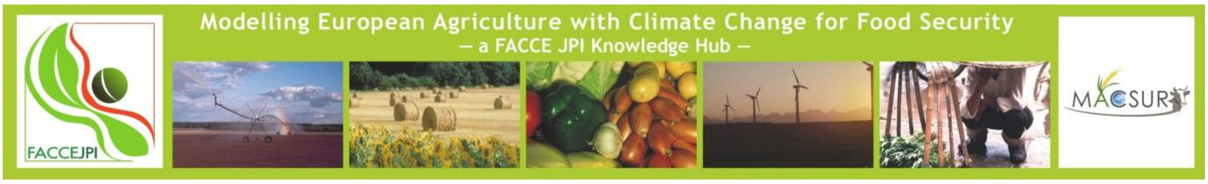

FACCE MACSUR

Standardised methods and protocols based on current best practices to conduct sensitivity analysis

Task leaders: Daniel Wallach* (P206) / Mike Rivington† (P150)

Partners involved: Ruget (P196), Martre (P201), Bergez (P206), Smith (P117), Palosuo/Rötter (P92) Eckersten/Arneth (P 94/163) Höglind et al (P128), Tychon/Destain/Dumont (P51), Nendel (P147), Ewert (P115), Acutis (P62), Niinemets (P202), Topp (47)

* INRA, Toulouse, France
daniel.wallach@toulouse.inra.fr

† The James Hutton Institute, Craigiebuckler, Aberdeen. AB15 8QH. UK.
mike.rivington@hutton.ac.uk

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Abstract/Executive summary

The purpose of this report is to propose a general procedure for sensitivity analysis when used to evaluate system sensitivity to climate change, including uncertainty information. While sensitivity analysis has been largely used to evaluate how uncertainties in inputs or parameters propagate through the model and manifest themselves in uncertainties in model outputs, there is much less experience with sensitivity analysis as a tool for studying how sensitive a system is to changes in inputs. This report should help make clear the differences between these two uses of sensitivity analysis, and provide guidance as to the procedure for using sensitivity analysis for evaluating system sensitivity to climate change.

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Introduction

Sensitivity analysis as applied to simulation models refers to the analysis of how strongly the model responds to changes in input variables or parameters (collectively referred to as factors). Put very simply, a model that shows a large change in the output of interest for a small change in one of the factors is sensitive to that factor, and conversely a model which shows only a slight change in output for a large change in a factor has only slight sensitivity to that factor.

Uncertainty analysis is normally conducted in order to respond to one of two major objectives. The first is to obtain information that is useful for improving the model. In particular, one wants to quantify how uncertainties in model inputs and/or parameters affect model outputs, in order to prioritize future work. One will concentrate on improving the estimates of those inputs or parameters to which the model is most sensitive, since this should lead to the greatest reduction in uncertainty of the simulated results. In the case of linear or simple nonlinear models, one can simply examine the equation and see how the output will respond to changes in the inputs. However, in general this is not possible for a crop model; the model is too complicated to understand from the equations how the inputs and parameters affect the outputs. One requires specific sensitivity analysis methods, in order to evaluate how much uncertainty in model outcomes results from the uncertainty in each input or parameter. Detailed descriptions of this type of sensitivity analysis can be found in (A Saltelli, Chan, & Scott, 2000; Wallach, Makowski, Jones, & Brun, 2014)

The second major use of sensitivity analysis is to obtain information about the system being simulated. According to the model, how will the system react if certain inputs are increased or decreased? This type of sensitivity analysis is widely used to investigate how crops will respond to climate change.

A sensitivity analysis, regardless of the objective, involves four steps. The first is the precise definition of the question. What output or outputs are of interest? What factors will be studied? What is the context, i.e. the values of all those inputs and parameters that are not varied? Secondly, the range of variation of each of the factors in the study must be defined. If the variations are correlated, then the joint distribution of the factors to be varied must be defined. Thirdly, one propagates the possible values of the factors through the model, in order to obtain the distribution of the model outputs. Finally, one analyses and summarizes the results.

Although both types of sensitivity analysis involve the above four steps, there are two important differences between them. The first is in the distributions of factors that are studied. When the objective is to aid in improving the model, the variation in the factors usually represents our uncertainty about the values of those factors. When the objective is to better understand the system, the variation in the factors represents the variation in inputs that the system is likely to experience. The second major difference is in the analysis of the results. When the objective is to aid in improving the model, the analysis aims at ranking the inputs and parameters, in order to identify those whose uncertainty leads to the largest uncertainty in simulated results. When the objective is to better understand the system, the analysis aims at quantifying system response to changes in inputs.

