CLIMATIC RISK ASSESSMENT TO IMPROVE NITROGEN FERTILISATION RECOMMENDATIONS : A STRATEGIC CROP MODEL-BASED APPROACH

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Abstract

Within the context of nitrogen (N) management, since 1950, with the rapid intensification of agriculture, farmers have often applied much larger fertiliser quantities than what was required to reach the yield potential. However, to prevent pollution of surface and groundwater induced by nitrates, The European Community launched The European Nitrates Directive 91/6/76/EEC. In 2002, in Wallonia (Belgium), the Nitrates Directive has been transposed under the Sustainable Nitrogen Management in Agriculture Program (PGDA), with the aim of maintaining productivity and revenue for the country's farmers, while reducing the environmental impact of excessive N application.

A feasible approach for addressing climatic uncertainty lies in the use of crop models such as the one commonly known as STICS (Simulateur multidisciplinaire pour les cultures standard). These models allow the impact on crops of the interaction between cropping systems and climatic records to be assessed. Comprehensive historical climatic records are rare, however, and therefore the yield distribution values obtained using such an approach can be discontinuous. In order to obtain better and more detailed yield distribution information the use of a high number of stochastically generated climate time series was proposed, relying on the LARS-Weather Generator. The study focused on the interactions between varying N practices and climatic conditions. Historically and currently, Belgian farmers apply 180 kgN.ha^{-1}, split into three equal fractions applied at the tillering, stem elongation and flag-leaf stages. This study analysed the effectiveness of this treatment in detail, comparing it to similar practices where only the N rates applied at the flag-leaf stage were modified.

Three types of farmer decision-making were analysed. The first related to the choice of N strategy for maximising yield, the second to obtaining the highest net revenue, and the third to reduce the environmental impact of potential N leaching, which carries the likelihood of taxation if inappropriate N rates are applied.

The results showed reduced discontinuity in the yield distribution values thus obtained. In general, the modulation of N levels to accord with current farmer practices showed considerable asymmetry. In other words, these practices maximised the probability of achieving yields that were at least superior to the mean of the distribution values, thus reducing risk for the farmers.

The practice based on applying the highest amounts (60-60-100 kgN.ha^{-1}) produced the best yield distribution results. When simple economical criteria were computed, the 60-60-80 kgN.ha^{-1} protocol was found to be optimal for 80-90% of the time. There were no statistical differences, however, between this practice and Belgian farmers' current practice. When the taxation linked to a high level of potentially leachable N remaining in the soil after harvest was considered, this methodology clearly showed that, in 3 years out of 4, 30 kgN.ha^{-1} could systematically be saved in comparison with the usual practice.

Keywords: climatic variability, stochastically generated weather, LARS-WG, crop model, STICS, nitrogen management

1. Introduction

Within the context of precision nitrogen (N) management, the rapid intensification of agricultural production systems since 1950 has resulted in a dramatic increase in inputs in general, and in fertilisers in particular (Van Alphen and Stoorvogel, 2000).In order to ensure that the yield potential (defined here as yield limited only by water availability) (Reid, 2002; Robertson et al., 2008), could be reached each year, farmers often applied quantities of N fertiliser that were far greater than the amount actually required to achieve the yield potential (Lemaire et al., 2008). Through N leaching, agriculture is an important source of N emissions to groundwater and surface waters (Basso and Ritchie, 2005; Basso et al., 2012b), and the European Community therefore issued several directives aimed at reducing water pollution caused or induced by nitrates from agricultural sources (EC-Council Directive, 1991). Thus, in 2002 the Walloon Government integrated the Nitrate Directive 91/676/EEC into the law and initiated the Sustainable Nitrogen Management in Agriculture Program (PGDA) (Vandenberghe et al., 2011). In order to maintain high yields while reducing environmental impact, it appears necessary to increase N-use efficiency through the promotion of good farming practices.

A promising approach for studying the effect of farming practices and optimising N fertiliser rates is based on using crop models. Since most of their processes are physically based, crop models are well suited to supporting decision-making and planning in agriculture (Basso et al., 2011; Ewert et al., 2011). As most physically based soil-crop models work on a daily time basis and therefore simulate the evolution of agronomic variables of interest through daily dynamic accumulation, climatic variables play a crucial role in the accuracy of model outputs (e.g., grain yield). For this reason, weather conditions need to be described as accurately as possible. It is first of all the sequencing of weather events, which induce interacting stresses, that has the greatest effect on the dynamics of crop growth simulation

(Riha et al., 1996).

One important reason for using crop models in advisory systems is that these models can take several factors into account, such as soil characteristics, management practices and climatic variables. Far more importantly, though, they take the possible interactions between these factors into account (Houlès et al., 2004). The complexity of decision-making, however, is linked to little or no knowledge of future weather conditions. A feasible approach for addressing such uncertainty is to quantify the one associated to different historical weather scenarios (Basso et al., 2011; Basso et al., 2012b; Houlès et al., 2004) or use seasonal weather forecasts (Asseng et al., 2012). Even more consistent methodologically is the use of a stochastic weather generator, instead of historical data, which are often rare (Dumont et al., 2013; Lawless and Semenov, 2005; Semenov and Porter, 1995). In conjunction with a crop simulation model, a stochastic generator allows the temporal extrapolation of observed weather data for agricultural risk assessment linked to the experiment site-specific historical weather data (e.g., to improve N-use efficiency) (Semenov and Doblas-Reyes, 2007).

