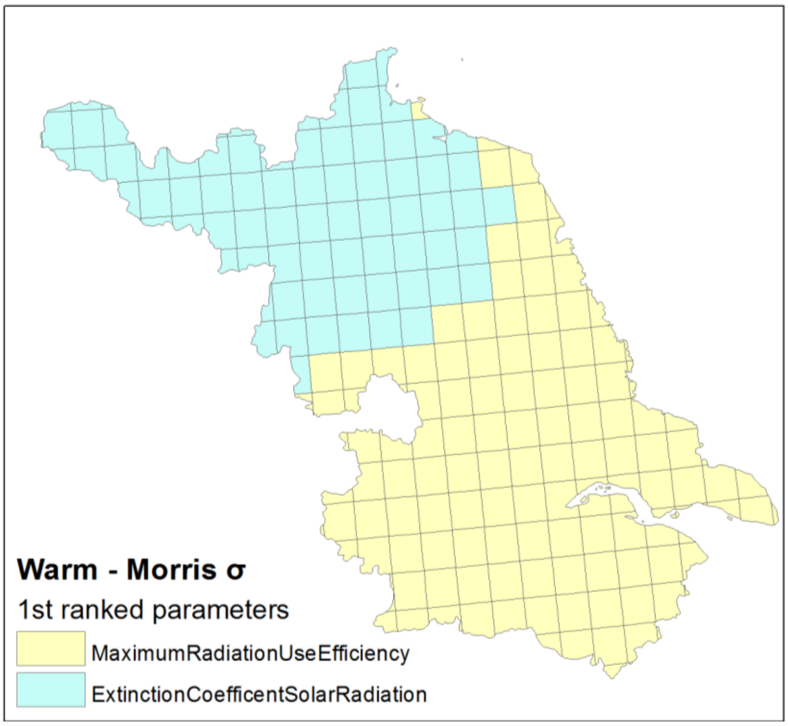

Figure 4: WARM parameters ranked first according to the values achieved for Morris σ

Figure 5 5 and Figure 66 show the mean values of μ* and σ, achieved by averaging the values estimated for all cells of the Jiangsu region. The histograms show that the remaing relevant WARM parameters under the conditions explored are Specific Leaf Area at tillering (SLAtill) and the extinction coefficient for solar radiation (k), confirming the importance of parameters related to the structure of the canopy, after RUE and Topt. With particular reference to Figure 6, a discontinuity appears after the first five parameters, thus determing the selection of them for the second step of the sensitivity analysis (Sobol' method).

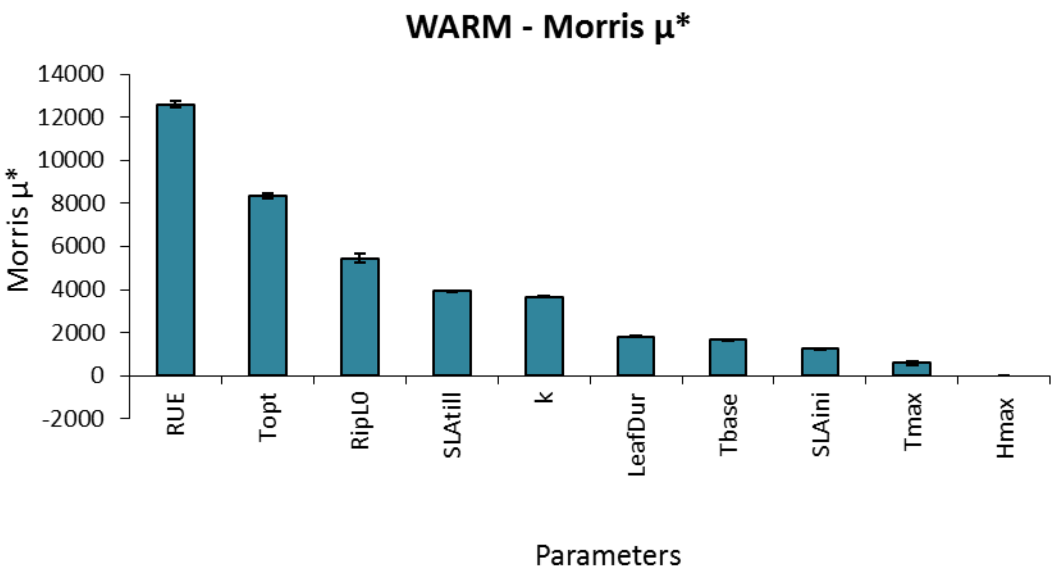

Figure 5: Mean values of Morris μ achieved by the WARM parameters in Jiangsu. The first five (from RUE to k) were selected for the second step of the analysis (Sobol' method)*

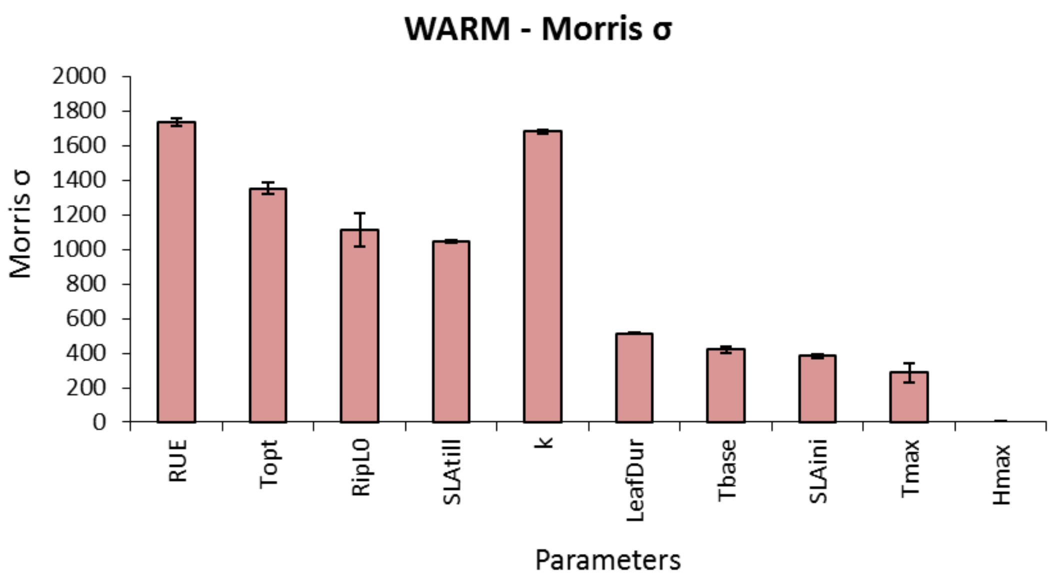

Figure 6: Mean values of Morris σ achieved by the WARM parameters in Jiangsu

Results of the SAs carried out on the WOFOST model using the Morris method are presented from Figure 7: WOFOST parameters ranked first according to the values achieved for Morris μ*Figure 7 to Figure 12.

Efficiency of conversion into storage organs (CVO) was the most relevant parameter in the study region (Figure 7). The parameters ranked second and third are maximum CO_2 assimilation rate at emergence (AMAXTB000) and at maturity (AMAXTB200). The spatial pattern of the second ranked factors (Figure 8) is exactly specular to the third ranked ones (Figure 9). The same parameters were found to be high-ranked in previous SA study carried out using the same model in Northern Italy conditions (Confalonieri, 2010).

