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Clémence Ravier, Rodolphe Sabatier, Damien Beillouin, Jean-Marc Meynard, Ronan Trépos, et al.. Decision rules for managing N fertilization based on model simulations and viability assessment. European Journal of Agronomy, 2021, 125, pp.126247. 10.1016/j.eja.2021.126247 . hal-03273588

HAL Id: hal-03273588

https://hal.inrae.fr/hal-03273588v1

Submitted on 10 Mar 2023

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Version of Record: https://www.sciencedirect.com/science/article/pii/S1161030121000198
Manuscript_07e8958567c94d35be260cae511f04f0

Decision rules for managing N fertilization based on model simulations and viability assessment

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Highlights:

- Fertilization strategies simulated with Azodyn model were evaluated with viability-based algorithms
- Robust decision rules for managing N fertilizer with no-detrimental N deficiencies were developed
- Compared to current recommendations, decision rules resulted in similar yields and improved grain protein contents, with lower N rates
- N losses were much smaller with the new decision rules than with the current recommendations
- The decision rules can be adjusted according to farmers' risk aversion

Abstract: Nitrogen (N) fertilizer is commonly applied to wheat crops (*Triticum aestivum L.*) during the vegetative growth to meet crop requirements. Current decision rules for N application result in N losses to the environment, and thus to low N use efficiency, due to excess of N fertilizer and/or poor synchrony between soil supply and crop N demand. Despite existing tools and methods to manage N fertilization, combining maximum grain yield, high grain protein content, and minimum N losses to the environment remains challenging. There is thus a need to provide decision rules to apply N fertilizer at the time of optimal weather conditions and high crop N demand, without exceeding N crop requirements, thereby increasing N use efficiency and limiting N losses. Here we developed for the first time, a modeling approach based on the Azodyn model and using the mathematical framework of the

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viability theory to build decision rules where 1) N is applied only if weather conditions are optimal and if there is a risk that a period of N deficiency becomes detrimental to grain yield and protein content, and 2) the N rate is the minimum sufficient to prevent from detrimental N deficiencies whilst minimizing N losses to the environment. We computed metric of robustness to build decision rules for timing and rates of N fertilizer in the view to manage crop N nutrition according to such targets. We showed that, comparing those decision rules with current recommendations, by simulations over 20 years, the average total N rate could be decreased by 50 kg N ha^{-1} and N losses by 42 kg N ha^{-1} whilst maintaining similar yield, and reaching grain protein content above 11.5% more often (17 years out of 20, compared to 10 years out of 20 with current recommendations). In respect of those theoretical results, the next step should be to experimentally assess performances in real situations and to assess to which extend the method could help farmers to change their practices.

Key words: crop model, N deficiency, NNI, weather uncertainty, N losses, robustness

1. Introduction

Minimizing nitrogen (N) losses towards the environment, whilst maintaining high wheat yield and grain protein content, requires a precise management of the synchrony between soil N supply and crop N demand (Cassman et al., 2002; Meynard et al., 2002; Shanahan et al., 2008). Furthermore, to maximize N uptake efficiency, N fertilizer should be applied when weather conditions are optimal for its valorization, i.e. when the uppermost soil layer is sufficiently moist to diffuse fertilizer to the roots (Campbell et al., 1995), or when it rains shortly after fertilizer application (Powlson et al., 1992). Moreover, to achieve high N use efficiency (NUE) and limit N losses, it is recommended to apply N fertilizer when soil N supply is limiting, and crop N uptake capacity is high, i.e. crop growth rate is high (Campbell et al., 1995; Limaux et al., 1999; Olfs et al., 2005; Samborski et al., 2009). Therefore, to adjust in-season N fertilizer application, methods based on plant indicators are considered as the most relevant (Olfs et al., 2005). Ravier et al. (2018) proposed a new N fertilizer management method, based on the regular monitoring of crop nitrogen nutrition index (NNI). NNI is defined as the ratio between the actual N concentration of the aerial parts of the crop, and the critical N concentration, which is the minimum concentration required to maximize aerial dry matter production. NNI showed to be a sensitive and specific indicator of crop N status (Lemaire, 1997). It can be used to detect N-limiting situations, which could cause a decrease in yield relative to the potential yield (Lemaire and Meynard, 1997). For wheat crop, NNI proved to be useful for determining both the time on which the N deficiency began and its intensity (Jeuffroy and Bouchard, 1999). Furthermore, these authors showed that not all N deficiencies were damaging wheat grain yield. Ravier et al. (2017a) determined a minimum NNI path, above which there is neither damage to grain yield nor to grain protein content. This minimum NNI path could be used as a threshold for managing fertilization strategies including periods of N deficiency, as long as crop N status is maintained above the minimum NNI path, from tillering until flowering. Yet, implementing this new NNI-based method, in the view to maximize NUE and minimize N losses, requires formalizing decision rules taking into account that:

1) N fertilizer should be applied only when weather conditions are optimal to valorize N, and if crop NNI is likely to fall under the minimum NNI path before the next application time;
2) N rate should be high enough to maintain crop N nutrition status above the minimum NNI path, thereby preventing from detrimental N deficiencies, and low enough to avoid N losses.

Soil-crop models are useful tools to simulate the consequences of various sequences of N fertilizer application timing and rates on daily changes of crop NNI (Gastal et al., 2015). Moreover, to identify the sequences making it possible to achieve the above set of constraints, decision rules for N application should be robust regarding weather uncertainty, linked with the low accuracy of weather prediction, particularly for rainfall (Kusunose and Mahmood, 2016). Such uncertainty can be considered by means of various weather scenarios in multiple simulations (Woodward et al., 2008). Viability theory is particularly suitable for quantifying and assessing the efficacy of management strategies in uncertain and unpredictable environments (Aubin, 1991; Doyen and De Lara, 2010), as it makes it possible to identify the whole set of management strategies that keep the system within the given constraints, thus named viable strategies. Viability theory thus appears to be a promising approach for identifying the sequences of N fertilizer application timing and rates that have the highest probability, across different weather scenarios, of ensuring the maintenance of a stochastic dynamic system within the defined set of constraints over time.

In this study, we aimed to build decision rules for fertilizer applications, based on the use of a plant indicator (NNI), from the end of winter until flowering. Based on a case study corresponding to one agronomic situation, we combined model-based simulations of N fertilizer application sequences, varying in number, timing and rates, with the mathematical framework of the viability theory, to estimate the proportion of weather scenarios for which N fertilizer application could maintain crop NNI above the minimum NNI path throughout the crop cycle and keep N losses to the environment below a sustainable threshold value. Our decision rules were therefore designed to indicate, for each level of crop NNI, measured at any time during the period of fertilizer application, the N fertilizer rate with the highest probability of controlling NNI and N losses until the end of the crop cycle. We then compared simulated performance of the wheat crop between those decision rules and current N recommendations, to identify the possible gains and risks associated with the NNI-based fertilizer management method.