The form of yield distribution is another important parameter to consider when the final decision has to be taken. A wide variety of methods has been used to forecast this parameter (Day, 1965; Du et al., 2012; Dumont et al., 2013, 2014c; Hennessy, 2009a, b; Just and Weninger, 1999). It is clear that field crop yields have a finite lower limit (zero). Similarly, a given crop variety has a finite upper limit that, under consistent cultural practices but variable weather conditions, reflects the maximum amount that can be expected even under the most favourable circumstances. Recent studies have demonstrated the importance of linking the theory of yield distribution analysis with on-farm data in order to reduce environmental risk while maximising farmer profit (Kyveryga and Blackmer, 2012; Kyveryga et al., 2013).

Although these major steps have been made in research on N practice optimisation, determining the optimum amount of N fertiliser remains an important task and needs to be investigated on a case-by-case basis. A promising approach involves optimising the economic impact of N practices. In essence, this means maximising the benefits derived from yields increases under varying N fertilisation levels, allowing plant needs to be met while simultaneously minimising the costs of N purchase and taxation liabilities linked to the environmental impact of poor N management (Basso et al., 2011; Houlès et al., 2004).

The objectives of this research were to develop a crop model-based approach for evaluating the economic impact of various N management strategies. In order to refine N fertilisation recommendations, crop growth linked to N strategies was simulated under a wide variety of climatic conditions. Stochastically generated climate conditions were derived so that the most advantageous and disadvantageous climatic variable combinations could be explored. In order to assess how various combinations of input constraints affect yield distribution, the crop model responses were analysed using the Pearsons system of distribution. Finally, N management was optimised on the basis of marginal net revenue (MNR) and environmentally friendly net revenue (ENR). The latter was designed according to the market prices observed over last-years and the Belgian's law for what concerns the environmental constraint.

2. Material and methods

2.1. Nitrogen management strategy

In Belgium, the current N fertiliser management practice consists of splitting the total 180 kgN.ha^{-1} application into three equal fractions and applying them at the tillering (Zadoks stage 23), stem extension (Zadoks stage 30) and flag-leaf (Zadoks stage 39) stages. Depending on the plant physiology, the number of grains is set by the plant between flowering (Zadoks stage 50) and the end of anthesis (Zadoks stage 69), and is driven by prevailing climate conditions. In terms of end-of-season yield prediction, as long as the final number of grains has not been fixed, the uncertainty linked to grain yield and climatic variability remains very high (Dumont et al., 2014a; Lawless and Semenov, 2005). The detrimental impact of climatic conditions before the flowering or anthesis stages can generally be mitigated by the ability of a crop to compensate for this during its growth period (e.g., lower plant density rates are compensated for a higher number of tillers produced). Once the number of grains is fixed, the end-of-season yield is driven mainly by the climatic conditions that influence grain filling, in terms of both carbohydrates and N exportation. In recent studies, Dumont et al. (Dumont et al., 2013, 2014c) successfully transposed the theory of yield distribution analysis to the study of crop model solutions. They found that the maximal skewness of yield distribution was reached at the N practice currently used by Belgian famers, ensuring that the probability of achieving yields greater than the distribution mean was the highest.

It was therefore decided to fix the first two N applications according to current Belgian practice (i.e., 60 kgN.ha^{-1}). As a strategic approach, different N levels where then applied on the third application, rising from 0 kgN.ha^{-1} to 100 kgN.ha^{-1}. This application strategy was referred to as the ‘modulo-60 (M60-X) treatment’.

2.2. Agro- economico-environmental decision criteria

The optimal N fertiliser rate for each of the simulation sets was based on marginal net revenue (MNR) as a function of yield response to the amount of N applied, taking account of the grain selling price and the cost linked to N (Basso et al., 2012a; Houlès et al., 2004) :

$$MNR = (Y_N . G_P) - (N . N_P) \qquad \textbf{Eq. 1}$$

$$ENR = MNR - Taxes \qquad \textbf{Eq. 2}$$

$$Taxes = \begin{cases} 0 \;\; eur.ha^{-1} & if \quad SNC < 40 \;\; kgN.ha^{-1} \\ 120 \;\; eur.ha^{-1} & if \quad SNC \geq 40 \;\; kgN.ha^{-1} \end{cases} \qquad \textbf{Eq. 3}$$

where MNR is the marginal net revenue (€.ha^{-1}), Y_N is the grain yield (ton.ha^{-1}), G_P is the grain price (€.ton^{-1}), N is the total amount of fertiliser applied during the season (kgN.ha^{-1}), N_P is the price of N (€.kgN^{-1}) and ENR is the environmentally friendly net revenue (€.ha^{-1}) computed according to taxation related to environmental risks. The grain and N prices were fixed at 180 and 300 €.ton^{-1}, respectively, reflecting observations made in recent years (2011 and 2012).

In the Wallonia region of Belgium, since the Nitrate Directive 91/676/EEC was integrated into Belgian law in 2002, a survey system has been put in place to control N leaching in sensitive areas. The system's taxation levels used in this study (Eq. 2 and 3) are based on the most stringent requirements of this directive, whereby a maximum tax of 120 €.ha^{-1} is levied if the total amount of N remaining in the soil profile (soil N content [SNC] kgN.ha^{-1}) is higher than the mean of the same data computed over 35 reference farms. As SNC varies depending on the climatic year and the preceding culture, in this study it was set at 40 kgN.ha^{-1}, which was deemed a strict threshold (crop culture with N trap-crop).

2.3. Weather database, weather generator and climate variability

The Ernage weather station, located 2 km from the experimental site and forming part of Belgium's Royal Meteorological Institute (RMI) observation network, was used in this study. The complete 31-year (1980-2011) weather database (WDB) was used to provide the inputs for the crop model (i.e., solar radiation, wind, precipitation, ambient temperature and relative humidity).