There have been many treatments of sensitivity analysis as a tool for model improvement, including detailed descriptions of how to carry out such a sensitivity analysis (Saltelli et al., 2000; Saltelli & Annoni, 2010; Wallach et al., 2014). Therefore we do not discuss this further here. Rather, we concentrate on using sensitivity analysis to better understand system response to inputs, in particular with respect to climate change. We will specifically consider the case where one uses multi-model ensembles in the sensitivity analysis, in order to obtain uncertainty information about the system sensitivity. The discussion is largely based on recent studies of this type that have been reported in the literature. This may serve as a guide in planning future studies of this kind.

In addition, we present a summary of past and planned work on sensitivity analysis by MACSUR partners.

Sensitivity analysis to better understand system sensitivity to changes in inputs

We discuss below each of the four major stages in sensitivity analysis.

Definition of the question

This type of sensitivity analysis is often aimed at better understanding the effect of climate change on crop production (Asseng et al., 2013; Bassu et al., 2014; Li et al., 2014). Commonly at least two factors, temperature and CO2, are varied. Other factors that may also be studied are precipitation, soil water holding capacity and management (sowing date, N application).

In the studies cited above, the sensitivity analysis was applied to a small number of sites (usually 4). The input variables that are not varied are the values appropriate to those sites.

The major output of interest in the above studies is yield, but of course many other outputs could also be of interest, including for example grain protein content, development times, water use etc. In particular, the studies consider future yield, averaged over multiple future weather series, divided by baseline yield, which is yield averaged over recent multiple weather series. In (Asseng et al., 2013) for example, 30 years of weather are used for future weather, and weather from 1980-2010 is used for baseline weather. (31 years of weather data are needed to obtain 30 crop years at some of the locations studied).

All the above studies involved multi-model ensembles (e.g. 27 different models in the case of wheat). The sensitivity analysis was done using a common protocol for all models. In this case the sensitivity analysis provides information about both average (over models) sensitivity of the simulated system, and uncertainty as to that sensitivity.

Range of variation of each input

The variation in each input represents the changes in those inputs that could be of interest. When the objective is to evaluate the impact of climate change, the changes represent possible future climates, and possible future management adaptations.

In (Asseng et al., 2013; Bassu et al., 2014; Li et al., 2014), temperatures were changed by -3°C, +3°C, +6°C or +9°C. These changes were applied systematically to the original temperature data. The CO_2 levels were simply fixed levels. (Asseng et al., 2013; Bassu et al., 2014) test the values 360ppm, 450ppm and 540ppm. (Li et al., 2014) included higher CO_2 concentrations. Other factors may also be studied. (Asseng et al., 2013) for example also studied how the system would react if N fertilization were halved or doubled.

Propagation through the model

This step is straightforward. One simply runs the model for each of the chosen changes in the inputs. In the above examples, this is done for each site, using the standard management for that site.

The total number of factors and levels of each factor is usually quite small, so that a full factorial design (all combinations of levels of different factors) is feasible. However, it may still be useful to limit the number of combinations, to simplify the study. Also, some combinations of levels may not be realistic.

Analysis and presentation of the results

For a single model and a single input variable, the major result is a response graph, which shows how the output (for example future yield averaged over multiple weather scenarios divided by average baseline yield) varies with changes in the input (for example CO_2 concentration). This can be summarized using an average slope, for example average yield change for each 100 ppm increase in CO2, or average yield change for each 1°C increase in temperature. This information will be specific to each context (site, climate, management).

With multiple models there is also uncertainty information, represented by the variability between models. Graphically, this can be represented by using a box and whiskers diagram to show the range of responses to each change in the input variable.

To represent simultaneously the effects of two input variables, response surfaces can be used.

Meta-analysis of sensitivity analysis studies

An alternative to using multi-model ensembles in the study of system sensitivity to changes in inputs, is to do a meta-analysis of published sensitivity analysis studies. Whereas in multi-model studies all models follow the same simulation protocol, in a meta analysis one analyses the results of diverse studies, each with its own protocol. Nonetheless, the objective is the same; obtain information on the average change in simulated system behaviour with changes in inputs, plus information on the uncertainty of the results as manifested in the variability between the different studies. An example of meta-analysis of the effect of changing temperature is the study by (Challinor et al., 2014)

Work on sensitivity analysis in MACSUR

The tables below show the responses of MACSUR partners to a questionnaire. The examples include both studies aimed at better understanding the model, and studies aimed at better understanding the effects of climate change.