2. Material and methods

2.1 The soil-crop model and main characteristics of the studied agronomical situation

The Azodyn soil-crop model (Jeuffroy and Recous, 1999) was used to simulate NNI dynamics resulting from various sequences of N fertilizer application timing and rates over different weather scenarios. Azodyn is a simple and accurate soil-crop model which simulates, on a daily basis, soil N supply and crop N uptake, from the end of winter until harvest. It simulates the consequences of N fertilizer timing and rates for crop yield and grain protein content, taking soil characteristics and weather conditions into account. The crop submodel simulates crop aerial biomass and its N concentration, using classic formalisms for radiation interception and efficiency (Monteith, 1972), and the critical N dilution curve (Justes et al., 1994) for the estimation of N requirement. Azodyn simulates NNI on a daily basis, from the ratio between actual and critical plant N concentrations.

The input data used for the case study were typical of luvisols in Normandy (north-western France), with low levels of N mineralization from the preceding crop (maize) and no organic manure application or grassland in the crop rotation (Table 1), a typical situation of wheat crop in Northern France. The sowing date for the wheat crop was October 25th, with average harvest date on July 20th. We used weather data for a 20-year period in this region (1995 to 2015) as model input. The maximum yield for the cultivar was set at 10 t ha^{-1}, which is a good and potential yield for this region. At the initialization of the model (end of winter, set as February 15th), crop N status was set as either not deficient, with a NNI of 1, or deficient, with a NNI value ranging between 0.4 and 0.9, with increments of 0.1.

Table 1. Input data for the soil submodel, for simulations implemented with the model Azodyn

Input data	Value
Soil type	Luvisol
Soil mineral N concentration at the end of winter (kg N ha^{-1})	50
Soil mineral N concentration at the end of winter in the 0-30 cm layer (kg N ha^{-1})	17
$CaCO_3$ content in the 0-30 cm soil layer (%)	0.5
N organic content in the 0-30 cm soil layer (%)	1.5
Clay content in the 0-30 cm soil layer (%)	14
Bulk density in the 0-30 cm soil layer (m^3 per m^3 of soil)	1.3
Maximum water content of the rooting zone (mm)	110
Soil water content at the end of winter (mm)	70
N derived from the mineralization of residues from the preceding crop (kg N ha^{-1})	20
C/N ratio of the residues of the preceding crop	60
C content of residues of the preceding crop (kg ha^{-1})	2990
N derived from organic manure mineralization (kg N ha^{-1})	0
N derived from grassland mineralization (kg N ha^{-1})	0

2.2 Simulation of various sequences of N-fertilizer application timing and rates

For each of the 20 weather scenarios, we first identified the days with optimal conditions for N fertilizer application as follows. We considered the period during which fertilizer application could take place from February 15th to booting stage. February 15th corresponds to the legal date before which N application is not permitted in France, because crop has low N requirements, and N fertilizer may be leached. Booting stage was considered to be the last stage at which any N fertilizer applied was likely to be used efficiently to improve grain yield and protein content. Based on technical recommendations (Cohan and Bouthier, 2010), and data from several studies (e.g. Limaux et al., 1999; Jones et al., 2013; Kissel et al., 2004), we defined that conditions were optimal for fertilizer application (i) each day followed by a cumulative rainfall exceeding 10 mm within three days, or (ii) each day with a positive difference between cumulative rainfall and potential evapotranspiration over the last five past days. Moreover, as Recous and Machet (1999) showed that most of the N-fertilizer applied is taken up by the crop within seven to fourteen days after application, we fixed the minimum interval between two consecutive N applications at 15 days. It ensures that the N from the previous fertilizer application was depleted before the next application. Optimal conditions for simulations involved this supplementary condition. Due to this last condition, and also in the perspective of building decision rules easy to use by farmers, we split the period in 15-day sub-periods, and identified, for each one, the first day with optimal moisture conditions, which corresponded to the precise dates of N application in the simulations, thus adapted to each year (Table 2). Depending on the year considered, there were two (2002 and 2010) to six (1998) days in which N fertilizer was applied in the simulations (Table 2).

At each of these days, we simulated five different N fertilizer rates: no fertilizer, and applications of 40, 60, 80 or 100 kg N ha^{-1}. The minimum N rate was set at 40 kg N ha^{-1}, based on the assumption that farmers would be unlikely to apply less than this amount. The maximum was fixed at 100 kg N ha^{-1} because French recommendations advise to split applications for amounts of fertilizer exceeding this value (COMIFER, 2013). As all simulations were performed with N applied just before a rainfall, we considered that the type of fertilizer should have no impact on N availability: gaseous losses (which are the main cause of difference in N availability between various fertilizers) are strongly reduced in such case.

Thus, for each year, we simulated different sequences of N fertilizer strategies, corresponding to the combinations of the days with optimal conditions and 5 fertilizer rates, ranging from 25 sequences, for years with only two possible days for N applications, to 15 561 sequences for years with six possible days. Using the 20 weather scenarios resulted in a total of 41 324 simulations. In addition, each sequence of N-fertilization was duplicated to simulate 7 possible initial values of crop NNI from 0.4 to 1, with increments of 0.1. The total number of simulations was therefore 289 268. Simulations were performed with the Record platform (Bergez et al., 2013). For each simulation, we extracted NNI dynamics from the time at which the simulations were initiated (February 15th) until flowering (May 20th), and grain yield (t ha^{-1}), grain protein content (%), and the total amount of N taken up by the crop (kg N ha^{-1}) at harvest.

Table 2. Possible days of N application, for each year from 1996 to 2015. A possible day of N application is here defined as the first day, within 15-day sub-periods from mid-February to mid-May, with optimal weather conditions[1] for N fertilizer application. For instance, for 1996, '15' within the first sub-period means that N fertilizer can be applied the 15th of February, and '8' within the second period means that N fertilizer can be applied the 8th of March. Crop development stages are presented on Zadoks' scale (Zadoks et al., 1974).

15-day Sub-periods	Feb 15-29	Mar 01-15	Mar 16-31	Apr 01-15	Apr 16-30	May 01-13	Total number of
Development stage	Z25	Z29	Z30	Z32	Z37	Z40	N applications
Years							
1996	15	8	23	-	-	4	4
1997	15	-	-	-	23	8	3
1998	29	-	30	14	29	-	4
1999	15	2	25	9	24	9	6
2000	15	1	26	-	26	11	5
2001	23	10	25	9	26	-	5
2002	15	14	-	-	-	10	3
2003	26	-	-	-	23	-	2
2004	15	4	19	3	-	9	5
2005	21	8	24	8	-	11	5
2006	15	2	20	-	-	5	4
2007	15	2	17	1	26	-	5
2008	26	12	27	-	17	7	5
2009	15	7	27	15	30	-	5
2010	21	-	31	-	-	8	3
2011	16	-	-	-	29	-	2
2012	16	2	17	7	-	-	4
2013	15	8	-	2	-	-	3
2014	15	2	21	-	22	-	4
2015	15	2	28	-	28	-	4

- No date with optimal conditions for N application during the sub-period

[1] Optimal weather condition: each day followed by a minimal cumulative rainfall of 10 mm within three days, or each day with a positive difference between cumulative rainfall and potential evapotranspiration over the last five days.