The WDB was initially analysed using the LARS-Weather Generator (WG) (Racsko et al., 1991; Semenov and Barrow, 1997). Thereby, a set of parameters representative of the experimental site were computed, involving (*i*) the daily maximum, minimum, mean and standard deviation values of analysed climatic variables, (*ii*) the seasonal frequency distribution of rainy events and (*iii*) the return period of wet and dry series.

As a second step, the LARS-WG was used to stochastically generate a set of synthetic time-series scenarios representative of the climatic conditions. The software enabled to generate synthetic data that have the statistical characteristics of the historical records (Semenov and Barrow, 2002). As recommended by Semenov and Barrow (2002), long weather sequences were used to perform the risk assessment study: the longer the time period of simulated weather, the higher the chances of covering the full range of possible weather events. Based on the work of Lawless and Semenov (2005), 300 stochastically generated weather time-series were used to ensure stability in predicted mean grain yield.

The stochastically generated daily climatic scenarios were then used as inputs for the STICS crop model. This approach ensured that a variety of combinations of climatic variables could be explored, leading to the simulation of stress conditions not previously observed during field experiments, but reflecting local weather conditions. As discussed and demonstrated in Dumont et al. (2014c), using a high number of synthetic time-series instead of a limited set of historical records as input of the model allow to finely and properly characterise the model behaviour. This issue is of major importance when probability risk assessment analysis have to be conducted.

2.4. Field trial for model calibration and validation

A field experiment was designed to study the growth response of wheat (*Triticum aestivum* L., cv. Julius) in the agro-environmental conditions of the Hesbaye region in Belgium. A complete randomised block design was used. The experimental blocks (2m*6m) were implemented on a classic loam soil. For each experimental unit there were four replicates. Four N fertilisation strategies were analysed, with different rates of fertilizer being applied, as described in Table 2. The experiment was designed to explore the complete response curve of wheat to N, with practices that range from non-nitrogen applied (*Exp. 1*) to over-fertilisation (*Exp. 4*).

Biomass growth, grain yield and N export by the whole plant were measured over 4 successive years (the 2008-09, 2009-10, 2010-11 and 2011-12 crop seasons). In 2008-2009, the yields were fairly high, close to the optimum for the cultivar. This was due mainly to good weather conditions and adequate N rates. In the 2009-2010 and 2010-11 seasons, there was severe water stress, resulting in yield losses. In 2009-10, water stress occurred in early spring and early June, but remained limited. In 2010-11, there was water stress from February to the beginning of June. That summer, rainfall returned early enough to allow normal grain filling, but the straw yield was very low. Apart from the fact that important rainfall occurred in early summer, overall the 2011-12 season was normal.

2.5. Crop model

The STICS crop growth model has been described in many papers (Brisson et al., 2003; Brisson et al., 2009; Brisson et al., 1998). It simulates the carbon, water and N dynamics of plants in the soil-atmosphere environment on the basis of daily weather data (i.e., minimum and maximum temperatures, total radiation and total rainfall, vapour pressure and wind speed). It allows the effect of water and nutrient stress on development rates (Palosuo et al., 2011) to be taken into account.

STICS model parameterisation (i.e., its calibration and validation) was performed according to the 4-year database used in the field trial previously described. The root mean square error (RMSE), Nash-Sutcliffe efficiency (NSE) and normalised deviation (ND) indices were used to judge the quality of the model (Table 3) (Beaudoin et al., 2008; Brisson et al., 2002; Dumont et al., 2014b; Loague and Green, 1991). The calibration process was performed using the DREAM Bayesian algorithm (Dumont et al., 2014b; Vrugt et al., 2009). Dumont et al. (2014b) provide more details on this procedure.

The parameters driving phenology (*stlevamf*, *stamflax*), leaf area development (*adens, dlaimaxbrut*, *durvieF*), biomass growth (*efcroijuv*, *efcroirepro*, *efcroiveg*), grain yield elaboration (*cgain*, *irmax*) and related to water and N stresses (*psisturg*, *psisto, INNmin*) were selected for optimisation. The parameters driving N exportation did not need to be optimised. The remaining parameters were considered representative of the species and fixed at the suggested default values (Brisson et al., 1998; 2003). The parameters were calibrated for all the crop seasons but only for the *Exp.1* and *Exp.3* treatments in the field trial (Table 2). The model was then validated for the treatments (*Exp.2* and *Exp.4*) for all crop seasons.

The experimental cases were selected to present important contrasts in terms of N management (0 and 180 kgN.ha^{-1}). This made the calibration process challenging but unavoidable to properly simulate nutrition stress. The 2009-10 and, in particular, 2010-11 crop seasons were clearly going to be challenging in terms of modelling because of the significant water deficit compared with the Belgian seasonal norm. Using all the seasons in the calibration process was considered necessary in order to improve the relevance of this process, bearing in mind that the model would be run on stochastically generated climate scenarios that would sometimes reflect highly disadvantageous combinations of climatic variables.

2.6. Simulation process

In order to simplify the simulation process, the same management techniques were applied to the different simulations. Wheat was simulated as being sown in late October, on Julian day 295. The sowing date was always used as the starting point of the simulations. The same soil description, corresponding to the soil used in the calibration process, was used for all simulations. The soil-water content was set at field capacity. The soil initial inorganic N content measurements conducted in 2008-09, considered to be representative of real field conditions, were used to initialise the model. Finally, as a first insight of the proposed method, the N fertilisation dates were fixed at the same value for all the simulated years (Table 2).