References:

Asseng, S., Ewert, F., Rosenzweig, C., Jones, J. W., Hatfield, J. L., Ruane, A. C., … Wolf, J. (2013). Uncertainty in simulating wheat yields under climate change. *Nature Climate Change*, *3*(9), 827–832. doi:10.1038/nclimate1916

Bassu, S., Brisson, N., Durand, J.-L., Boote, K., Lizaso, J., Jones, J. W., … Waha, K. (2014). How do various maize crop models vary in their responses to climate change factors? *Global Change Biology*, *20*(7), 2301–20. doi:10.1111/gcb.12520

Challinor, A. J., Watson, J., Lobell, D. B., Howden, S. M., Smith, D. R., & Chhetri, N. (2014). A meta-analysis of crop yield under climate change and adaptation. *Nature Climate Change*, *4*(4), 287–291. doi:10.1038/nclimate2153

Eckersten H, Herrmann A, Kornher A, Halling M, Sindhøj E, Lewan, E., 2011. Predicting silage maize yield and quality in Sweden as influenced by climate change and variability, Acta Agriculturae Scandinavica, Section B - Soil & Plant Science, Volume: 62 Issue: 2 Pages: 151-165

Li, T., Hasegawa, T., Yin, X., Zhu, Y., Boote, K., Adam, M., … Bouman, B. (2014). Uncertainties in predicting rice yield by current crop models under a wide range of climatic conditions. *Global Change Biology*. doi:10.1111/gcb.12758

Nkurunziza, L., Alois Kornher[1], Mårten Hetta[2], Magnus Halling[1], Martin Weih[1] & Henrik Eckersten, Crop genotype-environment modelling to evaluate forage maize cultivars under climatic variability (manuscript)

Saltelli, A., & Annoni, P. (2010). How to avoid a perfunctory sensitivity analysis. *Environmental Modelling & Software*, *25*(12), 1508–1517. doi:10.1016/j.envsoft.2010.04.012

Saltelli, A., Chan, K., & Scott, E. M. (2000). *Sensitivity analysis*. New York: Wiley .

Wallach, D., Makowski, D., Jones, J. W., & Brun, F. (2014). *Working with Dynamic Crop Models, 2nd Edition*. London: Academic Press.

Responses from CropM partners on sensitivity analysis methods they are currently using, or have already used in previous modelling exercises.

Sensitivity analysis method	Purpose	Used within (details of study)	Who undertook the work	References etc.
One-factor-at-a-time	Evaluation of the WAVE 2.1 and the EURO-ACCESS-II models for predicting crop water consumption, water losses by drainage and volumetric soil water content in a cropped soil under Mediterranean conditions.	Funds were provided by the European Union (contract STEP-CT90-0032) and the Junta de Andalucı´a (Research Group AGR 151).	Fernandez, J.E. Slawinski,. Moreno, C. F Walczak, R.T. Vanclooster M.	Agricultural Water Management 56 (2002) 113–129
simple one (or two) climate variables changed at the time and monitoring the changes	to examine crop yield responses to a set of plausible scenarios of climate change	barley yields in Finland with 30-year simulation period included constant changes in daily T, constant fraction changes in P, T combined with changes in CO2, changes in daily T variability, changes in T combined with changes in proabilities of wet days and for comparison SRES (A1 & B1) scenarios using HadCM3	Rötter, Palosuo, Pirttioja et al.	RÖTTER, REIMUND P., PALOSUO, TARU, PIRTTIOJA, N. K., DUBROVSKY, M., SALO, TAPIO, FRONZEK, S., AIKASALO, R., TRNKA, M., RISTOLAINEN, A., CARTER, T.R. 2011. What would happen to barley production in Finland if global warming exceeded 4 °C? A model-based assessment. European journal of agronomy 35 4: 205-214.

Discretized sensitivity analysis using EPIC	sensitivity of temperature, precipitation, and solar radiation from different CC-scenarios on crop yields, SOC, and nitrate leaching until 2040.	for the agricultural production region Marchfeld in Austria	Franziska Strauss, Elena Moltchanova, Erwin Schmid, et al.	Strauss, F, E. Schmid, E. Moltchanova, H. Formayer, and X. Wang (2012). Modelling climatic change and biophysical impacts of crop production in the Austrian Marchfeld region. *Climatic Change*, **111**, 641-664.
A total of five statistical measures were used to evaluate the EPIC model performance and sensitivity: *i*) linear regression, *ii*) Pearson correlation coefficient (*r*), *iii*) Root Mean Square Error (RMSE), *iv*) Nash-Sutcliffe efficiency (*E*) and *v*) Relative Error (RE).	A crop yield sensitivity analysis of crop nutrient and irrigation management factors and cultivar specific characteristics for contrasting regions in Europe revealed a range in model response and attainable yields. We show that modelled crop yield is strongly dependent on the chosen PET method.	Pan- European crop modelling for winter wheat, rainfed and irrigated maize, spring barley and winter rye.	Juraj Balkovič, Erwin Schmid, et al.	Balkovič, J., M. van der Velde, E. Schmid, R. Skalský, N. Khabarov, M. Obersteiner, and B.Stürmer, (2013). Pan-European crop modelling with EPIC: implementation, up-scaling and regional crop yield validation. *Agricultural Systems,* [in print].
Model inter-comparison on the sensitivity of crop models including DSSAT, EPIC,	Model inter-comparison on the sensitivity of models for winter wheat and maize to extreme weather conditions (heat and drought) during the short but critical period	Sensitivity analysis for 2 Austrian sites representing different agro-climatic zones and soil conditions and the years 2003 and 2004.	Josef Eitzinger, Erwin Schmid, Franziska Strauss, et al.	Eitzinger, J., S. Thaler, E. Schmid, F. Strauss, R. Ferrise, M. Moriondo, M. Bindi, T. Palosuo, R. Rötter, K. C. Kersebaum, J. E. Olesen, R. H. Patil, L. Şaylan, B. Çaldag, and O. Çaylak (2013.).