2.3 Viability analysis

According to state-control formalism, the system dynamics of Azodyn can be defined as follows: $NNI_{t+1} = f(NNI_t, N_t, \omega_t)$ Eq. 1

where NNI_t is the state descriptor of the system, N_t (the N rate applied on time *t*) is the control, ω_t are weather conditions between *t* and *t*+1, and *f* is the function describing the dynamics of the system (see Jeuffroy and Recous, 1999 for details). Time *t* belongs to [0,T], where T corresponds to the length of the entire crop cycle.

Following viability theory, we defined two viability constraints.

The first constraint required NNI to be kept above the minimum NNI path from tillering until flowering (Ravier et al., 2017a). The minimum NNI path was previously defined, for the period from the beginning of stem elongation to flowering, such that all NNI values above the threshold value at a given time point were sufficient to achieve the potential yield allowed by the specific conditions occurring in the year considered (Ravier et al., 2017a). For decision rules during tillering, we extrapolated the minimum value of NNI tolerable at Z30 to the Z25 and Z29 development stages. This constraint reads as follows:

$$NNI_t > NNI_t^* \qquad \text{Eq.2}$$

where NNI_t* is the minimum NNI path at time *t*. As soon as NNI fell below the threshold, the management option was considered as not viable, even though NNI increased again and exceeded the threshold.

The second constraint required to maintain N losses due to N fertilizer application below a sustainability threshold, fixed at 20 kg N ha^{-1}, the lowest value allowing solutions to be identified in the case study:

$$N_{loss} < 20\ kg\ N\ \text{ha}^{-1} \qquad \text{Eq.3}$$

During the considered period, the risk of N leaching is very low, thus N losses linked with fertilizer application are mainly gaseous losses, the largest amount being NH_3, but also N_2O and N_2 (Limaux et al., 1999). N losses were calculated from variables simulated with Azodyn. For each simulation, we estimated the amount of N uptake derived from fertilizer as the difference between total crop N uptake at harvest for a fertilized crop, and total crop N uptake at harvest for a non-fertilized crop grown in the same conditions. We estimated potential N losses as the difference between total N applied and total crop N uptake derived from fertilizer.

If a given simulation respected these two constraints (Eq.2 and Eq.3), the sequence of N fertilizer application times and rates was considered viable.

2.4 Simulations and analyses

Following Sabatier et al. (2015), we used the mathematical framework of the viability theory to compute metrics of robustness. Robustness was defined as the proportion of weather scenarios for which there is at least one sequence of N fertilizer application timing and rates (N_t, N_{t+1},…N_T) that keeps the stochastic dynamic system within the set of constraints (Eq.2 and Eq.3) over time. Different levels of robustness could be used in the construction of decision rules. For demonstration purposes, we selected a value of 0.7, which seemed to be neither too high (a higher value would lead to increase fertilizer rates), nor too low (a lower value would result in the farmers taking too often risks of N deficiency).

First, we assessed the robustness of N-fertilization sequences for various levels of NNI, i.e., for a given NNI at time *t,* the proportion of weather scenarios for which there is at least one sequence viable over time, starting from NNI_t. Second, we assessed the robustness of N fertilizer rates, i.e. the proportion, for a given N rate applied at a given NNI at time *t*, of weather scenarios for which there is at least one sequence viable over time starting from state NNI_t. As the precise days on which N was applied varied between years (Table 2), we assessed the robustness of N fertilizer rates applied to different weather conditions, by 15-day sub-period. For simplification purpose, each sub-period was characterized by the development stage corresponding to the specific situation simulated (i.e. a crop sown at the end of October in Normandy) (Table 2). Decision rules were built by identifying, for each NNI at time *t*, and for each sub-period, the minimum N fertilizer rate that maximized the robustness. In order to limit background noise, we started calculation of robustness only when a N rate (Nt) applied at a given NNI at time *t* (NNI_t) was simulated under more than five weather scenarios.

2.5 Comparison with current recommendations

Effects of sequences of N fertilizer application timing and rates, resulting from the implementation of the decision rules built by simulation with Azodyn, were compared to sequences of N fertilizer applications timing and rates resulting from current recommendations.

Firstly, we defined current recommendations by using the balance-sheet method to calculate the N rate that would be applied in the same agronomic situation (Table 1). The balance-sheet method is usually implemented at the end of winter. Thus, whatever the year-specific weather conditions, the N rate calculated *a priori* remains the same for a given agronomic situation. In our case study, each term of the balance-sheet equation was estimated based on regional references for similar soil types, and for the given preceding crop (here, a maize crop), on an average value of soil mineral N concentration at the end of winter, and for a target yield of 8.5 t ha^{-1} (corresponding, as recommended by the authorities, to the regional yield average for winter wheat in recent years). The total amount of N fertilizer was then estimated at 210 kg N ha^{-1}. Based on current recommendations, this total amount of N was split into three or four N applications: a first application of 50 kg N ha^{-1} at the end of winter (February 15th), a second application targeting the 'beginning of stem elongation' development stage (Z30) and split into two successive applications of 60 kg N ha^{-1} each in March, and a final application of 40 kg N ha^{-1} between the second node (Z32) and flag leaf (Z37) stages. In line with common practice, timing of application wqs as close as possible to the recommended development stage, with the precise day chosen when rainfall occurred. No fertilizer was applied if weather conditions, as defined above, were not optimal at the targeted development stage. This ruled out one or two N applications for 5 years out of the 20 simulated. Thus, for 15 years, 210 kg N ha^{-1} of N fertilizer was applied in four applications, but in five years, the total amount of N applied was reduced by 10 to 100 kg N ha^{-1} and split into two or three applications only. The crop was assumed not to be deficient at the end of winter, which resulted in the initial NNI being set to 0.9 in Azodyn. Simulations were run and grain yield (t ha^{-1}), grain protein content (%) and total N uptake (kg N ha^{-1}) at harvest (July 20th) were extracted.

Secondly, from the set of 289 268 simulations of N fertilizer sequences over 20 weather scenarios, only simulations with an initial value of NNI of 0.9 were selected. Within this batch of simulations, we identified those for which the sequence of N fertilizer applications respected the decision rules built for the NNI-based method.

Thirdly, simulated grain yield (t ha^{-1}), grain protein content (%), total N rate (kg N ha^{-1}) and N losses (kg N ha^{-1}), resulting from the sequences of N fertilizer application, were compared year-by-year, for the two different methods. We also compared the yearly values between methods using the least significant difference (LSD) with a 5% probability threshold, in Fisher's LSD tests.