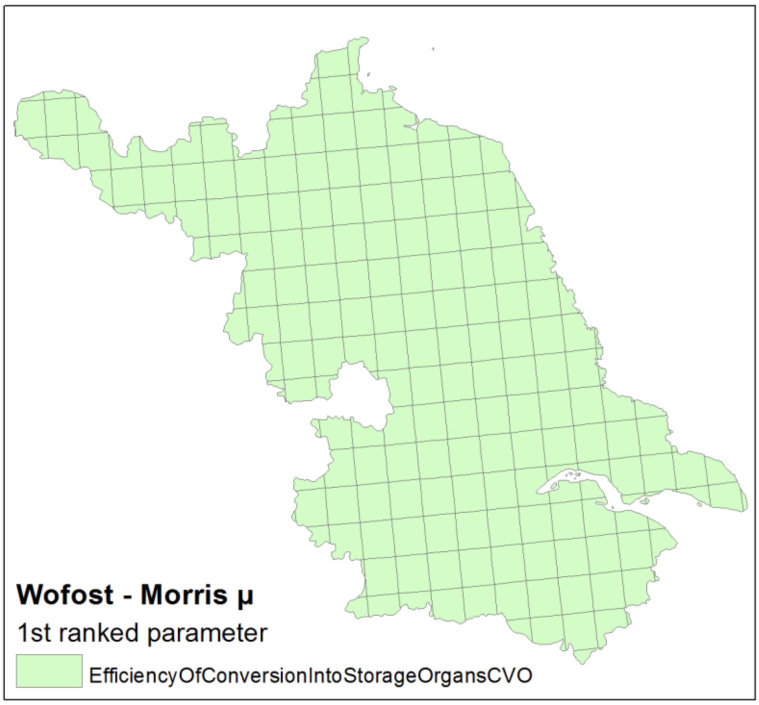

*Figure 7: WOFOST parameters ranked first according to the values achieved for Morris μ**

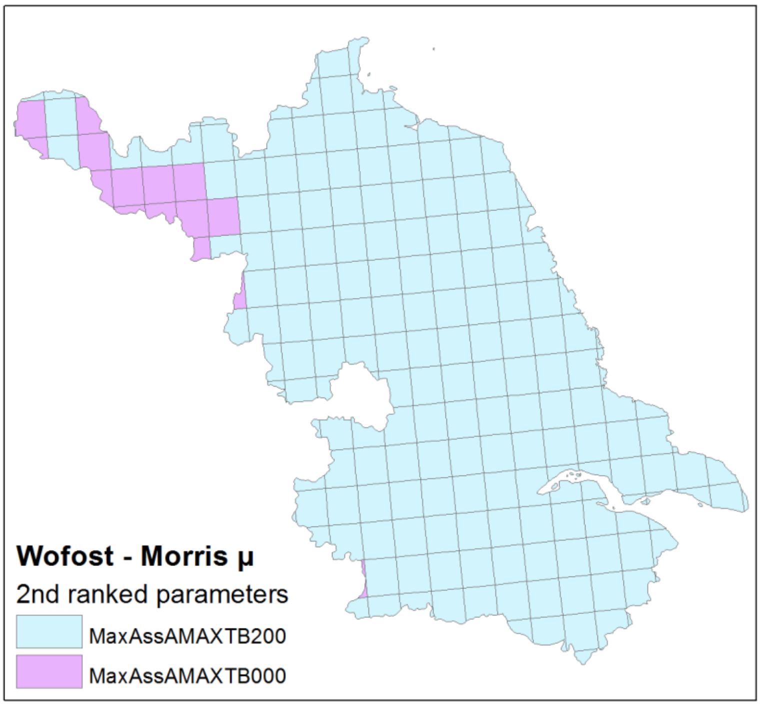

*Figure 8: WOFOST parameters ranked second according to the values achieved for Morris μ**

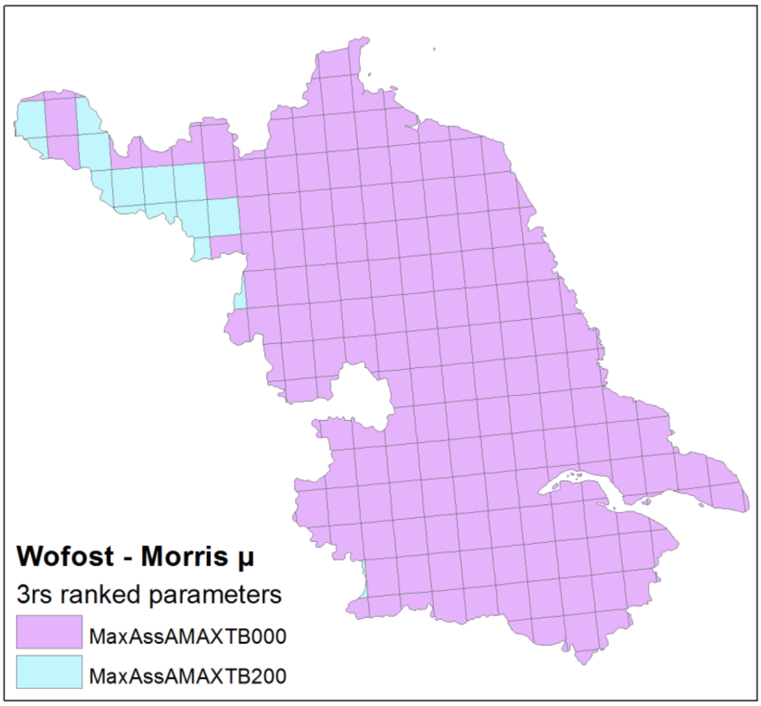

*Figure 9: WOFOST parameters ranked third according to the values achieved for Morris μ**

A spatially uniform result was found for the first ranked parameter according to the σ index, i.e., the efficiency of conversion to roots (CVR), thus identified as the factor most involved in non-linearities and/or interactions with other parameters.
Figure 11 and Figure 12 show the mean values of μ* and σ, obtained by averaging the values estimated for all the 25 x 25 km cells. It is possible to clearly identify the parameters to be used for the second step of the analysis (Sobol' method), i.e., CVO, AMAXTB200, AMAXTB000, CVL (efficiency of conversion into leaves) and CVS (efficiency of conversion into stems). In particular, Figure 12 reveals that the difference among the two maximum CO_2 assimilation rates is negligible, since their μ* values are only slightly different.
An interesting comparison with SA results for wheat in Morocco (sited at the same latitudes of Jiangsu region) allow to appreciate the plasticity (i.e., the tendency of a model to change its behaviour when applied to different conditions) characterizing WOFOST. For Morocco (refer to E-AGRI D34.1), we found that the parameters directly involved with temperature (i.e., TMPFTB14 and TMPFTB23) were high ranked according to their relevance, whereas their impact for rice simulation was negligible (Figure 11 and Figure 12). These results reflect the different thermal requirements of the two crops, with rice in Jiangsu experiencing conditions it is particularly adapted to, whereas wheat in Morocco often suffering for high temperatures. This explains the highest sensitivity of the model to temperature-related parameters Morocco.

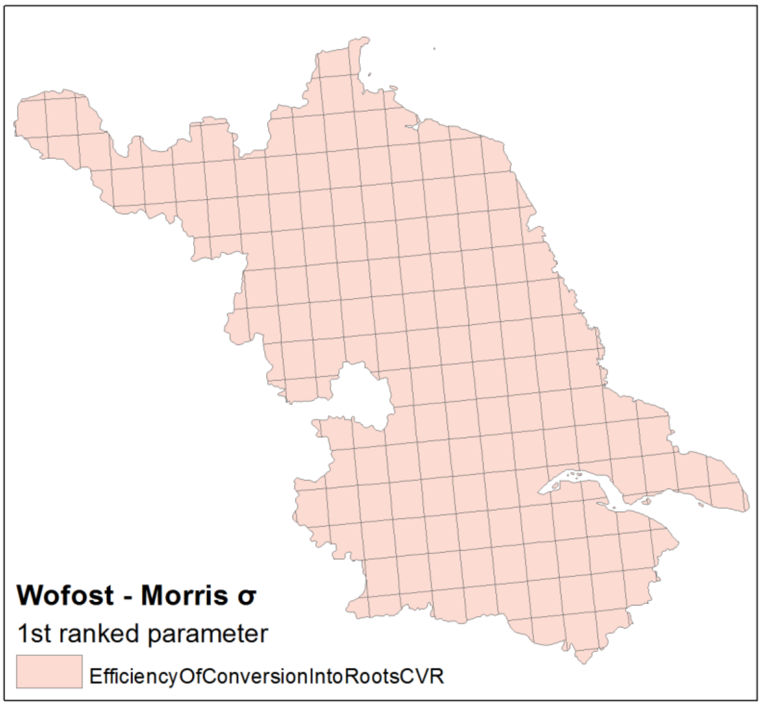

Figure 10: WOFOST parameters ranked first according to the values achieved for Morris σ

