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A Site-Specific Grain Yield Response Surface : Computing the Identity Card of a Crop Under Different Nitrogen Management Scenarios

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ABSTRACT

At the parcel scale, crop models such as STICS are powerful tools to study the effects of variable inputs such as management practices (e.g. nitrogen (N) fertilization). In combination with a weather generator, we propose a general methodology that allows studying the yield variability linked to climate uncertainty, in order to assess the best practices in applying fertilizers. Our study highlights that, using the usual practice of Belgian farmers, namely applying three doses of 60kgN/ha, the yield's distribution presents the highest degree of asymmetry. This implies the highest probability to achieve yields superior to the mean. The computed return time of expected yield shows that 9 years out of 10, a grain yield of 7.26 tons.ha⁻¹ could at least be achieved.

Keywords: Crop model, STICS, Yield prediction, Climate variability, N management, Probability risk assessment, Belgium.

1. INTRODUCTION

Within a context of continued pressure on agricultural land and of food insecurity, crop models are powerful tools to study the effects of variable inputs such as management practices, agro-environmental conditions, and weather events on harvestable organs. This explains why they are more and more often used to support the decision making process and planning in agriculture (Basso et al., 2011; Ewert et al., 2011).

A wide variety of methods have been applied to estimate the form of the yield probability distributions. Day (1965) has studied the effects of different nitrogen (N) rates on different crop species, like oat or maize. He concluded that (i) crop probability distributions are in general non-normal and non-lognormal and that (ii) the asymmetry and flattening of yield distributions depended upon the specific crop and the amount of

C0151 - B. Dumont, B. Basso, V. Leemans, JP. Destain, B. Bodson, MF. Destain.

"A Site-Specific Grain Yield Response Surface : Computing the Identity Card of a Crop Under Different Nitrogen Management Scenarios". EFITA-WCCA-CIGR Conference "Sustainable Agriculture through ICT Innovation", Turin, Italy, 24-27 June 2013. The authors are solely responsible for the content of this technical presentation. The technical presentation does not necessarily reflect the official position of the International Commission of Agricultural and Biosystems Engineering (CIGR) and of the EFITA association, and its printing and distribution does not constitute an endorsement of views which may be expressed. Technical presentations are not subject to the formal peer review process by CIGR editorial committees; therefore, they are not to be presented as refereed publications.

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available nutrients. More recently, other researchers came to the same conclusions (Just and Weninger, 1999; Hennessy, 2011; Du et al., 2012).

In particular field of nitrogen’s management, the complexity of decision making is linked to the non-knowledge of future weather conditions. As performed by Basso et al. (2011; 2012), a feasible approach to cope with such uncertainty is to study the model’s response as a cumulative probability under different monitored past climate scenarios.

However, a methodologically even more consistent approach is to use a stochastic weather generator to study the effects of climatic variability on crop answer, instead of historical climate data, which often are not numerous (Semenov and Porter, 1995; Lawless and Semenov, 2005).

In this paper, we propose to use a database of stochastically generated climates, which ensures the exploration of the most advantageous and disadvantageous climatic conditions, in combination with different nitrogen management’s strategies, in order to assess the expected yield distributions. The methodology is extended in order to compute the site-specific expected yields and to assess the return time of expected yields for farmers.

2. MATERIAL AND METHODS

2.1 Nitrogen management strategies

In Belgium nowadays, the farmers’ practice consists in applying a total dose of 180 kgN/ha (or uN) in three equal fractions, respectively at tillering, redress and last-leaf stages (respectively Zadoks stages 23, 29 and 30). This practice will be used as reference. It will be compared to different overall levels of N fertilization, ranging from 0 to 300 kgN/ha (3×100 kgN/ha), also applied in three equivalent fractions, at tillering, redress and last-leaf stages, (Table 1).

To simplify the simulation process, as first assumption, the same management techniques were applied to each simulation in terms of sowing and of fertilization dates.

Table 1. Fertilisation rate for the different N strategies

Treatment	Fertilisation level (in kg N/ha)			Total
	Tillering	Redress	Last leaf	
#	Z23	Z29	Z30	
T1	0	0	0	0
T2	10	10	10	30
T3	20	20	20	60
...
T11	100	100	100	300

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2.2 The Pearson system and coefficients

Pearson developed an alternative system of probability density functions, that takes a wide variety of forms (Day, 1965). In this paper, we focus on the type I distribution, for which random variable has a finite range (Eq. 1).

$$f(x) \begin{cases} = k \cdot (x - \alpha_1)^{\gamma_1} (x - \alpha_2)^{\gamma_2} & , \alpha_1 < y < \alpha_2 \\ = 0 & , y \leq \alpha_1 \text{ or } \alpha_2 \leq y \end{cases} \quad (1)$$

α_1 and α_2 are the boundaries of the distribution and γ_1 and γ_2 are the coefficients of shape.

2.3 Original weather database and climate variability

Provided that the agroenvironmental input data used to calibrate the model are representative enough to ensure robustness, a crop model could give satisfactory responses in presence of any other weather events. In this study, a 30-years (1980-2010) weather database (Ernage station, Belgium) located 4 km from the experimental site was available.