3. Results

3.1 Robustness of sequences of N fertilizer application timimg and rates

The robustness of sequences of N fertilizer application, i.e. the proportion of weather scenarios for which there is at least one viable fertilization sequence starting from a value of crop NNI at a time *t*, varied according to the crop development stages and to the crop NNI (Fig.1). Targeting a high level of NNI was not always the most robust way of managing N fertilization in the view of respecting the viability constraints. For example, there was no robust sequence of N-fertilizer application if the beginning of the crop cycle started with a very high plant N status (NNI at time *t* corresponding to Z29 ≥ 1.1) (Fig. 1). Within the non-viable simulations, 70% resulted in N losses higher than 20 kg N ha^{-1}, linked with the large total rate applied during the crop cycle. A total of 26% of the non-viable simulations did not respect any of the viability constraints (NNI above the minimum path and N losses lower than the fixed threshold), and 4% had their NNI falling below the minimum NNI path. Thus, robustness below 0.7 mostly reflected that, at time *t*, crop N requirements were too low compared to the applied N-fertilizer rate, resulting in low N uptake, and thus in losses higher than 20 kg N ha^{-1}.

The minimum NNI path requires to keep NNI above 0.4 at development stage Z30, 0.7 at stage Z32, 0.7 at stage Z37 and 0.8 at stage Z60 (Ravier et al., 2017a). When the crop NNI was higher but very close to the minimum NNI path, the robustness of the sequence of N fertilizer application appeared to be very low (Fig. 1). Managing fertilization to target NNI levels close to the minimum NNI path is, therefore, a risky strategy, mostly due both to the time lag from N application to N uptake, and to the uncertain time lapse between two application dates, during which NNI may fall below the minimum acceptable value. To limit risk and guarantee a minimum robustness of N fertilizer application for each level of crop NNI at any time *t*, the NNI dynamics should be maintained well above the minimum NNI path, particularly during tillering and the beginning of stem elongation (Fig.1). Thus, a 'robust NNI path' was adjusted to guarantee a minimum proportion of 70% of weather scenarios (robustness higher than 0.7) with at least one viable sequence of N fertilizer application for each level of crop NNI at time *t* (Fig. 1). The thresholds of this robust NNI path are 0.6 for development stage Z25, 0.7 for Z29, 0.8 from Z30 to Z37, and 0.9 at Z40, while the minimum NNI path, is 0.4 – 0.7 – 0.7 - 0.8 at Z30, Z32, Z37 and Z40 respectively (Fig.1).

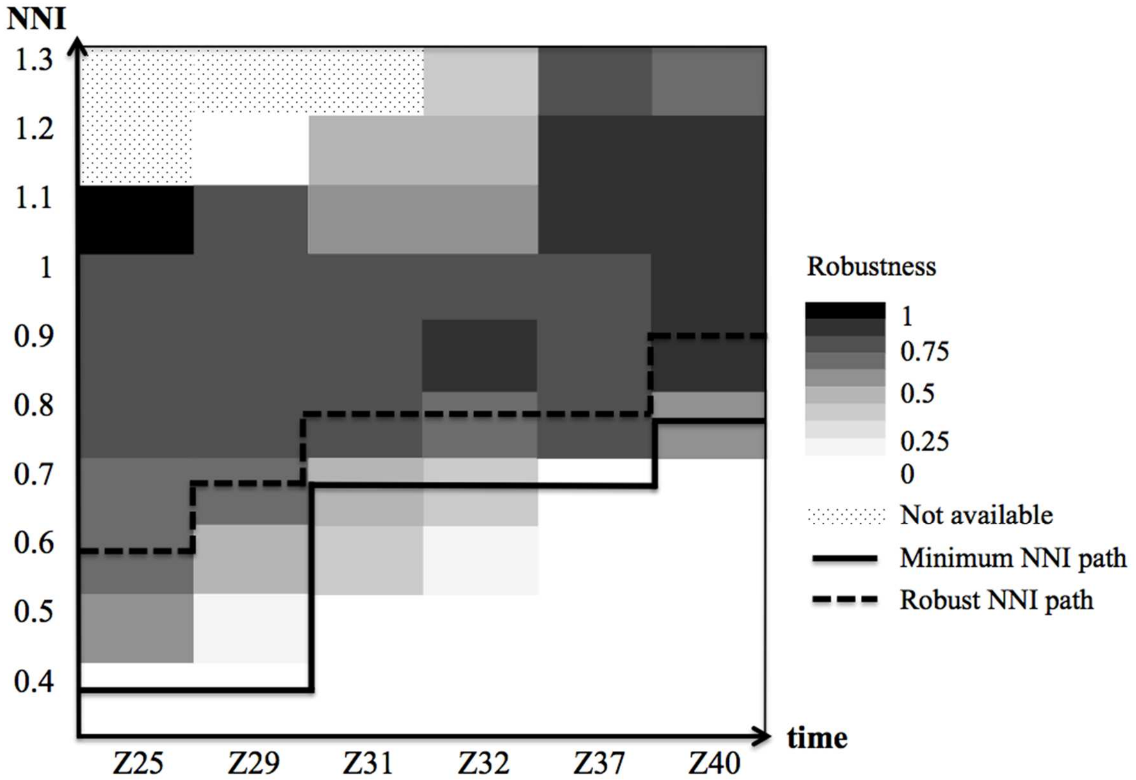

Fig. 1. Robustness of the sequences of N fertilizer application timing and rates at a given value of crop NNI (y-axis) at a given time t (x-axis) corresponding to wheat crop development stages (Zadoks et al., 1974). Robustness is the proportion of weather scenarios (out of 20 tested) for which there is at least one N fertilization strategy that maintains crop NNI above the minimum (or robust) NNI path throughout the crop cycle and keeps N losses below a threshold value, at each time t, characterized by crop stage and crop NNI. The black line is the minimum NNI path defined by Ravier et al. (2017a) and the dotted line is the robust NNI path identified to guarantee, for each given value of crop NNI at time t, a robustness of 0.7.

3.2 Robustness of N fertilizer application rates

For each time t, corresponding to a development stage, we then represented the robustness of the five N fertilizer rates (no fertilizer, 40, 60, 80 and 100 kg N ha^{-1}) as a function of crop NNI (Fig. 2.).

At development stages Z25 (February 15th to 29th) and Z29 (March 1st to 15th), for every level of crop NNI above 0.5, the robustness of the N fertilizer application rates decreased with increasing N rates (Fig. 2). It means that, over the twenty weather scenarios, sequences of N fertilizer applications, starting at a time *t* during this period, were most often viable without N fertilizer application rather than with a N fertilizer application. At the beginning of the crop cycle, the fact that robustness did not increase with N fertilizer application can be explained by the low crop growth rate at time *t* that resulted in low crop N uptake, leading to N losses higher than 20 kg N ha^{-1}. For low levels of crop NNI (i.e. those close to the minimum NNI path), the lower values of robustness are most often resulting from a decrease in NNI below the minimum acceptable value before uptake of the following N application.