The taxation system applied in Belgium is based on the remaining SNC. More precisely, in Belgian law ‘potentially leachable N’ is defined as the amount of $N\text{-}NO_3$ contained in the soil in autumn and being susceptible to being leached from the root zone during winter. In this study, the focus was therefore put on the SNC below plough level (about 30 cm).

Matlab software and toolboxes (Matlab, Mathworks Inc., Natick, Massachusetts, USA) were used for the data analysis and treatment.

3. Results

3.1. Grain yield probability risk assessment in response to N practices

Fig. 1 provides the model grain yield results as a function of N fertilisation management and cumulative probability density function (CDF) drawn from 300 synthetic climate scenarios. The characteristic values of each distribution (i.e., the mean, the median and the mode) were numerically derived and overlaid on the response surfaces. The *y*-axis (CDF) was inverted in order to reflect the risk facing farmers in attempting to achieve at least the expected corresponding yield.

The difference among the three characteristic values (mean, median and mode) was fairly constant. It exhibited a fairly consistent probability for the means, at about 58%. For the mode, however, there was a slight decrease in probability, from 42 to 36%.

The asymmetry level seemed to be generally very high under the modulo-60 strategies, whatever the third application level. A corresponding skewness value of -1.00 was observed under a 60-60-00 $kgN.ha^{-1}$ treatment, whereas the absolute lowest value was reached under the 60-60-30 $kgN.ha^{-1}$ (-1.06) treatment. A skewness value of -1.02 was obtained for the Belgium current practice (60-60-60 $kgN.ha^{-1}$).

The various N strategies were also analysed and compared in terms of yield associated with given return times (i.e., 1 year out of 2; 3 years out of 4; and 9 years of 10; see Table 4). The return time was directly proportional to the computed probability (e.g., the yield obtained at a probability of 90% corresponded to a minimum yield observed in at least 9 years out of 10). As an example, yields corresponding to the probability of achieving at least the median value ($p_{0.50}$) (i.e., yield obtained in at least 1 year out of 2) ranged between 9.8 $t.ha^{-1}$ (M60-1) and 11.3 $t.ha^{-1}$ (M60-11).

The distribution data were compared in pairs, using the Wilcoxon test, in order to evaluate their equivalence (Tables 5). The practices based on the modulo-60 N set with the last fraction of 0 and 10 kgN.ha^{-1} were judged as having a non-equivalent median. Where 20-50 kgN.ha^{-1} was applied as the third fraction, each increase of 10 kgN.ha^{-1} was judged as having a median statistically equivalent to the practice immediately prior to it. For treatments where the third fraction was 60-90 kgN.ha^{-1}, the equivalence of median distribution was confirmed up to a difference of 20 kgN.ha^{-1}. Finally, applying 100 kgN.ha^{-1} at the last-leaf stage was evaluated as giving a yield distribution equivalent to lower fractions where up to -30 kgN.ha^{-1} was applied (60-60-70 kgN.ha^{-1}).

3.2. Marginal net revenue analysis

Fig. 2 shows the marginal net revenue (MNR) as a function of N fertilisation management and CDF drawn from 300 synthetic climate scenarios. For each probability level, ranging from 1 to 99% in 5% steps, the N treatments giving the optimal MNR were highlighted (black dots). Table 6 gives the result of the comparison between distribution data, using the Wilcoxon test.

The modulo-60 set of N strategies showed that, for 99% of the time, a farmer can choose not to fertilise (M60-1). Under such a practice, the farmer could still achieve an adequate revenue. An important gap in terms of the optimal N to apply was also observed between the 5 and 10% probability lines, for which optimal amounts were obtained under the 60-60-20 kgN.ha^{-1} and 60-60-80 kgN.ha^{-1} strategies, respectively. Below a probability level of 70%, the highest N level was always the one that maximised the MNR.

Overall, the Wilcoxon test (Table 6) produced the same conclusions as those drawn when analysing grain yield distribution values. There was, however, an increasing significance level of no-statistical differences between the distribution values.

3.3. Environmental considerations

Tables 7 shows the results of comparing the environmentally friendly net revenue (ENR) distribution values using the Wilcoxon test. The lack of statistical differences among these values clearly increased this time, especially under higher N application levels.

Fig. 3 shows the MNR as function of the potentially leachable N amount and for the different N practices. The practices are ordered according to N level. The different probability levels, ranging from 5 to 95% in 5% steps, are represented by darkening grey lines.

It is worth noting that potentially leachable N was clearly reduced with a decreasing expected return time of favourable climatic conditions (darkest grey lines). At very low probability levels, the potentially leachable N amount did not increase with the N practice, whereas the net revenues clearly improved. Contrarily, at high probability levels of occurrence of climatic conditions (lightest grey lines), increasing the N practice led to increasing amount of N available for leaching, while MNR rapidly stagnated.

It is also worth noting that the expected revenue was far more dependent on climatic conditions than on the N amount applied. For all practices, for 95% of the time the revenue was limited to about 1,040 €.ha^{-1} (lightest grey line), whatever the practice. In contrast, for 5 years out of 100, the minimal expected revenue would be 2,110 €.ha^{-1}, even if the last N application was omitted, whereas the revenue would rise only to 2,340 €.ha^{-1} under actual farmer practice.

Fig. 4 shows the MNR and ENR as functions of the potentially leachable N amount and for the different N practices and puts the emphasis on three characteristic probability level (respectively 75%, 60% and 50%). The first (75% level) corresponded to the recommendation level that need special attention according to Basso et al. (2012). The 60% level was close to the expected return time of the mean of the distributions (58%) and the last (50% level) equalled the median.