This database was thus analyzed with the LARS-WG (Semenov and Barrow, 2002; Lawless and Semenov, 2005) to compute the set of parameters representing the experimental site. These characteristic values were then used to generate an ensemble of stochastic synthetic weather time-series representative of the climate conditions in the area. A climate database ensemble of 300 years was derived to ensure a stability of the simulated mean yield (Lawless and Semenov, 2005). The so-created ensemble of synthetic weather time-series was used as input of the crop model STICS.

2.4 Crop model

The soil-crop model STICS (INRA, France) was used in this study. A wide literature can be found concerning the STICS model formalisms and the way it simulates the yields (Brisson et al., 2003; Brisson et al., 2009). The STICS model requires daily weather climatic inputs, namely minimum and maximum temperatures, total radiation, wind speed, vapor pressure and total rainfall.

The STICS model parameterisation, involving calibration and validation, was performed on the three years database presented here beneath, using inverse modelling techniques (Vrugt et al., 2009). The contrasted years, in terms of climate and yields, were used to parameterize the crop water and thermal stresses dependence.

2.5 Case study

The data were acquired during field experiments carried out to measure a winter wheat

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crop's response (*Triticum aestivum* L., cultivar Julius) in the Belgian temperate climate in the Hesbaye Region (loamy soil conditions), in presence of different nitrogen fertilization levels ranging from zero to 240 kgN/ha. Reference measurements of biomass growth (LAI, total biomass and grain yield) were regularly performed, while continuous environmental measurements (climatic data and soil moisture) were acquired over the growing seasons.

Up to now, three successive years with highly contrasted weathers were monitored. During the season 2008-2009, yields were quite high and close to the optimum of the cultivar. This is mainly explained by the good weather conditions and the sufficient nitrogen nutrition level. The seasons 2009-2010 and 2010-2011 were known to induce deep water stresses and were characterized by important yield losses. During last both seasons, the water deficits did not appear at the same crop stages.

3. RESULTS AND DISCUSSIONS

3.1 Simulation of yield response to N practices

Figure 1 provides an insight of the results obtained at the end of the simulations conducted using 300 stochastic climate scenarios, with a 60-60-60 kgN/ha strategy (treatment T7). The cumulative distribution function (CDF) and the probability density function (PDF) are presented. The Type-I distribution appeared well suited to represent the model behavior resulting from a high number of stochastic climatic realizations.

3.2 Probability risk assessment

Figure 2 provides the modeled grain yield as a function of nitrogen fertilization and cumulative probability density function (CDF). The surface was drawn using the adjusted values of the Type-I distribution. The characteristics values, namely the mean, the median and the mode of each distribution were numerical derived and overlaid on the response surface.

The representation of the grain yield in this novel form was quite seductive, since it allowed extrapolating the model's answer from one treatment to another. The so-obtained curve can be seen as the site-specific N identity card of the studied crop, under the soil and climatic conditions characteristics of the area.

Under this form one could clearly see the evolution of the distributions from Gaussian shapes at low N strategies (0-0-0 and 10-10-10 kgN.ha⁻¹ protocols) towards asymmetric shapes in presence of higher N inputs.

Under low N strategies the mode, the median and the mean were confounded, while they diverged with increasing nitrogen fertilization dose. With N increase, the mean yield was always the lowest value, yields corresponding respectively to the median and

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the mode progressively moved away from the mean. The mode of the distribution was always the highest value out the three characteristics. At high nitrogen doses, the distance between the mode and the median was always superior to the difference between the median and the mean. These observations were true whatever the used strategy which consisted in splitting the total dose in two or three fractions.

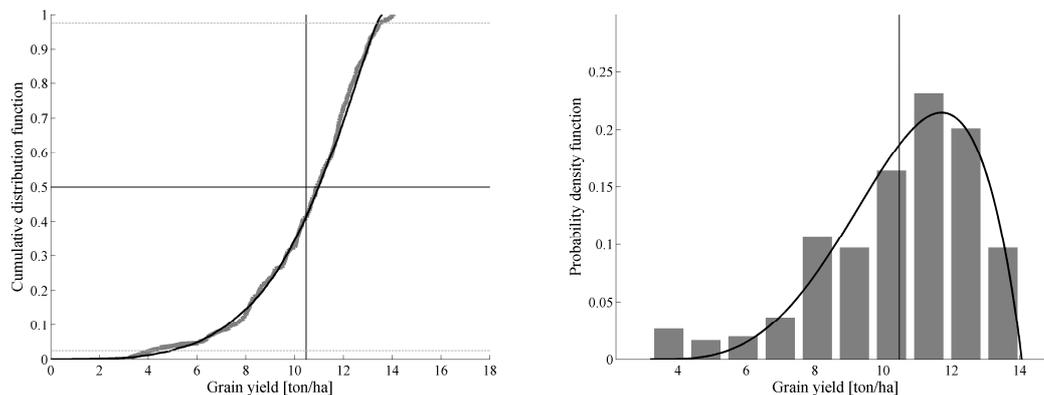


Figure 1. Cumulative distribution function (CDF) (left) and probability density function (PDF) (right) of grain yield corresponding to a '60-60-60' kgN/ha treatment (T7). Comparison of the numerical-experimental results (grey data) and the computed Type I distribution (black results). The vertical black line represents the mean of the distribution. On left graph, percentile 50 % (solid horizontal thick black line).