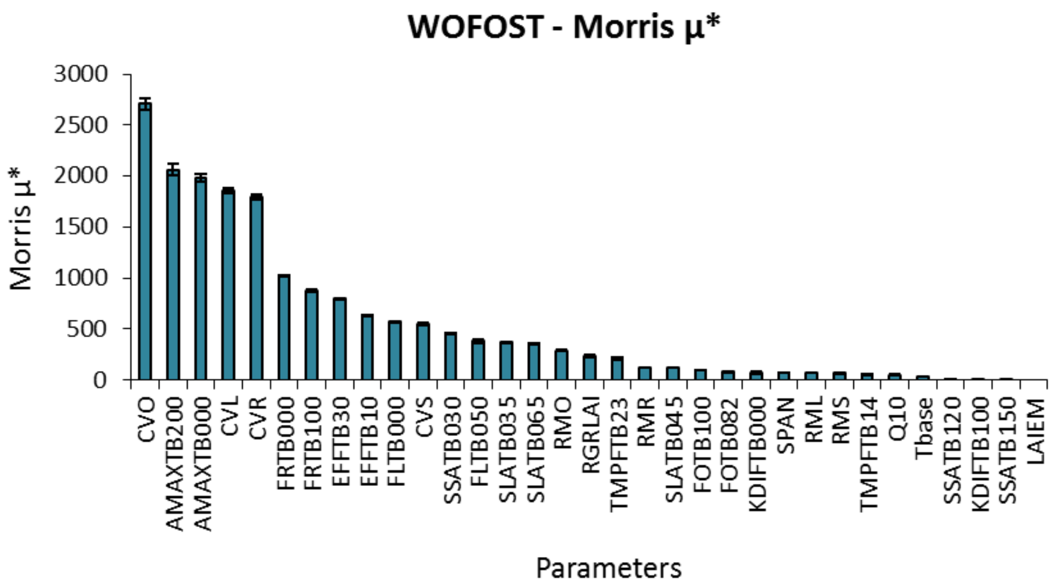

Figure 11: Mean values of Morris μ achieved by the WOFOST parameters in Jiangsu. The first five (from CVO to CVR) were selected for the second step of the analysis (Sobol' method)*

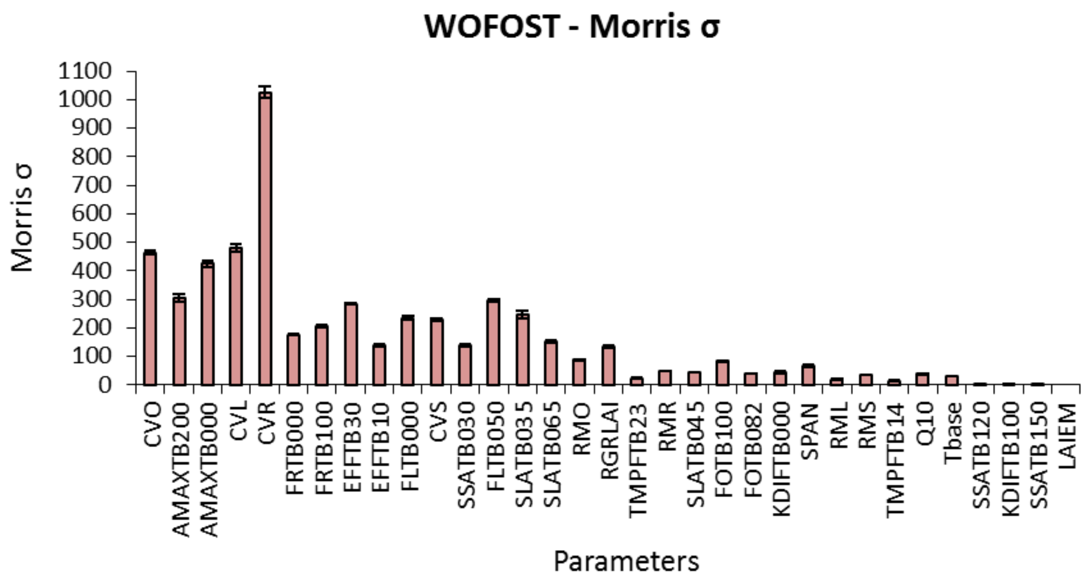

Figure 12: Mean values of Morris σ achieved by the WOFOST parameters in Jiangsu

SA results for the CropSyst parameters in Jiangsu using the Morris method are shown from Figure 13 to 18.

Maximum radiation use effficency (RUE) was the parameter with the highest influence on AGB in all study area (Figure 13), followed by optimum temperature for growth (Topt) and biomass-transpiration coefficient (BTR), ranked second (Figure 14). By combining the two maps, the RUE approach (based on RUE and Topt parameters) appears to be the most important compared to the TUE_{VPD} one (based on transpiration; Tanner and Sinclair, 1983). This behaviour is probably related to low values of VPD (at the denominator in the TUE_{VPD} equation).

Third ranked parameters map (Figure 15) confirms what discussed above, with BTR often ranked third. This rank is assumed more rarely by initial Leaf Area Index, and Topt.

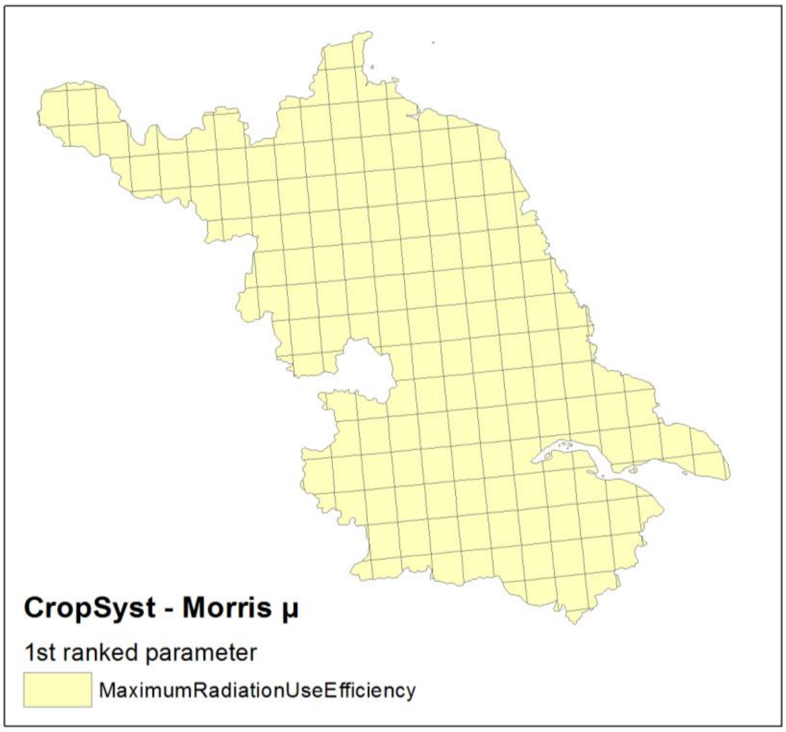

*Figure 13: CropSyst parameters ranked first according to the values achieved for Morris μ**

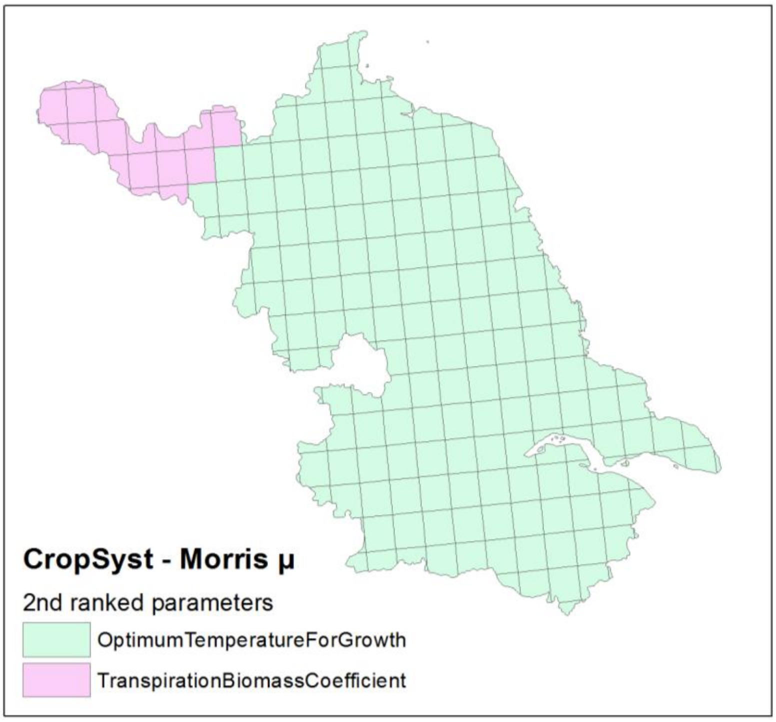

*Figure 14: CropSyst parameters ranked second according to the values achieved for Morris μ**

