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SELECTION AND COMBINATION OF MODELS FOR CROPPING SYSTEM DESIGN

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INTRODUCTION

Models can provide useful information to farmers, extension services, and policy makers. Given a practical problem, it is unlikely that only one model needs to be considered; an output variable of interest (crop yield, soil water content etc.) can generally be computed using different types of models with various levels of complexity. The traditional approach is to take a model selection process to find a model from which one makes practical applications. With this approach, it is necessary to define a criterion for assessing the candidate models and to estimate the criterion value from experimental data for all models (e.g., Makowski et al., 2009). Predictions are then based on the selected model only.

Various methods of model selection are commonly used by scientists but, generally, the uncertainty in model selection is basically ignored once a final model is found (e.g., Draper, 1995). Yuan and Yang (2005) showed that, when the model errors are large, a selection process is likely to lead to a completely different selected model when a slightly different dataset is used. Several statisticians emphasised that, in some cases, it may be better to mix all the available models than to use the single selected model. The basic idea is to use a weighted sum of the individual model predictions instead of the prediction derived from the single 'best' model (e.g., Raftery et al 2005).

This paper summarizes the results of a project funded by the French National Research Agency. Its purpose was i) to analyze the instability of the outcomes of several selection processes when slightly different datasets are used, ii) to review available methods for mixing all candidate models instead of using the single selected model, iii) to study the potential interest of model-mixing methods for crop scientists. These issues were addressed through several case studies and a statistical package was developed to help crop scientists to analyze instability of model selection processes and to implement model-mixing methods.

MATERIAL AND METHODS

Model-mixing methods generate a large set of models for a given set of candidate explanatory variables (at least 2^p models can be generated if p candidate explanatory variables are considered) and compute a weight for each model from experimental data. Predictions are then derived using a weighted sum of the individual model predictions. Various model-mixing methods were recently proposed; they use different type of weights based on the Akaike criterion (Aic) or on the Bayesian information criterion (Bic). With the most advanced model-mixing methods, model weights are computed using re-sampling techniques.

The package MMIX was developed to assess the instability of stepwise selection techniques and to implement model-mixing methods with the freely available R statistical software. This package was applied to several datasets in order to assess the value of model-mixing methods compared to i) two stepwise procedures based on Aic and Bic respectively, and ii) a naïve approach which consists in including all candidate explanatory variables in the model. This paper presents the results obtained in a case study where the grain number of organic winter wheat was predicted using 64 linear models including between one and six candidate explanatory variables. Each candidate explanatory variable corresponded to a potential limiting factor like nitrogen nutrition index, weed density, water balance etc. The performances of the selection and model-mixing methods were assessed by computing the relative increase of prediction errors resulting from the use of these methods instead of the naïve approach. A series of datasets including 10 to 50 observations was



used to select the explanatory variables, estimate the model parameters, and compute the model weights. The instability of the two stepwise methods was assessed by bootstrap.

RESULTS AND DISCUSSION

Results obtained by bootstrap showed that the frequencies of variable selection resulting from the implementation of the two stepwise selection techniques were close to 0.5 (i.e. to the frequency obtained by a random selection) when the number of available observations for variable selection and parameter estimation was lower than 15. The instability of stepwise techniques was thus large with small datasets. Model-mixing methods performed better than stepwise techniques with small datasets. With datasets including less than 15 observations, model prediction errors were increased by 5 to 20% when a stepwise selection technique was used instead of the naïve approach (Fig. 1). Relative prediction errors were decreased when a model-mixing technique was implemented instead of stepwise selection. This reduction reached 35% for small datasets and advanced model-mixing techniques (Fig. 1). When the number of available observations was higher than 30, all methods showed similar performances (Fig. 1). These results show that model-mixing methods can be useful for crop scientists when a limited number of observations are available for parameter estimation. These methods can be easily implemented with different types of models by using our R package.

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Figure 1. Relative increases of prediction errors (%) for grain number per m² in organic winter wheat crops in France. The increases resulting from the use of two stepwise procedures (Stepwise Aic, Stepwise Bic), two standard model-mixing techniques (Mixing Aic, Mixing Bic), and two advanced model-mixing techniques (ARMS Aic, ARMS Likeli) were expressed relatively to the error level obtained with the model including all candidate explanatory variables. Datasets including 10 to 50 observations were used for selecting the explanatory variables, computing the model weights, and estimating the model parameters.

