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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 kg N 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 kg N ha^{-1}) produced the best yield distribution results. When simple economical criteria were computed, the 60–60–80 kg N 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 kg N ha^{-1} could systematically be saved in comparison with the usual practice.

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 fer-

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tilisers 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, 2012a,b; 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 kg N 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 (Table 1). 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. (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 farmers, ensuring that the

Table 1
Fertilisation calendar for simulated nitrogen management practices.

	Fertilisation calendar (according to Zadoks stage and Julian day)			
	Tiller	Stem ext.	Flag-leaf	
Zadoks	23	30	39	
Julian day	445	475	508	
	Fertilisation rate (in kg N 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