Yield variability linked to climate uncertainty and nitrogen fertilisation

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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) fertilisation). In combination with a weather generator, we built up a general methodology that allows studying the yield variability linked to climate uncertainty, in order to assess the best N practice. Our study highlighted that, applying the Belgian farmer current N practice (60-60-60 kg N/ha), the yield distribution was found to be very asymmetric with a skewness of -1.02 and a difference of 5% between the mean (10.5 t/ha) and the median (11.05 t/ha) of the distribution. This implies that, under such practice, the probability for farmers to achieve decent yields, in comparison to the mean of the distribution, was the highest.

Keywords: crop model, STICS, yield prediction, climate variability, N management

Introduction

Analysing the future directions of precision agriculture (PA) research, McBratney *et al.* (2005) highlighted the researches devoted to yield mapping (Arslan and Colvin, 2002), or quantifying soil variation for zone management (Basso *et al.*, 2012). However, they pointed out some issues which require urgent attention by researchers to develop the PA concept to its full potential. Among these, they mentioned the recognition of crop quality assessment methods and the analysis of temporal variation, both at the inter-annual and within-season time step.

In the field of crop yield insurance, inter-annual variability is of prime importance. A wide variety of methods have been applied to estimate the form of yield probability distributions. Day (1965) studied the effects of different nitrogen rates on different species, namely oat, maize and cotton. He concluded that: (1) crop probability distributions are in general non-normal and non-lognormal; and (2) the skewness and kurtosis depends upon the specific crop and the amount of available nutrients. Since this, his works were corroborated by several researchers (Just and Weninger, 1999; Hennessy, 2009; Du *et al.*, 2012).

While these researches focused on real-life data, within the actual context of continued pressure on agricultural land and of food insecurity, crop models are more and more often used to support decision making processes and planning in agriculture (Basso *et al.*, 2011; Ewert *et al.*, 2011). Indeed, they are powerful tools to study the effects of variable inputs on harvestable organs, such as management practices, agro-environmental conditions (e.g. soil characteristics) and weather events. In this way, crop models appear as tools dedicated to assess the end-season crop-quality. However, in the particular field research of nitrogen (N) management, Basso *et al.* (2012) stated that the complexity of decision making was linked to the fact that the decision about the amount of N fertilizer to apply had to be taken without any prior knowledge of future weather conditions. To cope with such uncertainty, Basso *et al.* (2012) analysed the model cumulative probability under

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different monitored past climate scenarios. A methodologically more consistent approach to study the effects of climatic variability on the simulated crop yield is to use a stochastic weather generator, instead of historical data which are often not numerous (Semenov and Porter, 1995; Lawless and Semenov, 2005).

In this paper, we propose a new general methodology to assess the impact of N fertiliser rate on crop yield, using crop models. As an integration of previous knowledge (Day, 1965; Lawless and Semenov, 2005; Basso *et al.*, 2012), the methodology constitutes a new point of view to temporal and inter-annual analysis. It relies on a database of stochastically generated climates, which ensure the exploration of the most advantageous and disadvantageous climate conditions, in combination with a site-specific calibrated crop model, to assess the optimal N rate.

Materials and methods

Case study

Field experiments were carried out to measure a winter wheat crop response (*Triticum aestivum* L., cultivar Julius) to the Belgian temperate climate, more precisely in the Hesbaye Region (loamy soil conditions), and to different nitrogen fertilisation levels, ranging from zero to 240 kg N/ha.

Three successive years (2008-11) with highly contrasting weather were monitored. During the season 2008-2009, yields were very high. The exceptionally good weather conditions and sufficient nitrogen nutrition level indicated that yields may have been close to the optimum allowed by the cultivar. The seasons 2009-2010 and 2010-2011 were known to induce deep water stresses and were characterised by important yield losses. During the last two seasons, the stresses did not appear at the same crop stages.

Regular biomass growth reference measurements (LAI, total biomass and grain yield) and continuously monitored environmental measurements (climatic data and soil moisture) were performed over the growing seasons.

Moreover, a 30 year weather database provided by a reference meteorological station (Ernage Weather Station), located 4 km from the field, was available for this study.

Crop model

The soil-crop model STICS was used in this study. A wide literature can be found concerning the STICS model formalisms and the way it simulates yield (Brisson *et al.*, 2003, 2009). The STICS model requires daily weather climatic inputs, namely minimum and maximum temperatures, total radiation and total rainfall. In the case of more complex formalisms about potential evapotranspiration calculations, the wind speed and vapour pressure are needed.