From development stage Z30 (March 16^{th} to 31^{st}) to Z40 (May 1^{st} to 13^{th}), for a given level of crop NNI, the application of N fertilizer systematically increased robustness, compared to the no-fertilization strategy (Fig. 2). From Z30 to Z40, the N rates yielding maximum robustness varied, depending on the level of crop NNI: lower NNI values were associated with a need for higher N rates to achieve maximum robustness. At Z30 (March 16^{th} to 31^{st}), for values of crop NNI lower than 0.8, the highest robustness was achieved with 60 kg N ha^{-1}, whereas for levels of crop NNI higher than 0.8, 40 kg N ha^{-1} yielded maximum robustness. At Z32 (April 1^{st} to 15^{th}), for crop NNI of 0.7 (which corresponds to the threshold value of the minimum NNI path for this period), 100 kg N ha^{-1} is required to achieve maximum robustness, but this one (equal to 0.4) was far lower than the robustness achieved for the other values of crop NNI (due to higher risk of NNI dynamics falling under the minimum path, after this stage); for crop NNI of 0.8, the maximum robustness (equal to 1.0) was achieved with 80 kg N ha^{-1}; and for levels of crop NNI higher than 0.9, 40 kg N ha^{-1} was enough to achieve maximum robustness (also equal to 1.0). At Z37 (April 16^{th} to 30^{th}), for crop NNI of 0.8, the maximum robustness was reached with 80 kg N ha^{-1} (robustness was lower with a higher N rate); for levels of crop NNI higher than 0.9, 40 kg N ha^{-1} was enough to yield maximum robustness. At Z40 (May 1^{st} to 13^{th}), for each level of crop NNI between 0.8 and 1.2 or more, maximum robustness was reached with 40 kg N ha^{-1}.

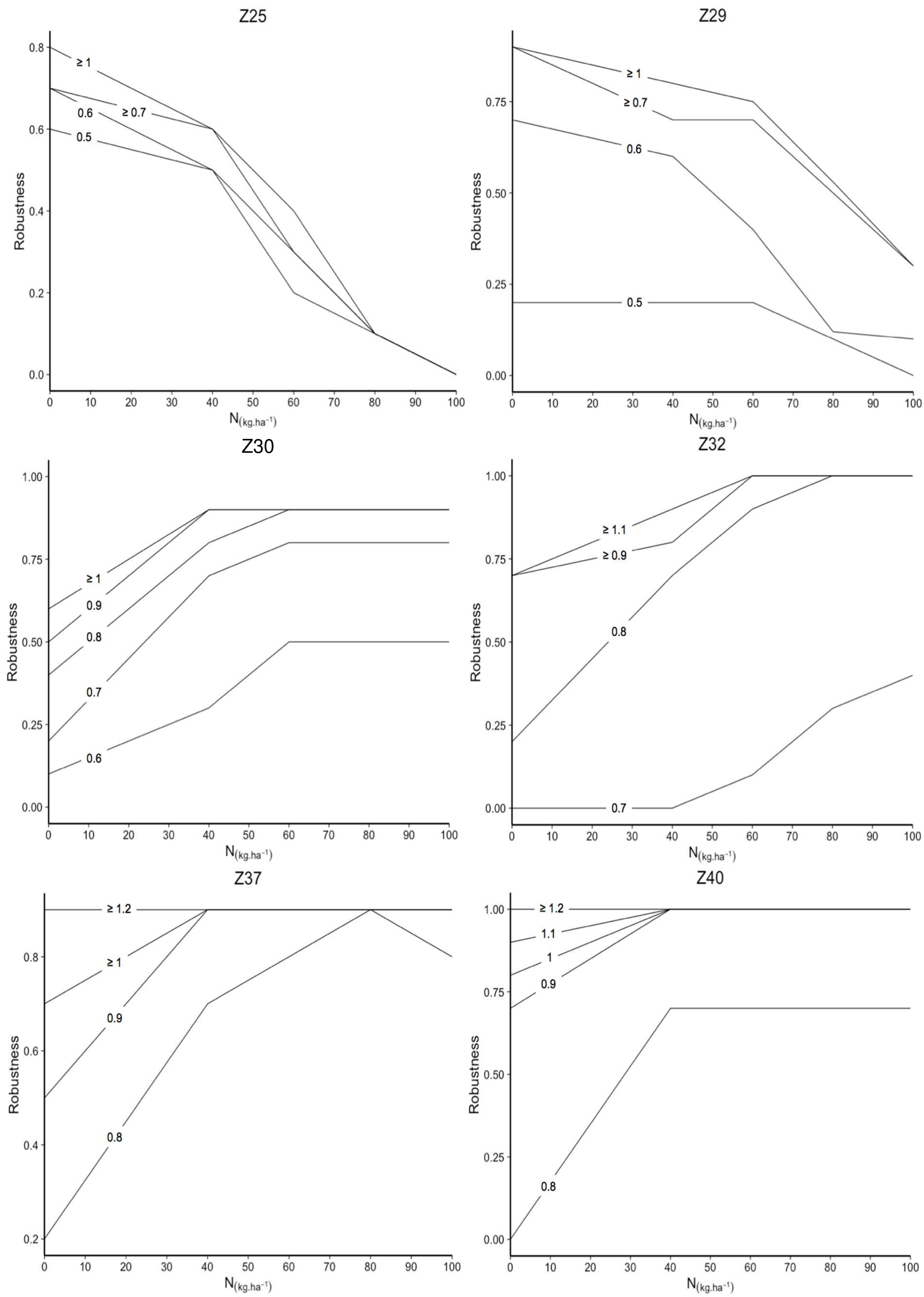

Fig. 2. Robustness (*y*-axis) of the fertilizer application options (*x*-axis) for different values of NNI (curves) for each sub-period of the crop cycle (subfigures). See Figure 1 for the definition of robustness (here calculated with the minimum NNI path. The successive figures correspond to development stages on Zadoks' scale Z25 (February 15th to 29th), Z29 (March

1st to 15th), Z30 (March 16th to 31st), Z32 (April 1st to 15th), Z37 (April 16th to 30th), and Z40 (May 1st to 15th)

3.3 Set of proposed decision rules

Based on the above graphical representation, each level of crop NNI at each development stage (time t) was associated with the lower N fertilizer rate that maximized the robustness of the system, called the recommended rate (Table 3a). As suggested in Fig.1, the constraint of viability concerning the minimum NNI path (Eq.2) was adjusted in order to ensure a minimum robustness of sequences of N fertilizer application timing and rates at each level of crop NNI at time *t.* Using the robust NNI path to guarantee a minimum proportion of 70% of weather scenarios with at least one viable sequence of N fertilizer application at each level of crop NNI at time *t* (Fig.1), changed the decision rules. Indeed, the proportion of viable sequences of N fertilization increased by 3%. As the robust NNI path required keeping the NNI dynamic well above the minimum NNI path, at the beginning of the crop cycle, the proportion of situations where non-viability resulted exclusively from NNI falling below the robust NNI path accounted for 35% of simulations, against 4% with the minimum NNI path. With the robust NNI path, in 52% of the cases, none of the viability constraints was met, and, in 13% of the cases, the non-viability of N-fertilization sequences resulted from N losses higher than 20 kg N ha^{-1}. The evolution of robustness of the five N fertilizer rates (no fertilizer, 40, 60, 80 or 100 kg N ha^{-1}) according to development stage and crop NNI was also assessed with the viability constraints of Eq.2 being set with the robust NNI path (data not shown), leading to recommended rates slightly different (Table 3b).