As illustrated for these three specific return period, with decreasing probability levels (darkening grey lines), the MNR and ENR curves tended to become closer. Above the probability of 90%, the two curves were clearly separated (unshown results), and the ENR curve led to obviously lower revenues. At 75% probability level, the ENR and MNR curves were very close up to an application of 60-60-40kgN.ha^{-1} (first five dots). For higher practices, at that return time, ENR and MNR diverged. At a 60% probability level, one had to reach the 60-60-60kgN.ha^{-1} practice to observe differences between both curves. At a 35% probability level and beneath, the curves were confounded whatever the practice (unshown results).

4. Discussions

Displaying grain yield solutions in a new 3D format was attractive because it allowed the model solutions to be extrapolated treatment by treatment. The lack of discontinuity on the surface argued in favour of a properly stabilised response curve, which supported the use of a build-up methodology in order to explore any kind of combination of N practices, under the range of climate conditions prevalent in the area.

The asymmetry levels observed under the modulo-60 strategy were generally very high and in good agreement with those observed by Dumont et al. (2013, 2014c). With this strategy, the degree of asymmetry seemed to be optimised, suggesting that the probability of achieving yields that were at least as high than the mean of the distribution values was maximal.

Whatever the probability level (or expected return time), the highest yields were always obtained under the highest N practice. The Wilcoxon test revealed, however, that applying 100 $kgN.ha^{-1}$ at the flag-leaf stage led to a yield distribution equivalent to that when 60-60-70 $kgN.ha^{-1}$ was applied. This made the M60-8 practice the best one to optimise grain yields.

Overall, the observed yield levels were higher than the reasonable expectations, while simultaneously the probability of achieving them was maximised. This argued in favour of systematically applying 60 $kgN.ha^{-1}$ at the tillering and stem elongation stages under Belgian conditions (climate and cultivar). Such a practice would give farmers the opportunity to decide, depending on crop growth at the last-leaf stage, if they had to increase or decrease the last N application.

The analysis then focused on simple economic considerations based on MNR computation. Basso et al. (2012) suggested that a suitable solution would be to select the N application rate that would perform better than others 75% of the time (highlighted by the dotted black line in Figure 2). At this expected return time, the corresponding optimal practice was the M60-10 protocol, where 90kg N.ha^{-1} is applied at the flag-leaf stage. A parallel analysis conducted with the Wilcoxon test, however, showed no statistical differences between the M60-10 and M60-7 protocols. This led to the conclusion that the current practice (M60-7: 60-60-60 kgN.ha^{-1}) would be the optimal solution in terms of economic return.

When environmental constraints were considered in the ENR criteria and using the same 3D response surface approach (graph not shown), at a probability level of 75%, the 60-60-50 kgN.ha^{-1} practice appeared to be the optimal one. The Wilcoxon test revealed that this practice was statistically equivalent to the 60-60-30 kgN.ha^{-1} practice. This meant that, on a basis of environmental considerations, the current Belgian practice should be revised/decreased in many of the climatic situations (for at least 3 years out of 4), saving 30 kgN.ha^{-1} compared with the amount used under current practices.

Finally, the analysis focused on three characteristic probability levels: the ones corresponding to the median and the mean, and the 75% recommendation probability level (Fig. 4). Initially, the emphasis was put on the MNR curves. The optimal practice was seen as one where the effects of increased N led to increased leaching without substantially improving gain (i.e., where the curves tended to become horizontal). Following the recommendations put forward by Basso et al (2012), the N practice was statistically limited in 3 years out of 4 to a maximum amount of 30 kgN.ha^{-1} for the application at the flag-leaf stage. Under more favourable conditions, the current practice of 60-60-60 kgN.ha^{-1} was used as a reference. This practice would allow good revenue (1,805 €.ha^{-1}) to be obtained under an expected return time of 3 years out of 5 (probability level of 60%). In most cases, applying more N would then increase the likelihood of N leaching without substantially increasing revenue (1,841 €.ha^{-1}). Finally, in 1 year out of 2, the last N fraction could be increased beyond the actual practice.

The comparison of the MNR and ENR curves confirmed these recommendations. Where the curves separated tended to correspond to the recommendation we had formulated. As a reminder, the ENR values were computed based on the highest taxation level (120 €.ha^{-1}), reflecting a low expected SNC remaining in the whole soil profile (40kgN.ha^{-1}). The allowed remaining N, however, might be much higher in some seasons, depending on the mean of the surveyed farms used to determine the acceptance threshold. It is highly probable that, under unfavourable climatic conditions in a given on-going season, which would therefore mean that the N level at which tax was levied would be higher, the separation between MNR and ENR curves would occur at a higher level of potentially leachable N. Our analysis demonstrated, however, that crop models have the potential to deal easily with systematically low tolerable thresholds of potentially leachable N in order to reduce the environmental risk.

5. Conclusions

This research sought to demonstrate the importance of a sound statistical basis when investigating optimal N management practice in the context of agronomic, economic and environmental considerations. A methodology for analysing crop model solutions was developed and applied. A calibrated soil-crop model (STICS) was coupled with a weather generator (LARS-WG) to achieve simulations of expected yields. Specific 3D response surfaces were produced in order to analyse the optimal economic N practices, with or without considering environmental constraints.

Overall, whatever the farmer strategy (optimising grain yield, optimising net revenue or reducing environmental pressure), the results showed that, under Belgian growing conditions, systematically applying 60kgN.ha^{-1} at tiller and stem extension stages appeared to be an optimal solution. The last dose could be modulated in front of the development and the in-field implementation of the plant achieved at the flag-leaf stage.