The STICS model parameterisation, involving calibration and validation, was performed on a three-year database previously presented, using inverse modelling techniques (Vrugt *et al.*, 2009). The parameters of the model were adjusted to accurately simulate the different components of the yield (i.e. biomass, grain yield and protein content) under the different nitrogen fertilisation levels. The contrasted years, in terms of climate conditions and corresponding yields, were used to parameterise the water and thermal stresses affecting the simulated dynamic biomass growth.

Original weather database and climate variability

For the experimental recorded crop seasons, data acquired by an in-field sensor network were compared with the data issued from the reference meteorological station. For each climatic variable, the results were found to be in good agreement. Provided that the input data used to calibrate the model were representative enough to ensure robustness, the STICS model could be run on the 30 year (1980-2009) Ernage weather database.

This database was thus analysed 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.

Nitrogen management strategies

In Belgium, the farmer current N fertilizer practice is to split a total 180 kg N/ha dose in to three equal fractions, applied respectively at tillering (Zadoks stage 23), redress (Zadoks stage 29) and last-leaf (Zadoks stage 39) stages. This practice will be used as reference and compared to different levels of N fertilisation, also applied in three equivalent fractions, at tillering, redress and last-leaf stages, with an increasing N step of 10 kg N/ha, ranging from 0 to 300 kg N/ha (3×100 kg N/ha) (Table 1). To simplify the simulation process, as first assumption, the same management techniques were applied to each simulation, in terms of sowing date (Julian Day 295) and of fertilisation dates (Julian days 445, 475 and 508).

Table 1. Fertilisation rate for the different N strategies.

Treatment no.	Fertilisation level (in kg N/ha)			
	Tillering (Z23)	Redress (Z29)	Last-leaf (Z39)	Total
T1	0	0	0	0
T2	10	10	10	30
…	…	…	…	…
T11	100	100	100	300

The Pearson system and coefficients

Pearson developed an alternative system of probability density functions that take a wide variety of forms (Day, 1965; Pearson, 1895). In this paper, we will focus on the type I distribution, for which random variable has a finite range (Equation 1).

The different types of distributions can also be identified independently from their mean and variance, rather referring to their asymmetry (*skewness*) and flattening (*kurtosis*) parameters (Equation 2)

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

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

$$\begin{aligned} Skewness &= \frac{m_3}{m_2^{3/2}} = \frac{m_3}{\sigma^3} \\ Kurtosis &= \frac{m_4}{m_2^2} = \frac{m_4}{\sigma^4} \end{aligned} \tag{2}$$

Where m_x is the momentum of order *x*, and σ is the standard deviation. The squared-*skewness* is typically known as the β_1 Pearson parameter, and the *kurtosis* is also typically found under the β_2 Pearson parameter denomination. Since it is signed, and thus gives the orientation of the asymmetry, the *skewness* parameter was preferred in this paper.

Specificities and genericity of the method

It is really important to remind that, although the methodology is generic, the results presented here remains site-specific. First, the model was parameterised and calibrated on a specific soil type and for a specific crop culture. Furthermore, the 30 year original weather database, and the so-derivate 300 year climatic conditions, are also representative of the climatic conditions in this specific area. In this paper, we focus on the grain yield (GY) simulations obtained with the STICS model but, being generic, the procedure could be applied to any other model or model output, e.g. the grain protein content.

Results and discussions

General assessment of the distributions

Figure 1 provides an insight, as a boxplots representation, of the results obtained at the end of the simulation process. To discuss these results in detail, two fertilisation levels are presented, respectively the 0-0-0 kg N/ha (T1), the 60-60-60 kg N/ha (T7) strategies, for which both the cumulative distribution function (CDF) and the probability density function (PDF) are presented (Figure 2).

It first appeared that the Type I distribution was particularly suited to describe the yield distribution (Figure 2). The distribution of the T1 treatment seemed very close to a normal distribution (Figure 2). Each increase in N supply allowed the yield to increase, both in mean and median values (Figure 1 and 2), but also tended to induce asymmetry among the distribution (Figure 2), with a median value situated closer to the highest yields than the lowest. This induced, in return, a negative *skewness* (Figure 3), with a median value superior to the mean (Figure 2 and 3).

Skewness and kurtosis of the distributions

A first insight into Figure 3 led to the conclusion that the *skewness* and *kurtosis* parameters evolved in opposite directions, in accordance with the theory. The more pronounced the dissymmetry, the more spread/flattened the curve.