At a given stage, the optimal N fertilizer rate decreased with increasing NNI, and, for a given crop NNI, the recommended N fertilizer rate increased with development stage. Recommended N rates slightly varied between the two NNI paths (minimum or robust). For a given crop NNI at time t, recommended N rates were always equal or higher when taking the robust NNI path. At Z25, there was no difference: whatever the NNI, the maximum robustness was achieved without N fertilizer. At Z29, using the minimum NNI path, the recommendation would be no fertilizer for each crop NNI while, using the robust NNI path, for NNI of 0.8, the N fertilizer rate of 40 kg N ha^{-1} yielded maximum robustness.

Table 3. Decision rules: recommended N fertilizer rates according to development stage on Zadoks' scale (columns) and corresponding crop NNI (lines). The recommended fertilizer rate yielded maximum robustness when the viability constraint concerning NNI was the minimum NNI path (Table 3a) or the robust NNI path (Table 3b). These decision rules are calculated for the specific agronomic situation studied.

a)

	Development stage					
	Z25	Z29	Z30	Z32	Z37	Z40
Minimum NNI path	0.4	0.4	0.7	0.7	0.7	0.8
≤0.4						
0.5	0	0				
0.6	0	0	60			
0.7	0	0	60	100		
0.8	0	0	60	80	80	40
0.9	0	0	40	60	40	40
1	0	0	40	40	40	40
>1	0	0	40	40	0	0

NNI levels that should be avoided to keep the system viable (shaded cells)

b)

	Development stage					
	Z25	Z29	Z30	Z32	Z37	Z40
Robust NNI path	0.6	0.7	0.8	0.8	0.8	0.9
≤0.7						
0.7	0					
0.8	0	40	80			
0.9	0	0	60	60	60	40
1	0	0	60	60	40	40
>1	0	0	40	0	40	0

NNI levels that should be avoided to keep the system viable (shaded cells)

3.4 Comparison between current recommendations and NNI-based method

3.4.1 Comparison of fertilization strategies

Sequences of N fertilizer application resulting from the implementation of decision rules of the NNI-based method (with both the minimum and robust NNI paths as viability constraint) were compared to those achieved with current recommendations under the same weather scenarios. For each year of simulation, the NNI-based method, whatever the NNI path, resulted in significantly lower total N rates than current recommendations ($p < 0.001$, Fig. 3a): mean N application rates were 200 kg N ha^{-1} for current recommendations, 130 kg N ha^{-1} for the NNI-based method considering the minimum NNI path, and 150 kg N ha^{-1} considering the robust NNI path, these two values for the NNI-based method being not significantly different ($p < 0.05$). The timing of N fertilizer applications did not differ between minimum and robust NNI path (data not shown).

The NNI-based method led to more diverse splitting strategies across years than the current recommendations. Following current recommendations, for 95% of the years, the total N rate was split in two (5% of the years), three (20% of the years) or four (75% of the years) N fertilizer applications, while, with the NNI-based method, splitting strategies were composed with three N fertilizer applications (45% of the years), two (40% of the years), or even only one application (15% of the years), depending on the rainfall conditions.

The NNI-based method resulted in a first application of N fertilizer later than current recommendations (Fig. 3b). Timing of the first application were the same for the NNI-based method with the minimum and the robust NNI path, whatever the year (Fig. 3b). Across all years, according to current recommendations, the first N application would take place between February 15th and March 1st, whereas, with the NNI-based method, the first N application would occur between March 16th and 31st or later, even after April 20th in four years. Furthermore, the date of the first application was more variable from year to year with the NNI-based method than with current recommendations, showing a better adaptation of the timing of N fertilizer application to the climatic specificities of the year (Fig. 3b).

For the early applications in the season, the NNI-based method led to lower rates of N fertilizer than current recommendations. For 75% of the years, the current recommendations led to apply more than half the total amount of N fertilizer before Z30, whereas crop growth rate is generally low until this stage. With the NNI-based method, N fertilizer was applied before Z30, only in five years, with N rates of 40 or 60 kg N ha^{-1} with the minimum NNI path, and 60 or 80 kg N ha^{-1} with the robust NNI path.

For applications after Z31, the NNI-based method led to higher rates of N fertilizer than current recommendations. With current recommendations, the last N application occurred at development stage Z37 (corresponding to flag leaf emergence). The last N application was canceled twice due to non-optimal conditions for the application of N fertilizer, and a rate of 40 kg N ha^{-1} was applied after April 1st (close to stage Z31) in 90% of the 18 years with a late N application. In both NNI-based methods, we assumed that N could be applied until booting, corresponding to about 15 days before flowering (around 25th May). For all years, a N application was thus simulated during the period from Z31 stage (April 1st) to the booting stage (around May 10th). The minimum amount applied during this period was 40 kg N ha^{-1} with both the minimum and robust NNI path constraints, and the maximum was 140 kg N ha^{-1}, with the minimum NNI path, and 160 kg N ha^{-1}, with the robust NNI path, split into two N applications.