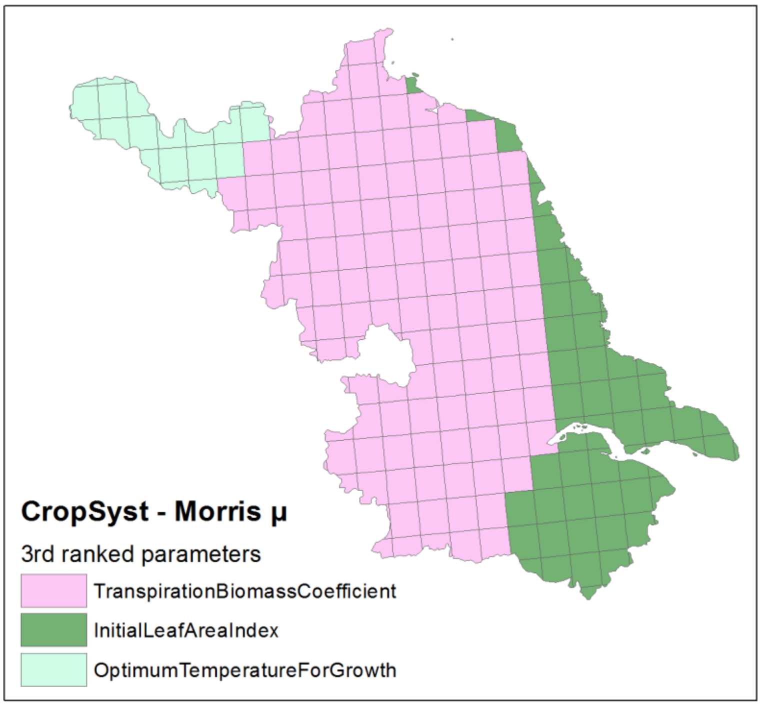

*Figure 15: CropSyst parameters ranked third according to the values achieved for Morris μ**

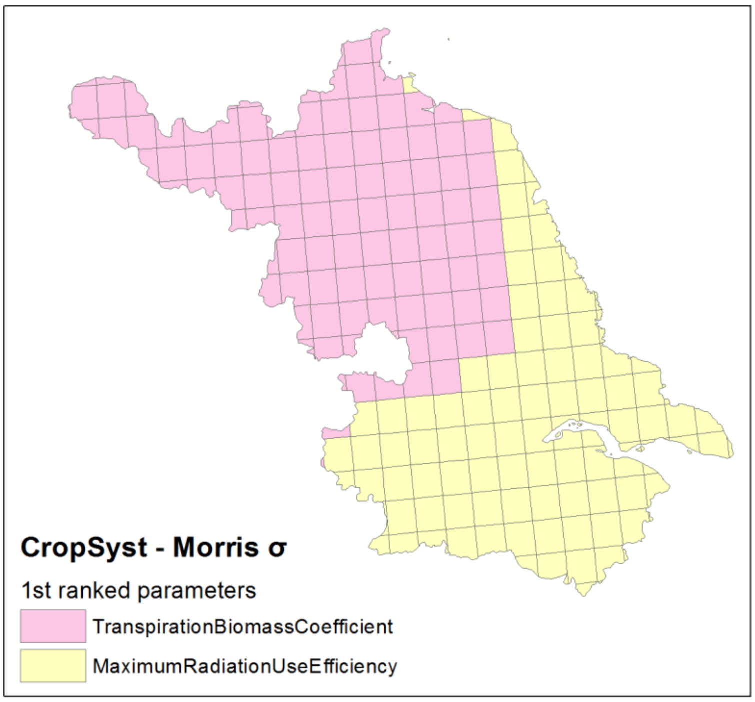

Figure 16: CropSyst parameters ranked first according to the values achieved for Morris σ

Figure 16 shows, for each 25 x 25 km cell, the parameters achieving the highest values for Morris σ. The spatial pattern underlines that BTR achieved the highest σ values in the northern part and RUE in the southern. The importance of the same factors was already discussed for the Morris μ*, thus confirming the high degree of non-linearity and/or level of interaction with other parameters, as inferred from σ values.

Figures 17 and 18 present the values of μ* and σ obtained by averaging the values estimated for all the cells in the study region. It is possible to notice that μ* values of RUE, Topt, BTR, LAIini, and extinction coefficient for solar radiation (k) are separated by the others by a kind of discontinuity. The same parameters are at the first five positions of σ index histogram (Figure 18). This allows selecting these parameters for the second step of the analysis, to be performed using the Sobol' method.

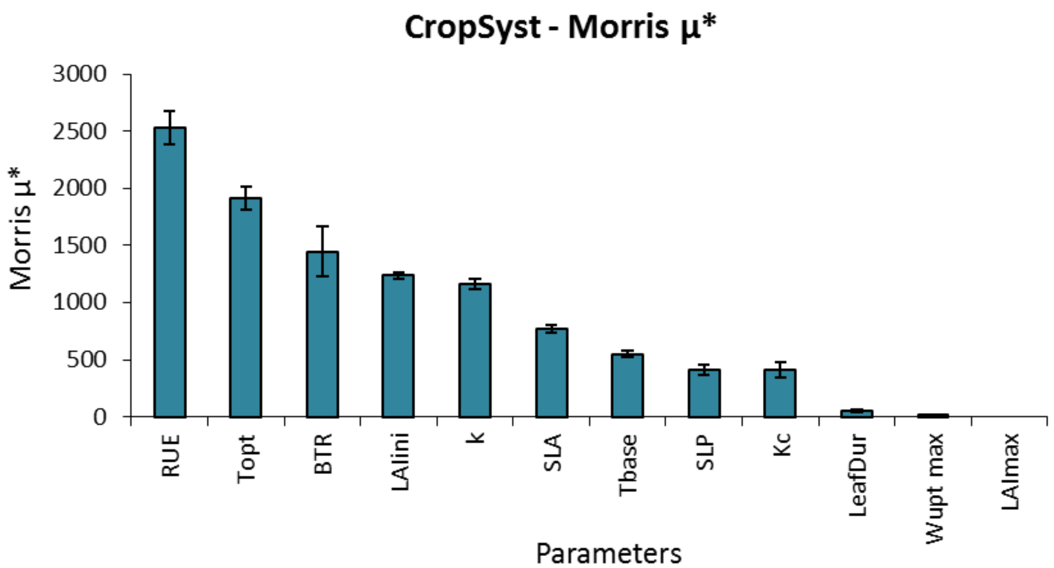

Figure 17: Mean values of Morris µ achieved by the CropSyst parameters in Jiangsu. The first five (from RUE to k) were selected for the second step of the analysis (Sobol' method)*

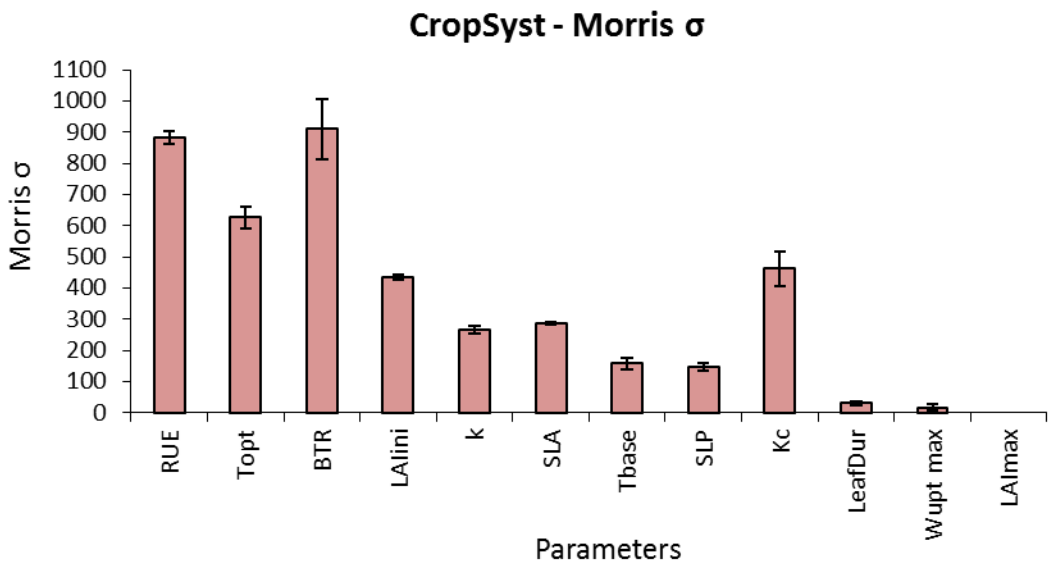

Figure 18: Mean values of Morris σ achieved by the CropSyst parameters in Jiangsu

3.1.2. Results obtained with the Sobol' method

Results of the SAs carried out on the WARM model using the Sobol' method are presented from Figure 19 to Figure 23, where the values of the index St (total order effect) for the five top-ranked parameters are shown.
On average, the parameter ranking reflects that obtained using the Morris method (σ, Figure 6), thus confirming the ability of Morris in ranking the parameters involved in interactions with others and/or in non-linear processes.
Maximum radiation use efficiency (RUE) resulted the parameter explaining the largest percentage of the total output variance (i.e., 53% by averaging the values estimated for all the grid cells). The relevance of the parameter depicted a clear spatial pattern, with highest values achieved in the North-Western part and a Soth-Easterly decreasing gradient. Apart from this gradient, the parameter resulted less influencing along the coast, where rice is actively grown in the central belt.