The non-application of nitrogen exhibited a distribution with close-to-zero *skewness* (-0.002) and a *kurtosis* close to three. This was pretty close to the Gaussian distribution (*skewness* and *kurtosis* of 0 and 3 respectively).

The 60-60-60 kg N/ha treatment led to the highest degree of asymmetry, with a *skewness* value of -1.02 and a *kurtosis* close to 3.85. The asymmetry was reduced with higher N practices, therefore characterised by less negative *skewness* parameters, to reach a value of -0.83 at 100-100-100 kg N/ha.

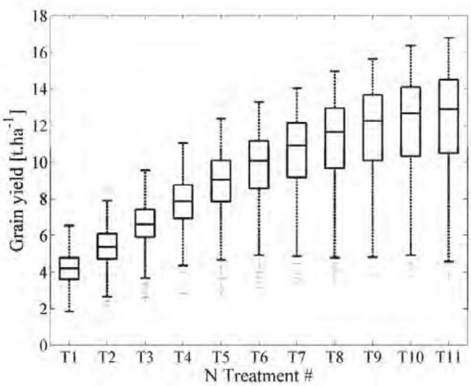

Figure 1. Boxplot analysis of the different N fertilisation strategies.

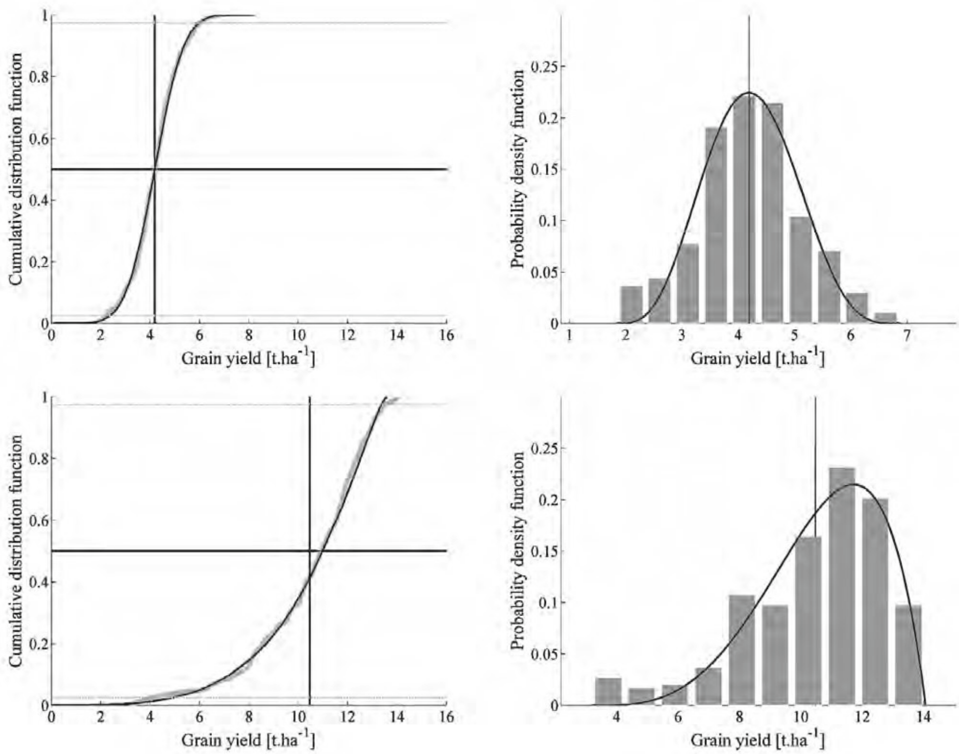

Figure 2. Cumulative distribution function (CDF) and probability density function (PDF) corresponding to the treatment T1 (top) and T7 (bottom). Comparison of the numerical-experimental curve out of the 300 simulations (grey line) and the computed Type I distribution of Pearson System (black line). Representation of percentile 50 (horizontal thick black line) and percentiles 2.5 and 97.5 (horizontal thick grey line). The vertical black line represents the mean of the distribution.