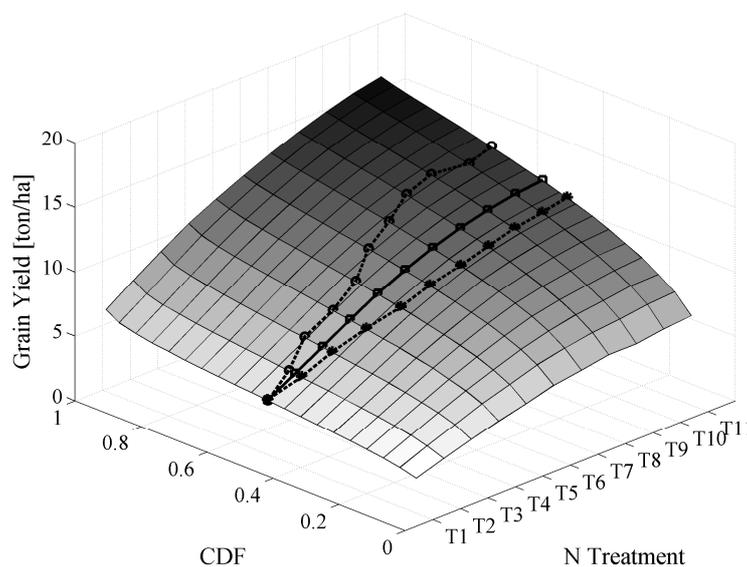


Figure 1 : Grain yield as a function of N fertilisation management and cumulative probability density function (CDF) drawn out of 300 synthetic climates. The dotted circled (-o-) line represents the mode distribution. The dotted starry (-*-) line represents the mean and the solid squared (-□-) line represents the median of the distribution.

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3.3 Return time of yields

What really interests the farmer is to know how often the minimum expected yield will be achieved. On basis of the methodology, the different nitrogen strategies were thus analyzed in terms of yield associated with a given return time, e.g. by calculating the yield obtained 9 years out of 10 (Table 2).

The characteristic values of return time were easily obtained by computing the yield associated with a given probability of occurrence (Fig. 1 and 2); e.g. a probability of 0.75 corresponded to a yield achieved 3 years out of 4. In this paper, the focus was put on three characteristic return times, computing the yields achieved at least 1 year out of 2, 3 years out of 4 and 9 years out of 10. Obviously, the lower yields were achieved at the highest return time.

With the usual practice of the farmers (T7), 9 years out of 10, the grain yield would at least achieve 7.26 tons/ha, while 1 year out of 2, the expected yield should be at least of 11 tons/ha.

Table 1 : Yields (t/ha) associated with a given return time, respectively 1 year out of 2 ($p=0.50$), 3 years out of 4 ($p=0.75$) and 9 years out of 10 ($p=0.90$).

T#	T1	T2	T3	T4	T5	T6	T7	T8	T9	T10	T11
p=0.50	4.19	5.41	6.65	7.91	9.09	10.1	11.0	11.7	12.2	12.6	12.9
p=0.75	3.56	4.61	5.65	6.70	7.63	8.48	9.21	9.71	10.1	10.4	10.6
p=0.90	3.00	3.83	4.65	5.44	6.11	6.78	7.26	7.63	7.81	8.13	8.27

4. CONCLUSIONS

This research aims to demonstrate the importance of a sound theoretical and statistical basis when the optimal nitrogen management practice needs to be highlighted.

The Type-I Pearson distribution was used to analysed and extrapolate the yield of wheat simulated by the crop model STICS coupled to a climate database ensemble of 300 years. Using this method, the effect on the yield of different nitrogen practices has been investigated and the risk for farmers has been quantified.

Overall, the proposed methodology allowed representing as a 3D surface the expected yield of a crop in function of the nitrogen dose and the probability density function. This was done in specific agro-environmental conditions corresponding to the cultivated area. The method was easily extended to compute the return time of expected yield.

In front of the results, the method has a real potential to stand as basis to develop decision support tools to improve the decision making process. This research could thus be used to develop alternative management strategies in order to optimize the economical nitrogen use efficiency.

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4. ACKNOWLEDGEMENTS

The authors would like to thank the SPW (D GARNE – DGO-3) for its financial support for the project entitled ‘*Suivi en temps réel de l’environnement d’une parcelle agricole par un réseau de microcapteurs en vue d’optimiser l’apport en engrais azotés*’. The authors would also like to thank the *OptimiSTICS* team for allowing them to use the Matlab running code of the STICS model. Finally, the authors are very grateful to CRA-W, especially the *Systèmes agraires, Territoire et Technologies de l’Information* unit, for providing them with the Ernage station climatic database.

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