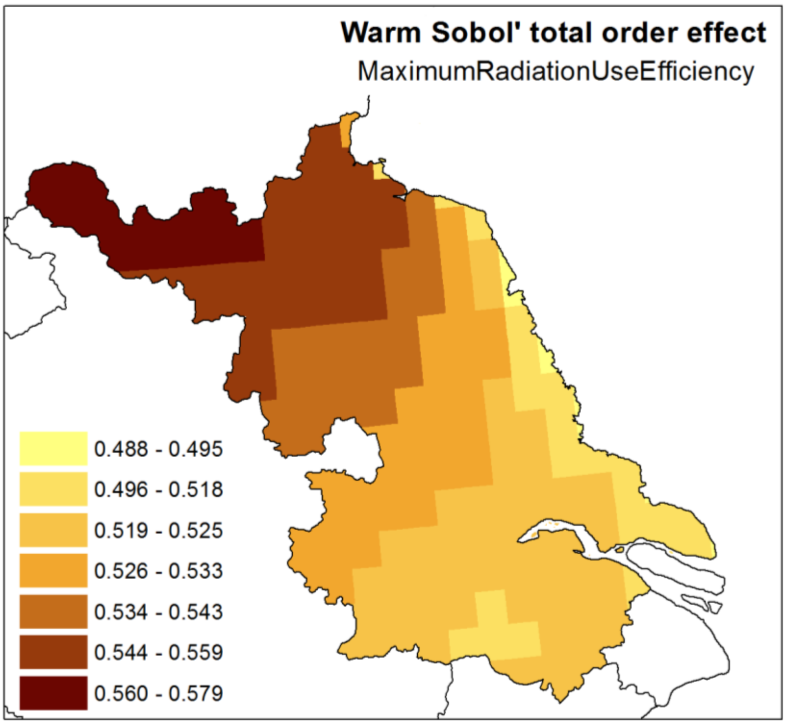

Figure 19: Sobol' total order effect for the WARM parameter maximum radiation use efficiency (RUE)

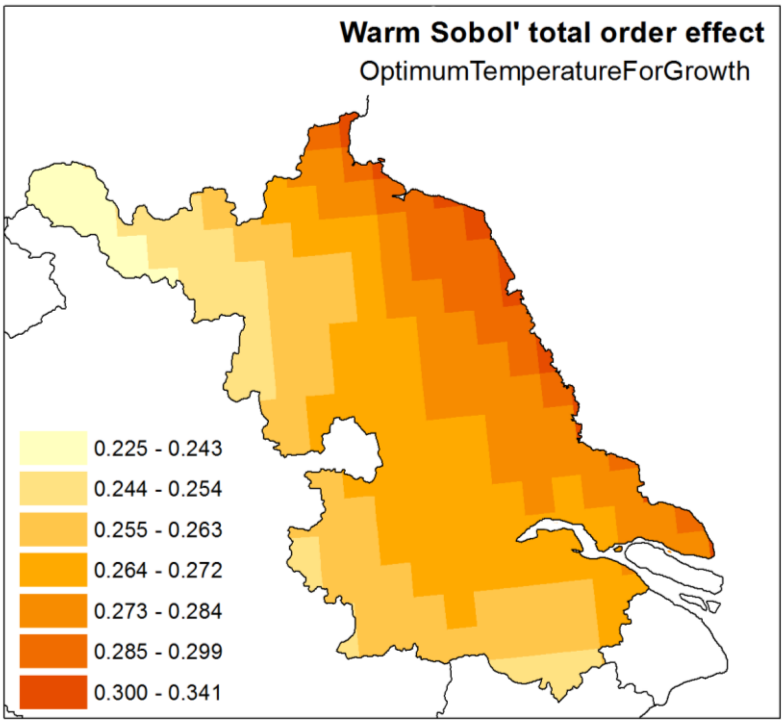

Figure 20: Sobol' total order effect for the WARM parameter optimum temperature for growth (Topt)

St values achieved by optimum temperature for growth (Topt) allow considering this parameter as the second most relevant, explaing the 27% of the of AGB variance in the Jiangu region (Figure 20). Unlike the RUE spatial gradient (Figure 19), the highest St values for Topt were obtained along the coast and are decreasing towards the Western boundary of the study area.

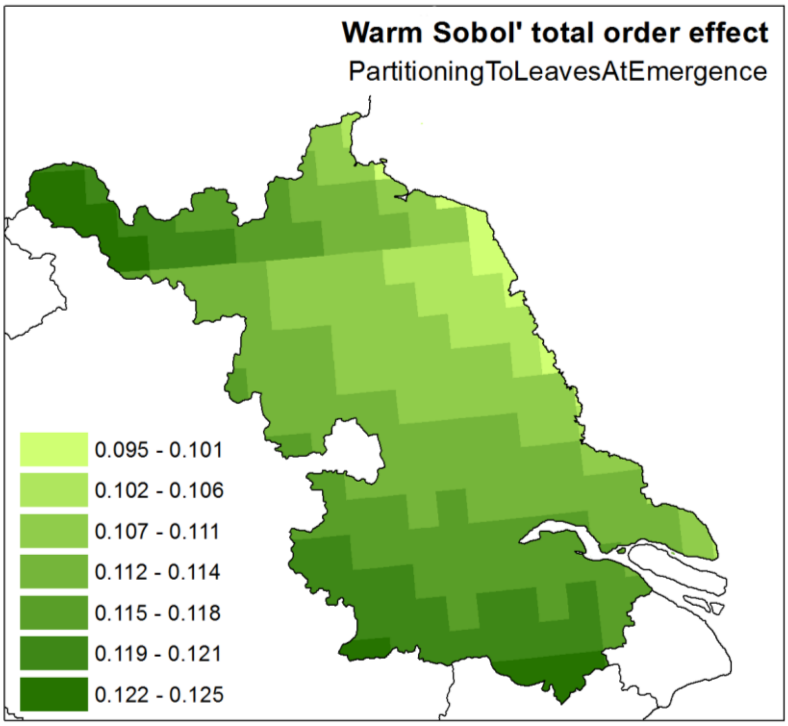

Figure 21: Sobol' total order effect for the WARM parameter partitioning to leaves at emergence (RipL0)

The third parameter in order of relevance – explaing on average the 11% of the output variance – was the Partitioning to leaves at emergence (RipL0; Figure 21). Its highest relevance was distributed mainly in the Northern and Southern inland, where the climatic conditions resulted less mitigated by the effect of the Yellow Sea. However, spatial patterns in the variability of St values for this parameter were less clear with respect to what observed for RUE and Topt.

Extinction coefficient for solar radiation (Figure 22) and Specific Leaf Area at tillering (Figure 23) resulted ranked forth and fifth, respectively. They explain together the 11% of the total output variance, still with almost uniform spatial distribution (i.e., cells values variability resulted less than 2.5%).

Previous SAs carried out with the same technique, but applied in Europen conditions, ranked the model parameters similarly (Confalonieri et al., 2010a).