Using the proposed methodology, an investigation was conducted to identify the optimal N treatment economically. It showed that, in most (70%) climatic situations prevalent in Belgium, the costs of increasing N application rates were compensated by the corresponding yields simulated. It was also shown, in the 3D MNR response surface analyses, that the current farmer practice in Belgium (60-60-60 kgN.ha^{-1}) was equivalent to the recommendation that would produce a significant gain in at least 3 years out of 4 (60-60-90 kgN.ha^{-1}).

When the taxes levied for environmental impact were considered, however, it appeared that the optimal N strategies should be reduced in order to meet the agro-economic-environmental criteria. Our analysis showed that a 60-60-30 kgN.ha^{-1} strategy was sufficient to ensure a good revenue. In at least 3 years out of 4, 30 kgN.ha^{-1} could be saved in comparison with the amount currently applied by farmers.

In conclusion, the potential of using a crop model as a decision tool for improving economic returns for farmers by maximising yield while reducing N input and protecting the environment was demonstrated. The methodology of N management analysis proposed in this study, based on stochastically generated climate scenarios, in combination with appropriate data analysis, appeared to be a powerful tool for accelerating the decision making process and determining the optimal N strategy in line with the climatic variability of the considered area. This research therefore has the potential to provide a basis for developing alternative management strategies that will optimise real-time N application practices.

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List of tables :

Table 1: Fertilisation calendar for simulated nitrogen management practices

	Fertilisation calendar (according to Zadoks stage and Julian day)			
	Tiller	Stem ext.	Last leaf	
Zadoks	23	30	39	
Julian day	445	475	508	
	Fertilisation rate (in $kgN.ha^{-1}$)			
Treat.#	Tiller	Stem ext.	Flag leaf	Total
M60-1	60	60	0	120
M60-2	60	60	10	130
M60-3	60	60	20	140
M60-4	60	60	30	150
...	...	...	...	...
M60-11	60	60	100	220

Table 2: Field trial

	Fertilisation level (in $kgN.ha^{-1}$)			
Treat.#	Tiller	Stem ext.	Flag leaf	Total
Zadoks	23	30	39	
Exp 1	0	0	0	0
Exp 2	30	30	60	120
Exp 3	60	60	60	180
Exp 4	60	60	120	240

Table 3: Model evaluation conducted in the experiments

Variable	Unit	RMSE [unit]	RRMSE [%]	NSE [/]	ND [/]
Biomass	[$t.ha^{-1}$]	2.01	0.27	0.88	0.10
Grain yield	[$t.ha^{-1}$]	1.81	0.35	0.74	0.13

Table 4 : Yields ($t.ha^{-1}$) associated with a given return time (probability of occurrence), 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), respectively, for N fertiliser applied as a modulation of the third N fraction

T#	M60-1	M60-2	M60-3	M60-4	M60-5	M60-6	M60-7	M60-8	M60-9	M60-10	M60-11
$p_{0.50}$	9.76	10.0	10.3	10.5	10.7	10.8	11.0	11.1	11.1	11.2	11.3
$p_{0.75}$	8.38	8.53	8.75	8.88	9.01	9.10	9.21	9.23	9.34	9.36	9.34
$p_{0.90}$	6.80	6.92	7.12	7.13	7.18	7.21	7.26	7.19	7.38	7.28	7.28

Table 5: Comparison of grain yield distribution values using the Wilcoxon test for various N treatments involving a modulation of the third application, based on a 60-60-XX kgN.ha^{-1} protocol

Treat.		60-60-100 (M60-11)	60-60-90 (M60-10)	60-60-80 (M60-9)	60-60-70 (M60-8)	60-60-60 (M60-7)	60-60-50 (M60-6)	60-60-40 (M60-5)	60-60-30 (M60-4)	60-60-20 (M60-3)	60-60-10 (M60-2)
60-60-90	(M60-10)	0.607									
60-60-80	(M60-9)	0.288	0.540								
60-60-70	(M60-8)	0.090	0.201	0.459							
60-60-60	(M60-7)	0.016*	0.048*	0.141	0.400						
60-60-50	(M60-6)	0.001**	0.005**	0.021*	0.093	0.345					
60-60-40	(M60-5)	0.000***	0.000***	0.001**	0.008**	0.051	0.282				
60-60-30	(M60-4)	0.000***	0.000***	0.000***	0.000***	0.002**	0.030*	0.233			
60-60-20	(M60-3)	0.000***	0.000***	0.000***	0.000***	0.000***	0.001***	0.012*	0.154		
60-60-10	(M60-2)	0.000***	0.000***	0.000***	0.000***	0.000***	0.000***	0.000***	0.002**	0.084	
60-60-0	(M60-1)	0.000***	0.000***	0.000***	0.000***	0.000***	0.000***	0.000***	0.000***	0.000***	0.030*

Table 6: Comparison of MNR distribution values using the Wilcoxon test for various N treatments involving a modulation of the third application, based on a 60-60-XX kgN.ha^{-1} protocol

