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Estimating soil parameters of a crop model to improve crop behavior prediction: interest of global sensitivity analysis.

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Crop models are very useful to predict the behavior of crops in their environment and they are of common use in decision-making system for managing cultural practices. Nevertheless, this behavior is well predicted when all the parameters of the model are well known. Among them, the parameters defining the soil properties have a major contribution to the variability of the model outputs but they are particularly difficult to measure at any point of interest. Assimilating data observed on crop status into the model is a way of estimating those parameters and allow consistent prediction of the variables of interest for decision making.

As the potential number of soil parameters should be high, leading to a bad estimation quality, it is highly recommended to choose the main soil parameters to be estimated, through a global sensitivity analysis (GSA) [1]. If some rules have been defined in order to use the results of GSA for designing the estimation process, quantification of the link between GSA and the result of parameter estimates or prediction has been done. Moreover, it is interesting to measure the quantity of information existing in different sets of observed data acquired in the different pedoclimatic configurations in order to identify those that are the most suited to retrieve the unknown parameters.

We address this issue in this paper. Using the STICS crop model [2] applied to wheat crops, we simulated an experimental design considering different pedoclimatic configurations (characterized by several types of climates, soil depth and soil initial conditions) and different amounts of information contained in observed data. The observed

data consisted of different variables (leaf area index, absorbed nitrogen, crop yield) at various dates during the growing season, on several years.

Pseudo-observations were created from simulations by adding a random error. For 50 soils within each pedoclimatic configuration, different sets of observed data were composed, containing 1, 2 or 3 variables, 10 to 21 dates taken within 1, 2 or 3 cropping seasons. Then, for evaluating the prediction, 60 scenarios (combining various climates and cropping techniques) were run for each soil.

We chose an importance sampling method based on Bayes theory: GLUE (generalized likelihood uncertainty estimation) [3] for estimating the soil parameters, and a variance-based method using the Fourier theory: EFAST (Fourier amplitude sensitivity test) [4, 5] for GSA. GSA was applied for a set of soil parameters on the variables of the crop model STICS and dates, that represent available observations. The parameter distribution was considered as uniform for both GSA and GLUES (prior information) and was derived from real measurements when available.

Analogously to the well known FIM, we proposed to characterize the information available in the observed data of a given configuration by using a scalar function of the Global Fisher Information Matrix (GFIM): det(GFIM) [6, 7], based on global sensitivity indices (main effects and total effects).

GSA was applied to 13 initial soil parameters; among them, only 7 had a non negligible effect on the observed output variables and were selected. A new GSA was made on these 7 parameters. For each data set, soil and pedoclimatic configuration, we summarized the sensitivity of the variables to each parameter by several indices based on GSA: sum of main (SM) and total (ST) effects, and det(GFIM) criterion.

GLUE was applied and the estimated parameters used to predict the variables of interest over the 60 scenarios. Several statistical criteria were therefore computed (RMSE on parameters, MSEP on predictions) and compared to the reference values obtained by setting parameters to the mean of the prior information.

One of the first results is that the more SM or ST was high, the best the parameter estimation was. In other words, more sensitive is the parameter, better it is estimated. Also, it appeared that det(GFIM) was more closely linked to the quality of prediction than to the quality of estimation.

It appeared as a good criterion that enables us to measure the information available in the observed data of a given configuration and compare it to that of others data sets.

We noticed that the quality of estimation and prediction increased when the size of observed data increased. For a given size of observed data, quality of estimation and prediction was in average slightly better with dates taken within 1, 2 or 3 cropping seasons than with dates taken within one single season.

The comparison of different pedoclimatic configurations showed that the drier was the climate, the better the parameter estimate and the prediction were. In addition, the shallower was the soil or the drier was its initial condition, the better the prediction of the variables of interest was.

For a given pedoclimatic configuration and a given size of observed data, the quality of the prediction was correlated to the value of the det(GFIM) criterion and the quality of the prediction increased with the amount of information.

Finally, GSA appeared to be greatly interesting to interpret and predict the performance of the estimation of parameters and the prediction of variables of interest, without implementing an estimation method.

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