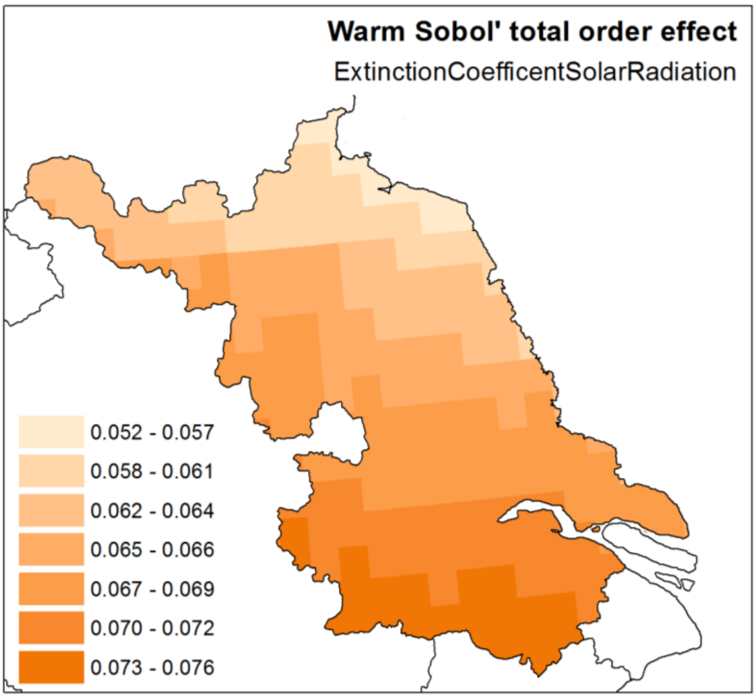

Figure 22: Sobol' total order effect for the WARM parameter extinction coefficient for solar radiation (k)

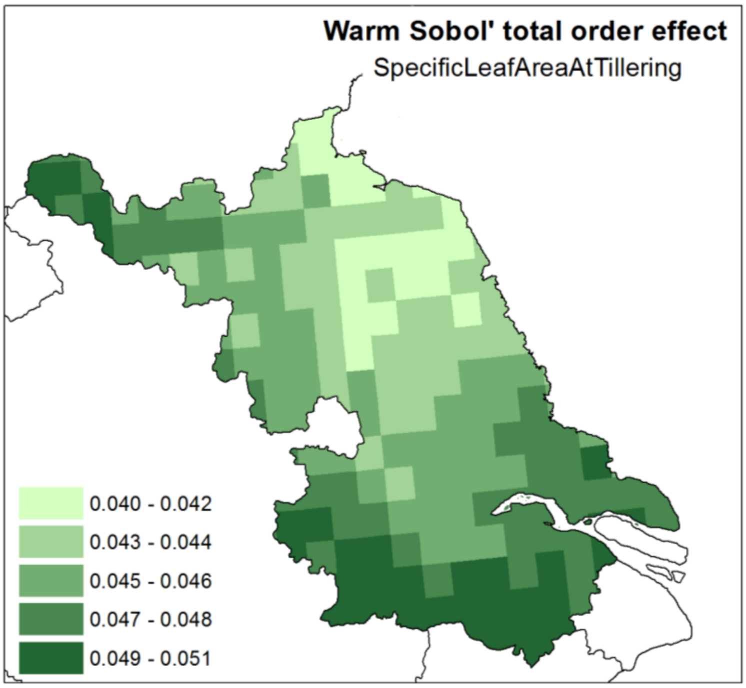

Figure 23: Sobol' total order effect for the WARM parameter Specific Leaf Area at tillering (SLAtill)

Results of the SAs performed on the WOFOST model using Sobol' method are shown from Figure 24 to 28.
On average, the ranking of parameters resulted very similar to that achieved by Morris μ*, with the last two parameter relevance (CVL and CVR) nearly equal.
The efficiency of conversion to storage organs (CVO) was the parameter explaining alone, on average, the 35% of the output variance. Its St spatial distribution (Figure 24) show a decreasing gradient from the coast belt to the inland with minimum values in the North-Western regions of Jiangsu.

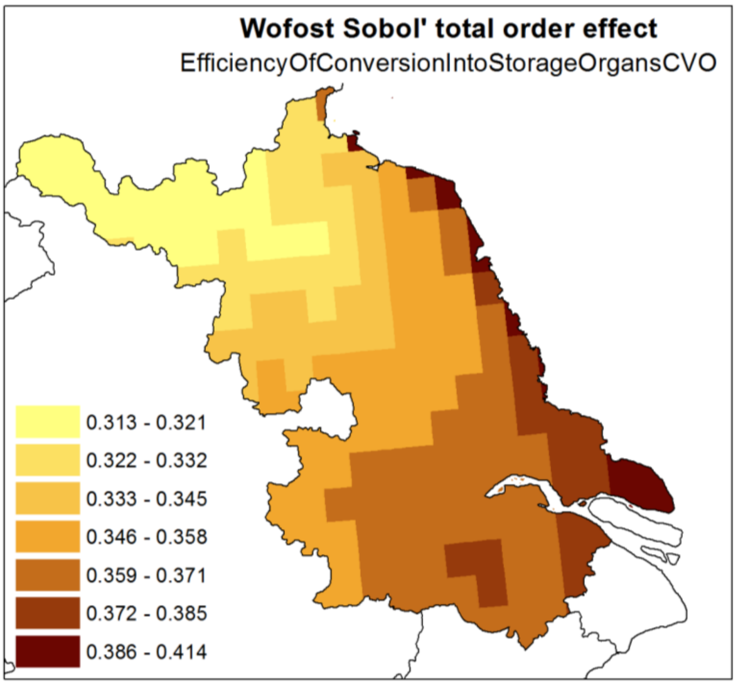

Figure 24: Sobol' total order effect for the WOFOST parameter efficiency of conversion into storage organs (CVO)

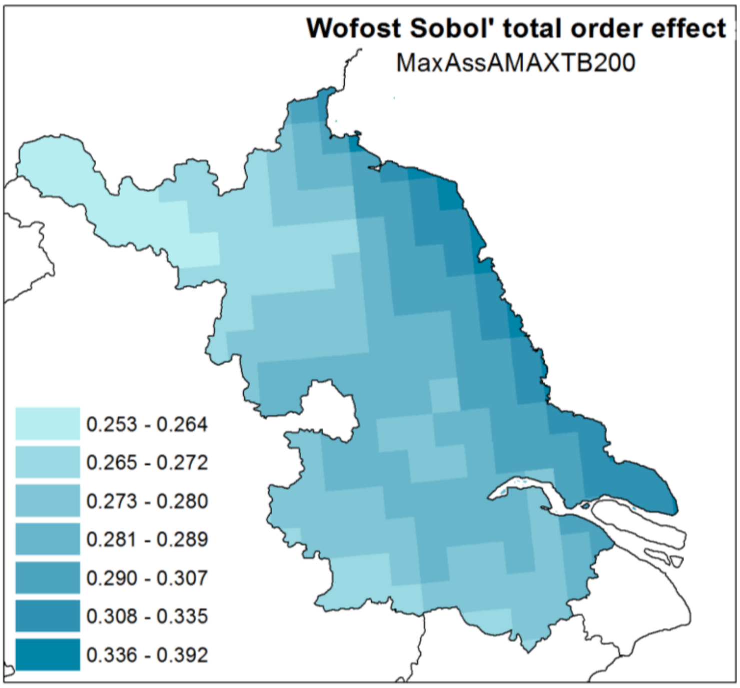

Figure 25: Sobol' total order effect for the WOFOST parameter maximum CO2 assimilation rate at maturity (AMAXTB200)

Results achieved by the parameter ranked second (AMAXTB200) show a similar spatial distribution (Figure 25), except for the central area, where the parameter relevance on AGB variance was explained with St values often overcoming 30%.
The spatial patterns in the St values for CVO and AMAXTB200 are probably related to the influence of more temperate thermal conditions (due to the Yellow Sea influence) during the maturity phase.

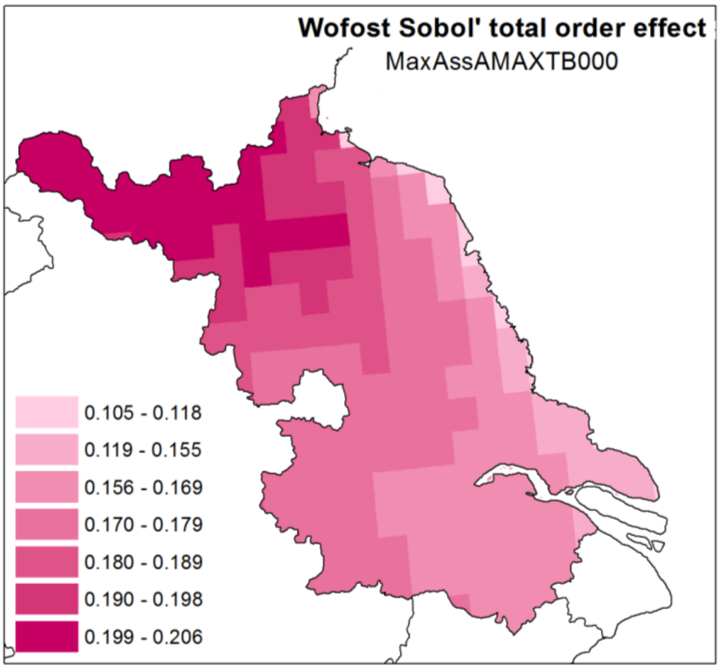

Figure 26: Sobol' total order effect for the WOFOST parameter maximum CO2 assimilation rate at emergence (AMAXTB000)

On the contrary, the remaing parameters showed a spatial pattern characterized by higher parameter relevance in the North-Eastern regions of Jiangsu.