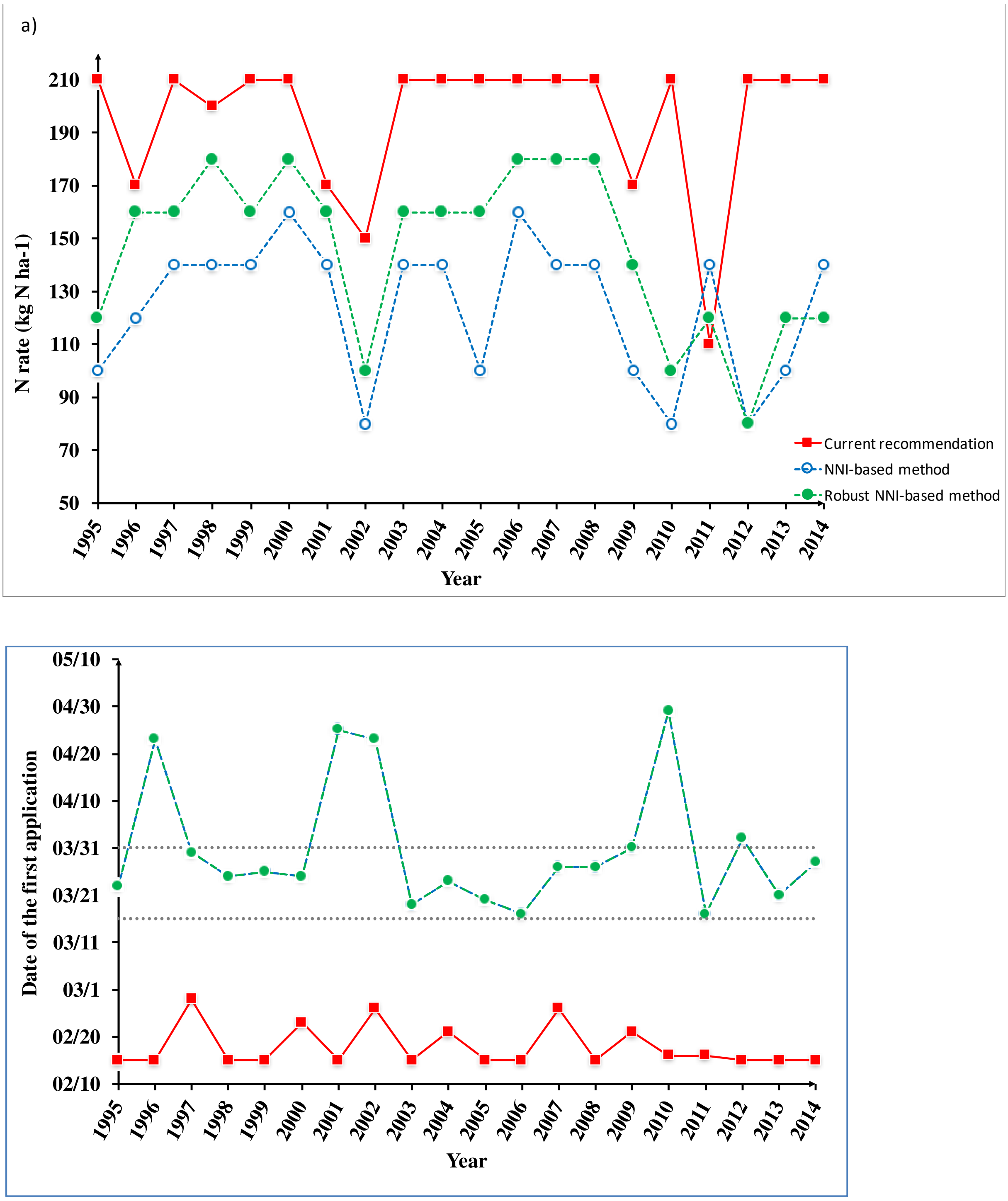

Fig. 3. Comparison of (a) the total N rate and (b) the date of the first N application (Month/Day) with the NNI-based method with the minimum NNI path (**o**) and the robust NNI path (o) and current recommendations (■). The dates of N application were the same for the NNI-based method with minimum and robust NNI path. Dotted black lines on Fig b represent the beginning and end of the 2nd subperiod (Z31)

3.4.2 Comparison of performance

Mean yields were not significantly different when both NNI-based methods and current recommendations were compared ($p > 0.05$; Fig. 4a). Based on 20-year averages, mean yields were 8.7 t ha^{-1} with current recommendations, 8.4 t ha^{-1} for the NNI-based method with the minimum NNI path, and 8.6 t ha^{-1} with the robust NNI path. In the case of current recommendations only, the total N rate was calculated from a target yield (8.5 t ha^{-1}), defined as soon as the end of winter. Nevertheless, this target was not reached in 11 years out of 20 (Fig. 4a), due to unfavorable weather conditions during spring, thus leading to higher values of unused N fertilizer.

The NNI-based methods resulted in significantly lower N losses due to N applications ($p < 0.001$, Fig. 4b): mean N losses were 55 kg N ha^{-1} with current recommendations, 5 kg N ha^{-1} for the NNI-based method with minimum NNI path, and 7 kg N ha^{-1} with robust NNI path. The difference between the two NNI-based methods (with the minimum and robust NNI path) was not significant ($p > 0.05$). Across the 20 years considered, the NNI-based methods, with both the minimum and robust NNI path, resulted in N losses higher than 20 kg N ha^{-1} only 2 years, whereas N losses exceeded 20 kg N ha^{-1} in 19 years out of the 20 simulated years with the current recommendations (Fig. 4b). The NNI-based method clearly outperformed current recommendations in this respect. Furthermore, for the only year in which N application rates were lower with current recommendations (2011 on Fig. 3a), yield (Fig. 4a) and grain protein content (Fig. 4c) were higher, and N losses (Fig. 4b) were lower with the NNI-based method, thus indicating that the supplement of N rate in the NNI-based methods was necessary to reach higher performance.

With the current recommendations, grain protein content was above 11.5%, a required grain protein content for the bread market, for 50% of the weather scenarios (Fig. 4c). With the NNI-based method, the grain protein content was above 11.5% for 70% of the years, with the minimum NNI path, and for 85 % of the years, with the robust NNI path (Fig. 4c). Indeed, for three years, the decision based on the robust NNI path led to significantly higher grain protein content than those based on the minimum NNI path. Mean grain protein content did not differ significantly between current recommendations and NNI-based methods ($p > 0.5$). When grain protein content did not exceed 11.5% with NNI-based method, it did not exceed 11.5% with current recommendations either, whereas the opposite pattern (below 11.5% with the current recommendation and above 11.5% with the NNI-based method) was observed in four years with the minimum NNI path and in seven years with the robust NNI path.