Treat.		60-60-100 (M60-11)	60-60-90 (M60-10)	60-60-80 (M60-9)	60-60-70 (M60-8)	60-60-60 (M60-7)	60-60-50 (M60-6)	60-60-40 (M60-5)	60-60-30 (M60-4)	60-60-20 (M60-3)	60-60-10 (M60-2)
60-60-90	(M60-10)	0.682									
60-60-80	(M60-9)	0.401	0.613								
60-60-70	(M60-8)	0.161	0.287	0.523							
60-60-60	(M60-7)	0.043*	0.090	0.210	0.466						
60-60-50	(M60-6)	0.007**	0.015*	0.044*	0.146	0.398					
60-60-40	(M60-5)	0.000***	0.001**	0.004**	0.019*	0.087	0.334				
60-60-30	(M60-4)	0.000***	0.000***	0.000***	0.001***	0.007**	0.052	0.282			
60-60-20	(M60-3)	0.000***	0.000***	0.000***	0.000***	0.000***	0.002**	0.022*	0.187		
60-60-10	(M60-2)	0.000***	0.000***	0.000***	0.000***	0.000***	0.000***	0.000***	0.005**	0.105	
60-60-0	(M60-1)	0.000***	0.000***	0.000***	0.000***	0.000***	0.000***	0.000***	0.000***	0.000***	0.039*

Table 7: Comparison of ENR distribution values, using the Wilcoxon test for various N treatments involving a modulation of the third application, based on a 60-60-XX kgN.ha^{-1} protocol

Treat.		60-60-100 (M60-11)	60-60-90 (M60-10)	60-60-80 (M60-9)	60-60-70 (M60-8)	60-60-60 (M60-7)	60-60-50 (M60-6)	60-60-40 (M60-5)	60-60-30 (M60-4)	60-60-20 (M60-3)	60-60-10 (M60-2)
60-60-90	(M60-10)	0.802									
60-60-80	(M60-9)	0.630	0.761								
60-60-70	(M60-8)	0.389	0.486	0.643							
60-60-60	(M60-7)	0.197	0.251	0.362	0.581						
60-60-50	(M60-6)	0.061	0.079	0.118	0.241	0.467					
60-60-40	(M60-5)	0.009**	0.012*	0.019*	0.046*	0.126	0.369				
60-60-30	(M60-4)	0.001***	0.001**	0.002**	0.005**	0.016*	0.080	0.350			
60-60-20	(M60-3)	0.000***	0.000***	0.000***	0.000***	0.001***	0.004**	0.038*	0.215		
60-60-10	(M60-2)	0.000***	0.000***	0.000***	0.000***	0.000***	0.000***	0.001***	0.007**	0.122	
60-60-0	(M60-1)	0.000***	0.000***	0.000***	0.000***	0.000***	0.000***	0.000***	0.000***	0.001***	0.052

<u>List of figure captions :</u>

Figure 1: Grain yield as a function of N fertilisation management and cumulative probability density function (CDF) drawn from 300 synthetic climate scenarios. The dash-empty circle line (--o--) represents the mode of the distribution. The dash-star line (--*--)represents the mean of the distribution. The dash-empty square line (-□-) represents the median of the distribution. The probability levels represented correspond to 1%, 5%, 10%, ..., 95%, 99%.

Figure 2: Marginal net revenue (MNR) as a function of N fertilisation management and cumulative probability density function (CDF) drawn from 300 synthetic climate scenarios. The dash line (--) represents the MNR reached 3 years out of 4. The dots (•) represents the N treatment producing the optimal MNR under different probability levels. The probability levels represented correspond to 1%, 5%, 10%, ..., 95%, 99%.

Figure 3: Marginal (MNR) as a function of potentially leachable N, N fertilisation management and probability levels computed for 300 synthetic climate scenarios. The dots (•) represents the N treatment. The filled circle solid line (-•-) represents the MNR. The dash-empty circle line (--o--) represents the ENR. The darkening grey lines represent the decreasing probability levels (95%, 90%, ..., 10%, 5%).

Figure 4: Marginal (MNR) and environmentally friendly net revenue (ENR) as a function of potentially leachable N, N fertilisation management and probability levels computed for 300 synthetic climate scenarios. The dots (•) represents the N treatment. The filled circle solid line (-•-) represents the MNR. The dash-empty circle line (--o--) represents the ENR. The lightest grey, medium grey and dark grey correspond to the 75%, 60% and 50% probability levels, respectively.

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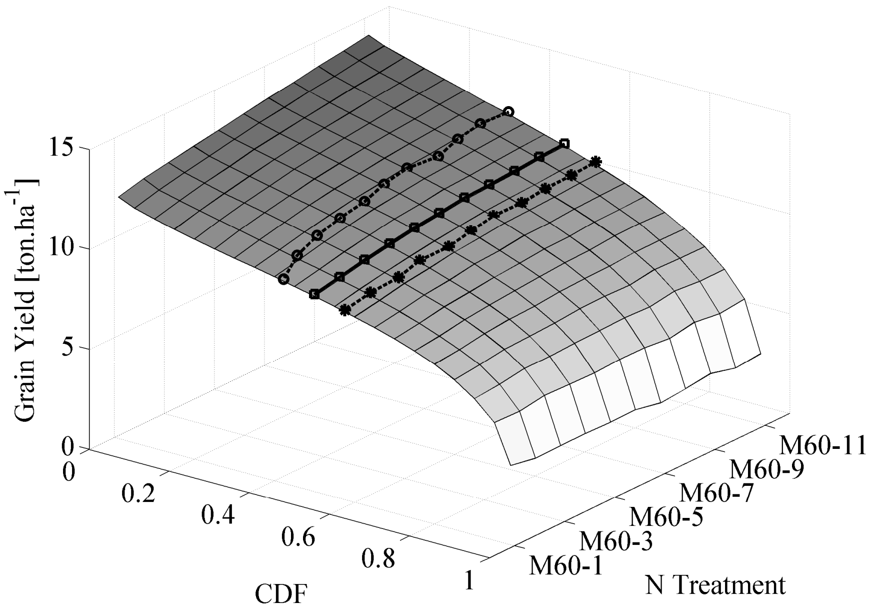