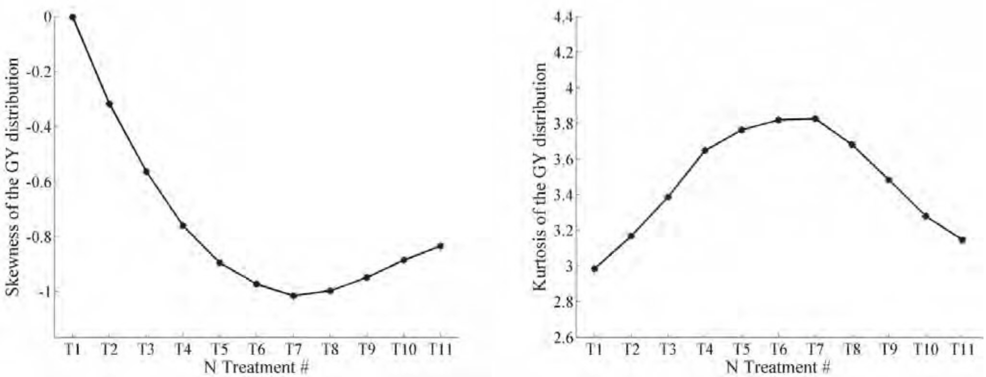

Figure 3. *Skewness* and *Kurtosis* of the different N fertilisation strategies.

At the farmer current N practice, a difference of 5% between the mean (10.5 t/ha) and the median (11.05 t/ha) of the distribution was observed.

Assessing the normality of the distributions

In the face of the results obtained on the *skewness* and *kurtosis* parameter values, the normality of the distributions was assessed using a Kolmogorov-Smirnov test (Table 2).

It appeared that the distribution could be considered as being normal up to a 10-10-10 kg N/ha treatment. As soon as the total amount of 60 kg N/ha (20-20-20 kg N/ha) was provided to the crop, the yield distribution was considered as being asymmetric.

The equivalence of the mean of the distributions were analysed the one with the other, using an ANOVA test (results not shown). In a global way, each additional N fertilisation level led to, at least, significantly ('*') higher grain yields. However, a N management strategy with N supply higher than 90-90-90 kg N/ha (T10) did not improve significantly the expected mean; treatment T9-T10 and T10-T11 were found statistically equal. This was confirmed by Figure 1 analysis, where the expected yield seemed to reached a plateau.

Return time of yields

Finally, at this stage of the research, the proposed methodology was extended and used to assess the probability of occurrence of yields, in other words, to estimate the probability encountered by the farmers to achieve a determined amount of yield. The different N practices were thus analysed in terms of yield associated with a given return time, e.g. by calculating the yield obtained 9 years out of 10 (Table 3).

These characteristic values were easily obtained by computing the yield associated with the 1-α probability, were α is the probability associated with the return time (e.g. 0.75 when the return time is 3 years out of 4).

In this way, at the current N practice (T7), in 9 years out of 10, the farmer would at least achieve a grain yield of 7.26 t/ha. In the same way, 3 years out of 4, the expected yield should be at least 9.21 t/ha for the same N management.

Table 2. Evaluation of the normality of the distribution, using a Kolmogorov-Smirnov test (*P*-value and significance level).

T#	T1	T2	T3	T4	T5	T6	T7	T8	T9	T10	T11
P-value	0.766	0.339	0.023	0.017	0.018	0.013	0.007	0.006	0.002	0.004	0.003
Significance			*	*	*	*	**	**	**	**	**

Table 3. Yields (t/ha) associated with a given return time (probability of occurrence), respectively 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=0.75	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

Conclusions

As a specific conclusion of this study, we think that the shape of a distribution, characterised by its skewness and kurtosis, is of prime importance, at the same level (or even more) than its mean, and its standard deviation. In this way, the type I distribution of the Pearson system was found as a systematically good predictor of the crop model answer. The analysis showed that, without fertilisation, the crop model behaviour seemed to exhibit a Gaussian distribution in response to the climatic inputs, here considered as random input variables.
The different increasing N practices induced a behaviour characterised by a negative skewness in comparison of the T1 treatment (0-0-0 kg N/ha), i.e. exhibiting a median value superior to the mean of the distribution. Moreover, the farmer current N practice (60-60-60 kg N/ha) exhibited the highest degree of asymmetry, i.e. with the lowest *skewness* value. This practice is therefore the one that most increases the probability of obtaining a final yield that is higher than the mean of the expected distribution.
In front of the results, the methodology has a real potential to cope with new issues of the PA concept, namely the consideration of temporal variation and crop quality assessment. Furthermore, provided that the crop model answer is correctly validated for a given crop cultivated under different soil types within the same field, the method would allow the best N practice to perform zone management. Since it is based on a high number of stochastically generated climates, it includes the study of the yield uncertainty link to inter-annual climate variability. For all reported reasons, the method appears as an interesting tool to develop decision support systems.

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