WOFOST, AQUACROP, FASSET, HERMES and CROPSYST	of two weeks after the start of flowering.			Sensitivities of crop models to extreme weather conditions during flowering period demonstrated for maize and winter wheat in Austria. Journal of Agricultural Sciences. [in print].
Elasticities between percent changes in simulated dry matter crop yields and annual precipitation sums	Three meteorological drought scenarios have been developed for Austria in the period 2008-2040. The severity of long-term drought scenarios is characterized by lower annual and seasonal precipitation amounts as well as more significant temperature increases compared to the observations and impacts have been simulated with EPIC on crop yields and evapotranspiration.	Impact and sensitivity analysis for all Austrian cropland including 20+ crops.	Franziska Strauss, Elena Moltchanova, and Erwin Schmid	Strauss, F., E. Moltchanova, and E. Schmid (2013). Spatially Explicit Modeling of Long-Term Drought Impacts on Austrian Crop Production. *American Journal of Climate Change*. [in review].
Delta change method	German forage maize cultivars performance under CC in Sweden		See author list	Eckersten et al. 2011
Delta change method	Swedish forage maize cultivars performance at different locations under crrent climate and under CC in Sweden		See author list	Nkurunziza et al. (amnuscript)

Responses to request for details on what partners might further do that can be developed into protocols and methods to facilitate identification and quantification of model differences, and to evaluate the sensitivity of model outputs to those differences. It would be particularly useful if these are for model equations that are most relevant to responses to climate change, i.e. CO2, water and temperature.

Model equation, modelled process, parameters or data	Proposed sensitivity analysis method	Model name	Modelling what crop or process	Where	Who by?
Alternative evapotranspiration equations; soil moisture, soil depth, crop management including crop rotations, planting and harvesting dates, fertilization and irrigation.	Model intercomparison; extreme weather scenarios; statistical analysis	EPIC	e.g. wheat, maize, soybeans	Austria, Europe	Erwin Schmid, Hermine Mitter
Evapotranspiration, soil moisture, temperature	One-factor-at-a time, Local methods	WOFOST, CERES, DNDC	wheat	Institute of Agrophysics Polish Academy of Sciences, Lublin, Poland	Prof. Cezary Slawinski
Aboveground biomass, dry wight and starch concentration	See WP1 questionaire (Submitted to Kurt-Christian Kersebaum, 20130614)	MAISPROQ	Forage maize	See WP1 questionaire (Submitted to Kurt-Christian Kersebaum, 20130614)	Henrik Eckersten, Alois Kornher

Crop processes, Soil processes, Multi layer soils C, N, water and heat dynamics.	See WP1 questionaire (Submitted to Kurt-Christian Kersebaum, 20130614)	COUP model	Cereals, see WP1 questionaire submission	See WP1 questionaire (Submitted to Kurt-Christian Kersebaum, 20130614)	Henrik Eckersten, Annemieke Gärdenäs, Lisbet Lewan
Crop processes, Soil processes, Multi layer soils C, N, water and heat dynamics.	In accordance to Phase 1 of WP4 questionaire, Send by Nina Pirttioja 20130620	COUP model	In accordance to Phase 1 of WP4 questionaire, Send by Nina Pirttioja 20130620	In accordance to Phase 1 of WP4 questionaire, Send by Nina Pirttioja 20130620	Henrik Eckersten, Annemieke Gärdenäs, Lisbet Lewan
Crop processes, Soil processes, Multi layer soils C, N, water and heat dynamics.	In accordance with parts of WP3 scaling protocol from 11-12 March meeting in Bonn. Frank Ewert and Lenny van Bussel	COUP model	In accordance with parts of WP3 scaling protocol from 11-12 March meeting in Bonn. Frank Ewert and Lenny van Bussel	Germany	Henrik Eckersten, Lisbet Lewan
Soil processes, C-dynamics mainly	In accordance with parts of WP3 scaling protocol from 11-12 March meeting in Bonn. Frank Ewert and Lenny van Bussel	ICBM	In accordance with parts of WP3 scaling protocol from 11-12 March meeting in Bonn. Frank Ewert and	Germany	Thomas Kätterer

			Lenny van Bussel		