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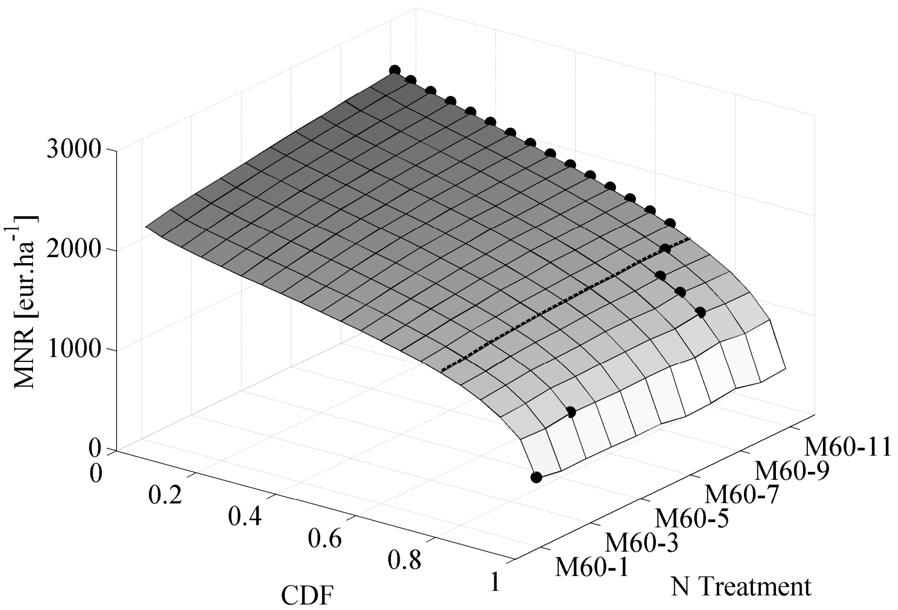

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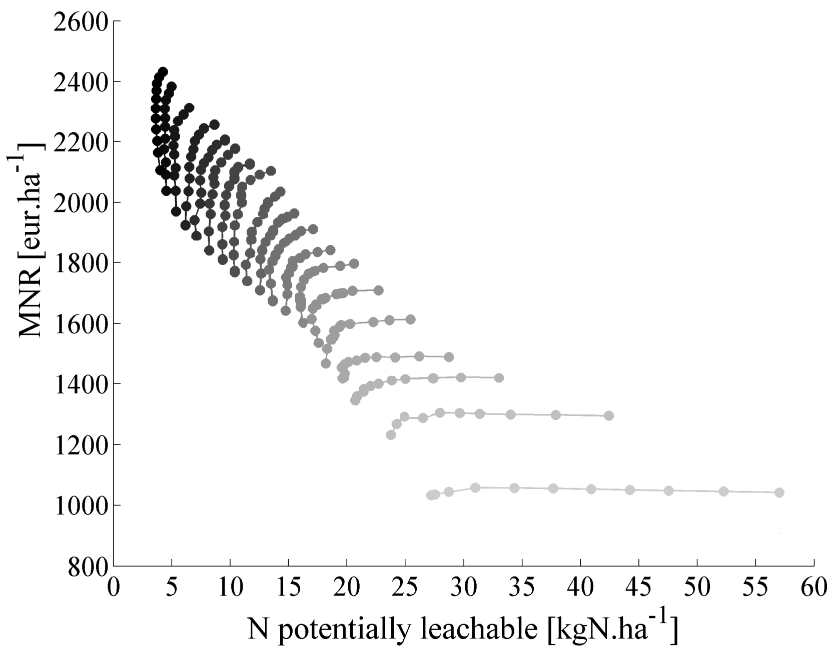

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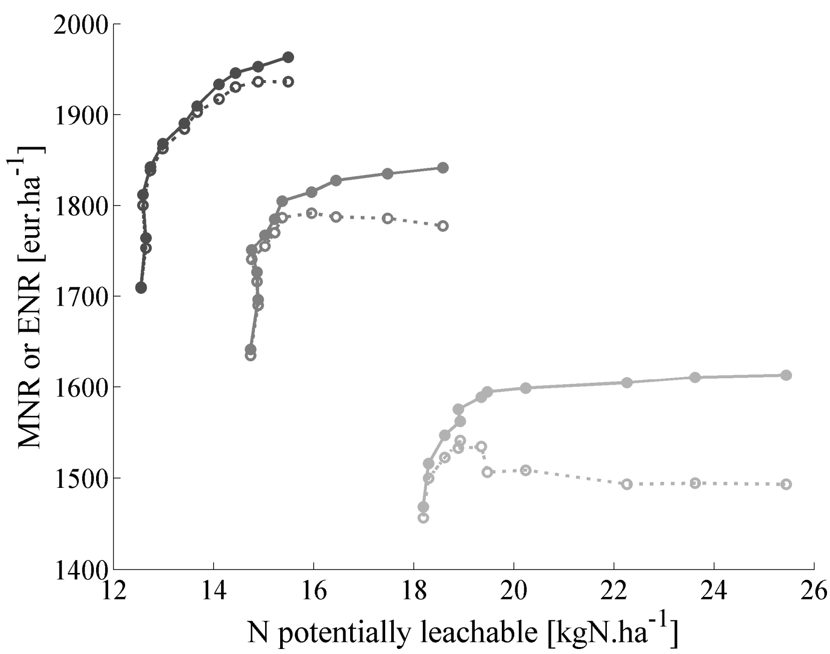

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