In particular, the third-ranked parameter was maximum CO_2 assimilation rate at emergence (AMAXTB000), accounting – by averaging on all cells – for 17% of the output variance (Figure 26).

The forth parameter in order of relevance (i.e., efficiency of conversion into roots, CVR) is also related to ABG accumulation at early stage, explaing alone the 14% of total output variance (Figure 27).

Efficiency of conversion into leaves (CVL) was ranked last among those analyzed with the Sobol' method. Its spatial pattern (Figure 28) is particularly similar to CVR one, highlighting the importance of the two parameters also in the warmer South-Eastern area.

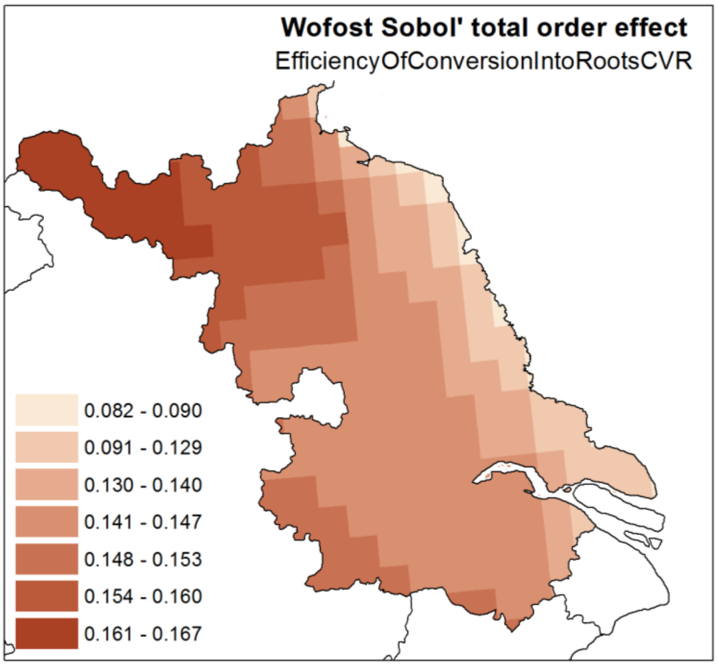

Figure 27: Sobol' total order effect for the WOFOST parameter efficiency of conversion into roots (CVR)

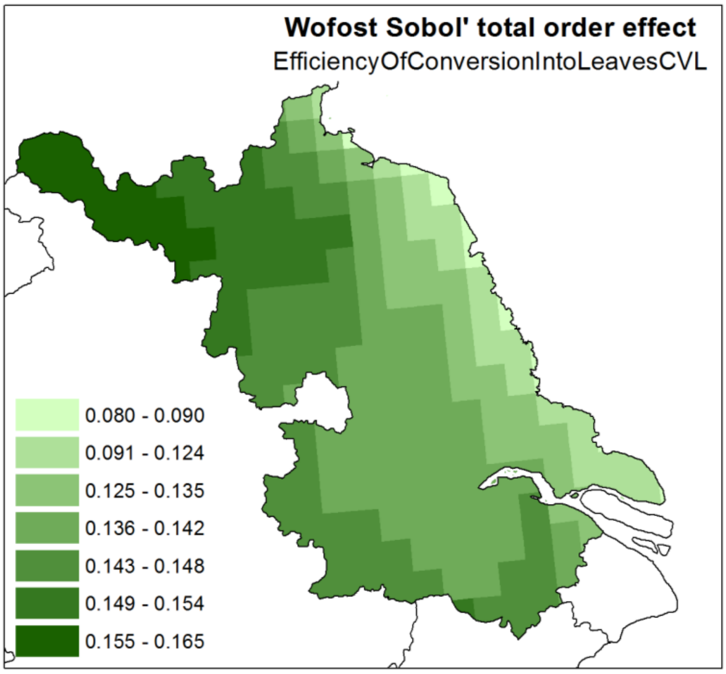

Figure 28: Sobol' total order effect for the WOFOST parameter efficiency of conversion into leaves (CVL)

Results of the SAs carried out on the CropSyst model using the Sobol' method are shown in Figures from 29 to 33. The ranking of parameters is similar to that achieved according to Morris μ*, except for Leaf Area Index at the emergence, that resulted more relevant with respect to the biomass-transpiration coefficient.

Figure 29 shows the St values for the first ranked parameter, that explains alone about the 50% of the total AGB variance. The spatial pattern highlights RUE relevance in the North-West side of the region, along the Yellow Sea coast.

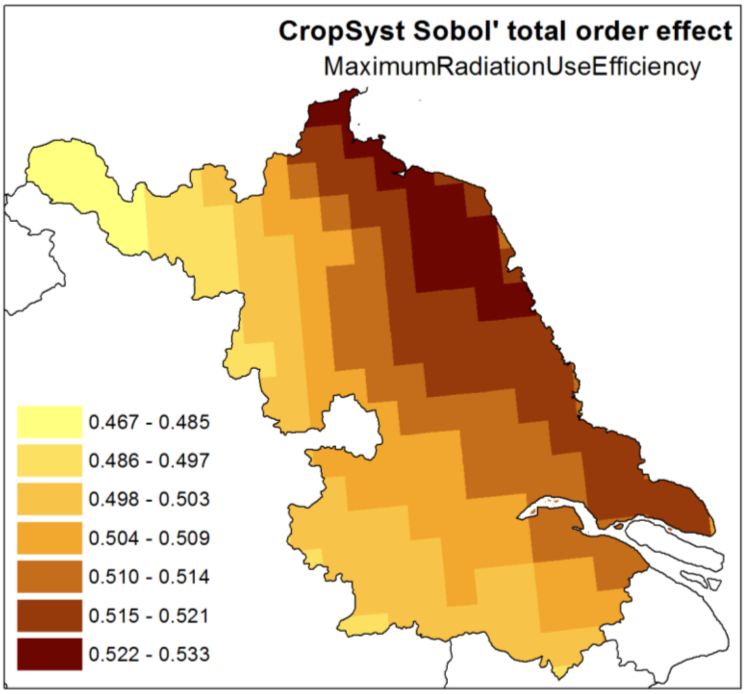

Figure 29: Sobol' total order effect for the CropSyst parameter maximum radiation use efficiency (RUE)

The parameter ranked second was Topt (Figure 30). As already discussed for the Morris analysis, Sobol' St values related to RUE and Topt highlighted the explicit presence of thermal limitation due to the RUE-based biomass accumulation. Moreover, the spatial pattern of the relevance of this two parameters is very similar, meaning that they are strictly involved in the same process.

A completely different ranking was achieved using the same model for rice simulations in Northern Italy (Confalonieri, 2010), where the conditions of applications favoured the prevalence of the TUE_{VPD} approach (Tanner and Sinclair, 1983).

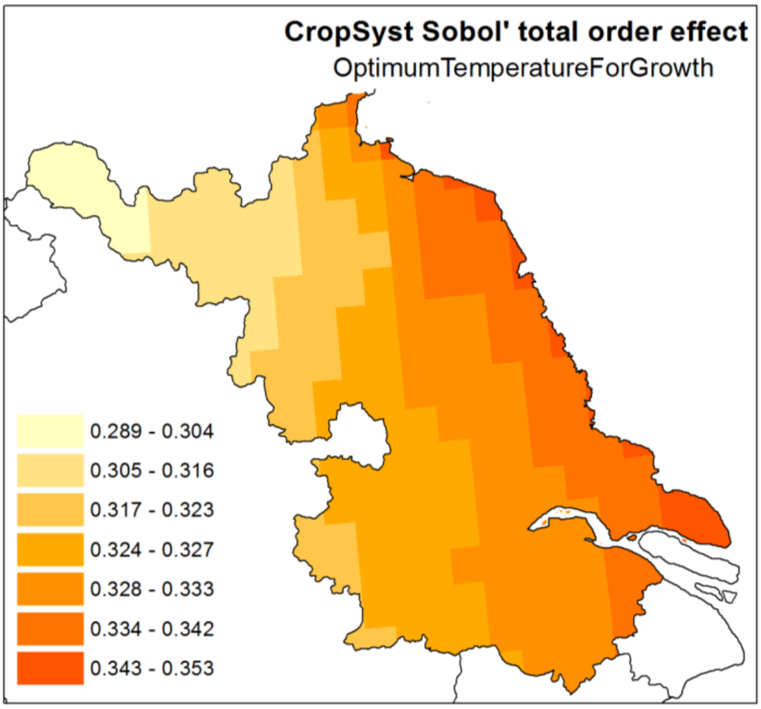

Figure 30: Sobol' total order effect for the CropSyst parameter optimum temperature dor growth (Topt)

