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V. Houlès, Martine Guerif, Bruno Mary, David Makowski, J.M. Machet, Sophie Moulin, Nicolas Beaudoin

A TOOL DEVOTED TO RECOMMEND SPATIALISED NITROGEN RATES AT THE FIELD SCALE, BASED ON A CROP MODEL AND REMOTE SENSING DATA ASSIMILATION.

V. Houlès[1], M. Guérif[1], B. Mary[2], D. Makowski[3], J.M. Machet[2], S. Moulin[1], N. Beaudoin[2]

[1] INRA, Unité CSE, Domaine St Paul, Site Agroparc, 84914 Avignon Cedex 9, France.
Email: houles@avignon.inra.fr
[2] INRA, Unité d'Agronomie de Laon-Reims-Mons, R. F. Christ, 02007 Laon Cedex, France.
[3] UMR d'Agronomie INRA/INA P-G, BP 01, 78850 Thiverval-Grignon, France.

Introduction

To limit the consequences of nitrogen fertilisation on water and air quality, within-field variability should be taken into account to recommend spatialised nitrogen (N) rates in the frame of precision agriculture. To achieve this goal, we propose a method based on the crop simulation model STICS (Brisson *et al.*, 1998) implemented at a high spatial resolution scale in the field. This method optimises the nitrogen rate in order to maximise farmer's income and to minimise nitrogen losses. Two main steps were necessary: (1) defining a decision rule on N recommendation; (2) developing a convenient way to assess the model inputs at the within-field scale (Houlès, 2004).

Materials and methods

We hypothesised that for a 10 ha field, the main source of spatial variability was the soil, and thus neglected the heterogeneity linked to microclimate, cultural practices and pests. These last ones were furthermore controlled in our experimental design.

1/ Choice of a decision rule of N recommendation based on a model

To combine economic and environmental concerns, we chose to associate 3 variables predicted by STICS (yield, grain protein content and N balance) into an "agro-environmental criterion" (*AEC*). The optimal N rate was thus defined as follows:

- N rate maximising gross margin (function of yield, grain protein content and N rate);
- N rate conducting to a value of N balance at harvest below a given threshold. N balance is the difference between N inputs and outputs in the field.

We evaluated the interest of this *AEC* on 14 field trials consisting in N rates experiments. To test STICS ability to perform N recommendations according to this *AEC*, we evaluated two aspects:

- STICS ability to predict the variables involved in the *AEC*, taking into account the climate uncertainty between the date of decision and harvest thanks to 30 climatic series;
- the consequences of the use of STICS to recommend N rates (as compared to a standard recommendation method) on the gross margin and the environmental variable.

2/ Assessment of the model inputs at the within-field scale

Two fields were used, the first one grown with winter wheat in 2000 and 2002, the second in 2001 and 2003. In 2000 and 2001, remote sensing measurements were made. Each year, soil water and nitrogen at sowing, end of winter and harvest were measured on a regular grid, as long as grain protein content. These data were kriged. Yield maps were also established each year.

Two different approaches of soil variability characterisation were compared: (i) soil characterization and (ii) use of variables issued from remote sensing measurements and data assimilation methods.

(i) Soil maps were established thanks to soil properties observations/measurements at the grid points ; soil inputs of the crop model were then determined by using pedotransfer rules determined on these fields.

(ii) The data assimilation method consisted in estimating model inputs by minimising the differences between observed and simulated variables (see Launay *et al.*, this issue). Three methods were compared (see Houlès *et al.*, this issue) and the GLUE algorithm (Beven & Freer, 2001) was chosen. The estimated model inputs concerned soil reservoir capacity, roots growth, organic N in soil and soil mineral nitrogen and water content at sowing. Prior information on model inputs was used and consisted in a possible range assessed thanks to measurements.

Results

1/ Ability of STICS to recommend N rates

The first result to point out is that according to the experimental database used, environment protection has a cost for the farmer: the gross margin decreases from about 600 € ha^{-1} for a low environmental constraint (N balance above 100 kg ha^{-1}), to 500 € ha^{-1} for a medium constraint (50 kg ha^{-1}) and to 350 € ha^{-1} for a high constraint (0 kg ha^{-1}). The model predicts fairly well yield (RMSE=0.95 Mg ha^{-1}) and grain protein content (RMSE=1%) with a bias for the last one. As a consequence, N balance is pretty well estimated (RMSE=20 kg ha^{-1} for a range from –100 to 200). With this database, the climate uncertainty has no significant effect on the simulations of the model.
The N rates recommended by STICS are close to the optimal rates determined from the observed data for a large range of environmental constraints, that is to say for different values of N balance thresholds. The loss on gross margin in relation to an ideal situation where the optimal rate would be known *a priori* are rather weak for medium constraint but can attain 50 € ha^{-1} for high constraints. The environmental constraint is nearly fulfilled for most constraint levels.

2/ Quality of the spatialised simulations

The soil characterisation established at the within-field scale leads to simulations very weakly spatialised: at early stage, *LAI* variability is underestimated, while at late stages, *LAI* and yield variability is largely overestimated. The estimation of roots growth could be the main reason for this situation. The model inputs estimated thanks to assimilation of variables issued from remote sensing lead to biased simulations but the spatial variation is fairly well simulated. In 2001 for instance, while the systematic part of root mean square error (Willmott, 1981) is 1.1 Mg ha^{-1} for soil map and it is 2.1 for assimilation method; the unsystematic part of root mean square error is 1.3 for soil characterisation and 0.4 for assimilation. The results of assimilation method are potentially linked to the bad definition of prior information relative to model inputs as long as the values attributed to fixed parameters.

Conclusion

The use of an agro-environmental criterion predicted by a crop model to recommend N rates can be easily adapted to a large range on environmental constraints and provides satisfactory results. The main issue concerns the estimation of model inputs: soil characterisation proved not to be a relevant approach at the scale necessary for precision agriculture. Data assimilation is promising, but needs to be improved. Main issues concern the quality of both model and ”observations” and the relative weight of both within the assimilation process.

References

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