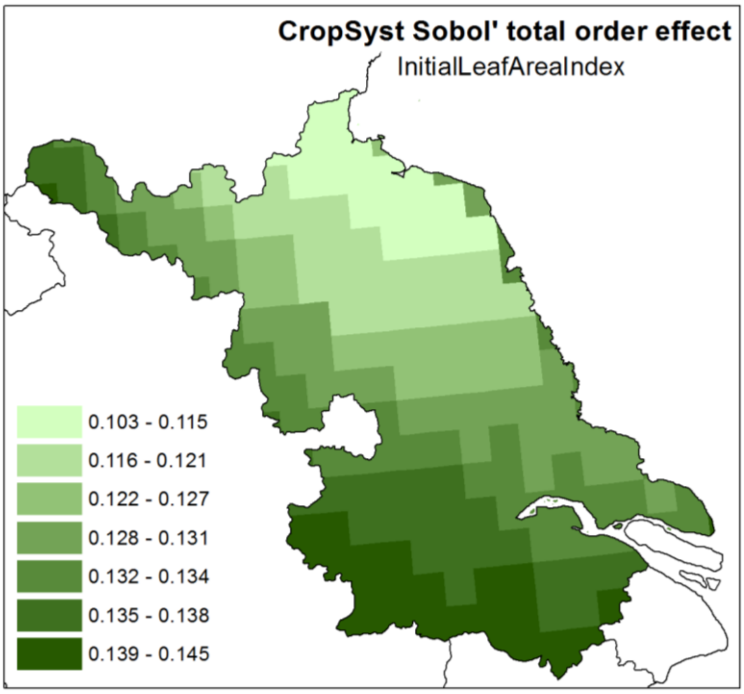

Figure 31: Sobol' total order effect for the CropSyst parameter initial Leaf Area Index (LAIini)

Figure 31 shows Sobol' total order results for initial LAI, that explained the 13% of the total output variance. The spatial pattern seems to suggest the highest relevance of the parameteres in the inland, in particular in the warmer South area.

The spatial distribution of the St values for BTR was complementary to the Topt one (Figure 32). This behaviour was expected, since it confirms the importance of the TUE_{VPD} approach for the calculation of AGB in cells where RUE and Tmax were less important (i.e., in the North – Western area, Figures 29 and 30). In the specific condition explored by rice in Jiangsu, this result underline the warmer thermal condition occurring in that part of the area, where higher VPD values were simulated.

The extinction coefficient for solar radiation was ranked fifth (Figure 33). It shows a spatial pattern particularly similar to the LAIini one (Figure 31), although the range of variability of its St value is very small (i.e., 2.5 persentage points).

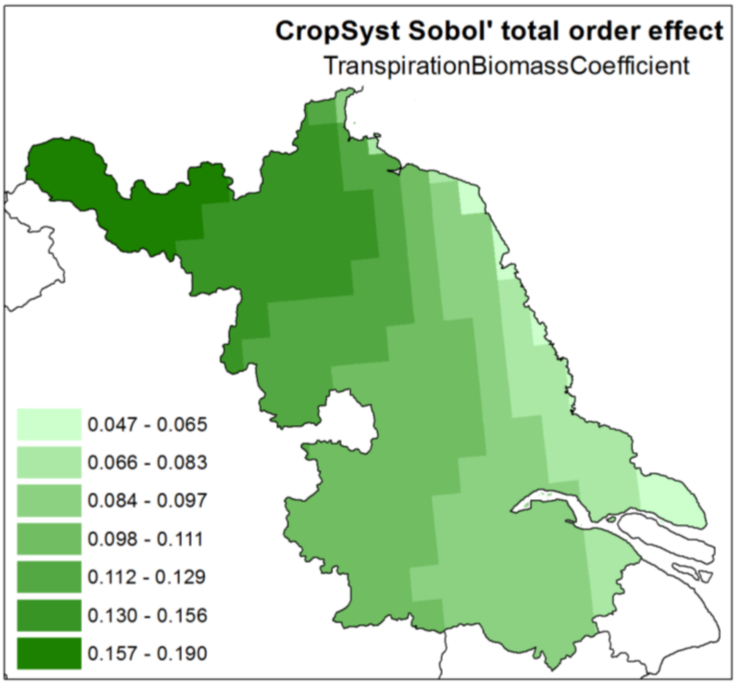

Figure 32: Sobol' total order effect for the CropSyst parameter biomass-transpiration coefficient (BTR)

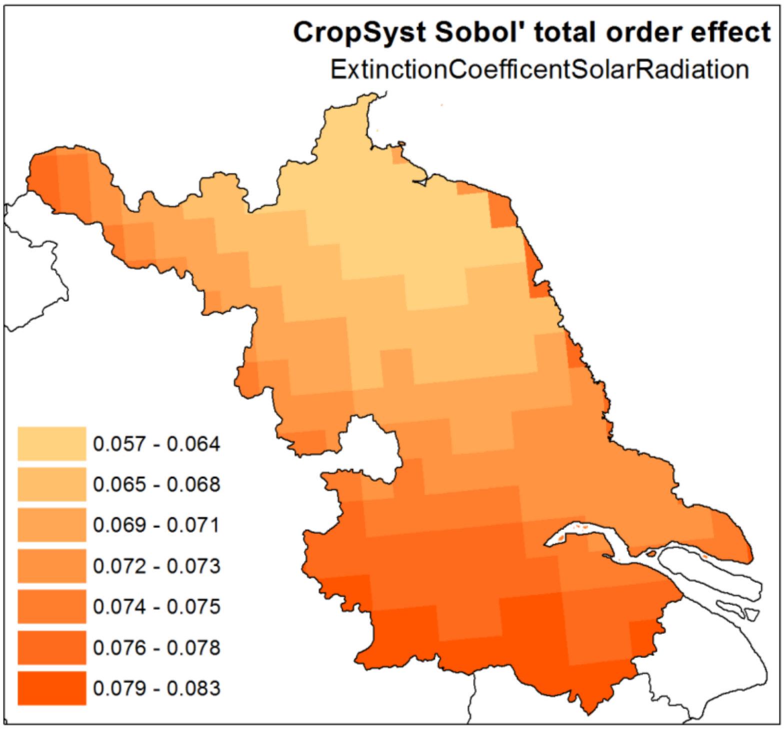

Figure 33: Sobol' total order effect for the CropSyst parameter extinction coefficient for solar radiation (k)

4. Conclusions

The spatially distributed sensitivity analysis experiments carried out in this study allowed to get an in-depth knowledge of the behaviour of the WARM, WOFOST and CropSyst models while simulating rice in Jiangsu.

For the WARM model, the variability of rice aboveground biomass accumulation is mainly explained by:

(i) maximum radiation use efficiency (RUE),
(ii) optimum temperature for growth (Topt),
(iii) partitioning to laves at emergence (RipL0),
(iv) extinction coefficient for solar radiation (k), and
(v) Specific Leaf Area at tillering (SLAtill).

For the WOFOST model, the five most important parameters resuted:

(i) efficiency of photosynthates conversion into storage organs (CVO),
(ii) fraction of total biomass partitioned to roots at maturity (FRTB200),
(iii) fraction of total biomass partitioned to roots at emergence (FRTB000),
(iv) efficiency of photosynthates conversion into leaves (CVL), and
(v) efficiency of photosynthates conversion into root (CVR).

The same analysis carried out on the CropSyst model ranks parameters as follows:

(i) maximum radiation use efficiency (RUE),
(ii) optimum mean daily temperature for growth (Topt),
(iii) initial Leaf Area Index (LAIini),
(iv) biomass-transpiration coefficient (BTR), and
(v) extinction coefficient for solar radiation (k).

In addition, qualitative hints on model plasticity property (i.e., the aptitude of the model to change the sensitivity to its parameters under different conditions of applications) can be also retrieved from this analysis. As already quantitatively observed for rice in Europe (Confalonieri et al., 2012), WOFOST resulted the model showing the highest plasticity for rice in Jiangsu, followed by CropSyst and by WARM, with the latter achieving the best value for the robustness metric. The lowest plasticity of WARM underlined in that study can also be assumed in Jiangsu, since the St spatial pattern shown was the most uniform.

Consequently, the next step will be the calibration of these parameters against measured data, in order to define the parameter sets characterizing the varieties (high- and low-yielding) for both the crop growth models.

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