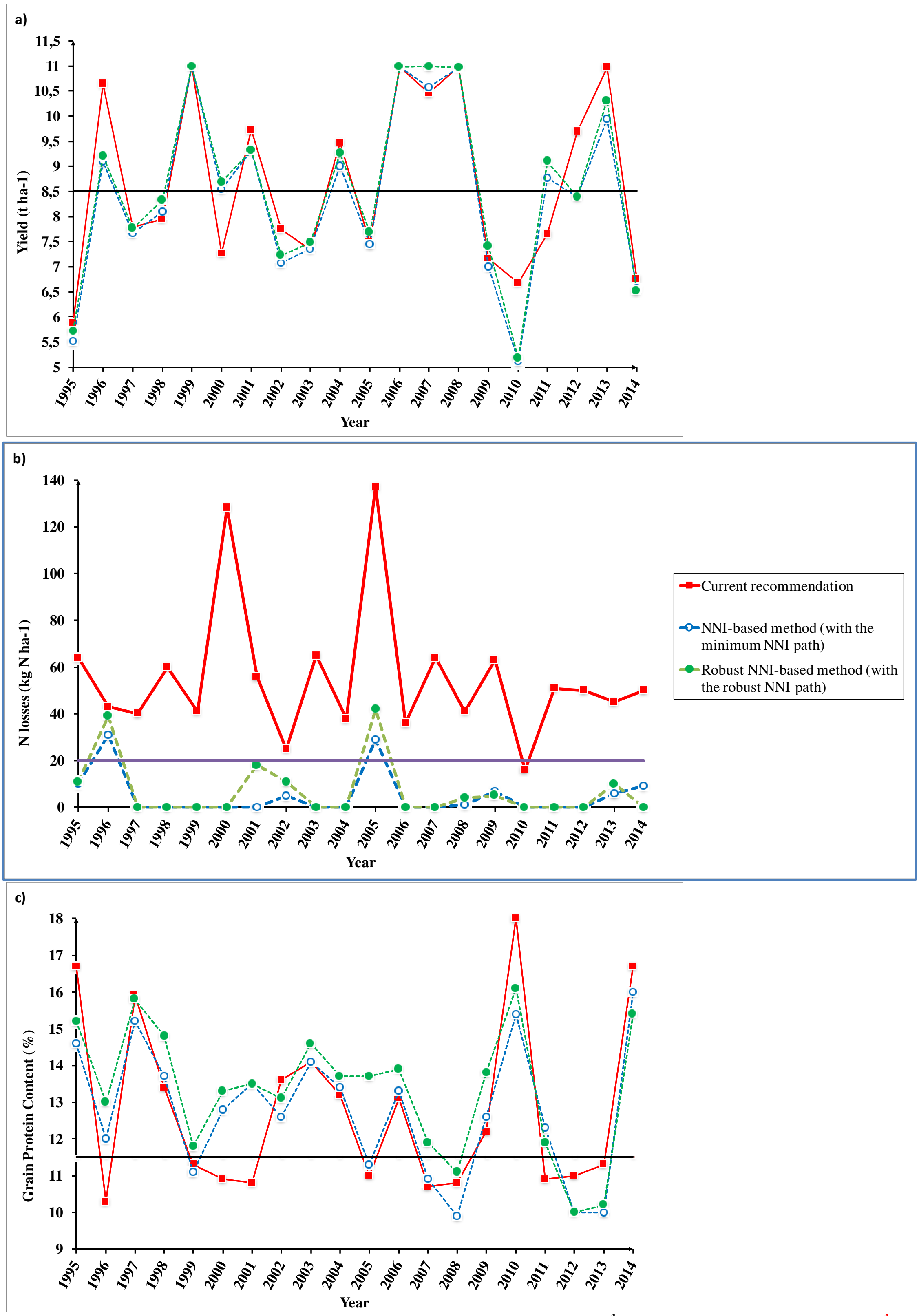

Fig. 4. Year-by-year comparison of **a)** grain yield (t ha^{-1}), **b)** N losses (kg N ha^{-1}), and **c)** protein content (%), achieved with the current recommendations (■), the NNI-based method with the minimum NNI path (o) and the robust NNI path (●). Yield was compared with the target yield fixed for the calculation of N application rates by the balance-sheet method (8.5 t ha^{-1}, a); N losses were compared with the sustainable threshold value we suggested (20 kg N

ha^{-1}, b); Grain protein content was compared with the desirable grain protein content for market (11.5 %, c).

4. Discussion

4.1 An innovative model-based method to manage N fertilization

Until now, the total rate of N fertilizer to be applied on a crop was managed based on average response curves to N fertilization (Meynard et al., 1981; Berti et al., 2016), or with a non-dynamic balance-sheet method (Meynard et al., 1997; Alvarez et al., 2004; Corbellini et al., 2006). Improvements have been proposed with decision-support tools based on the measurement of an indicator (nitrate concentration of stem base sap; indirect measurement of chlorophyll concentration in the leaves through reflectance or transmittance) and the corresponding recommended rate (Justes et al. 1997; Olfs et al., 2005; Samborski et al., 2009). However, these improved tools mainly aim at managing the last fertilizer application (around flag-leaf or booting stages), either to refine the adjustment of the total rate, taking partly into account the climatic conditions of the year, or to improve grain protein content. The method we propose in this paper is thus innovative, as it is based on the ongoing assessment of the crop N status, all along the period of possible N fertilization, without the total rate of N fertilizer being calculated a priori. NNI can be estimated through measurement taken via a chlorophyll-meter (Ravier et al., 2017b), and the partial fertilizer recommended rate is identified at each date, from recommendations based on numerous simulations using a soil-crop model and taking into account climatic variability.

This method also proposed an original way to use models for decision. According to Passioura (1996), agronomic models can be grouped into two categories: those improving our understanding of crop physiology in interaction with the environment, and those providing sound management advice. In this second approach, models are generally used to identify an optimal solution, through a comparison of alternatives, often with artificial intelligence algorithms (Loyce et al., 2002, Bergez et al., 2010). They also can be used as support of exchanges with stakeholders in participatory approaches (Woodward et al., 2008). Models can thus be seen as exploratory tools for assessing the effects of a diverse range of options (Rossing et al., 1997). In this study, we proposed an original way to use models, to define robust fertilization strategies aiming at maintaining NNI over a minimum detrimental path, taking into account climatic variability, and simultaneously minimizing the risks of environmental degradation and yield losses. These robust fertilization paths are presented through a table with recommended decision rules, an example being given in this paper

(Table 3). Most often, future users are not involved in the design of decision-support tools based on the use of models, thus leading to low uses (Prost et al., 2012; Matthews et al., 2002). On the opposite, to develop our innovative method, we involved the future users at two steps of the design process: (i) at the very beginning, through a diagnosis of uses, allowing to characterize the problems encountered by farmers in the implementation of current fertilization methods, and (ii) after the prototyping phase, through the test of a mockup of the method in on-farm conditions (Ravier et al., 2018). Using a model, we here aimed to identify an optimal N rate to be applied while taking into account the possibility, conditioned by the weather, to still apply N fertilizer later, if required by the crop.

In this aim, we combined multi-simulations with a viability-based approach, similar to that described by Sabatier et al. (2015), to assess the robustness of the decision rules. Our method was sought to achieve a compromise between the risk of N losses following the application of fertilizer in non-optimal conditions for valorization, and the risk of damaging yield with detrimental N deficiency, taking into account of the weather uncertainty. Viability-based approaches can be used to achieve such a compromise, by making it possible to define a set of constraints of different types reflecting production and environmental objectives, and to identify the good instantaneous decision that allows to meet these constraints in the future (e.g. Sabatier et al., 2010; Mouysset et al., 2014). The analysis of robustness showed that, for some values of crop NNI (for example, low NNI at early development stages), few sequences of N fertilizer application were viable (see Fig. 1), and no N fertilizer rate was highly robust (Fig. 2). Low robustness can be due to N application that causes N losses higher than 20 kg N ha^{-1} due to low N uptake (Foulkes et al., 2009), or to the time lag between N application and N uptake, or between two N applications, which may lead to NNI falling below the minimum NNI path for a short period. In practice, both risks have certainly not the same importance for the farmers, some wishing to minimize losses through environment, others preferring to minimize yield losses. It thus could be interesting to refine the decision rules by giving the information of each risk, to support each farmer in his own choice.

The reduction of N losses to the environment is higher in our decision rules, compared to the current recommendation based on the balance-sheet method. Indeed, in this reference method, losses are considered as minimal as soon as all the components of the equation are well estimated (Meynard et al., 1997). Yet, some estimations are not always precise, due to uncertainty (e.g. climatic conditions) or to average references, ill-adapted to some situations (e.g. the estimation of N mineralization from humus content of each field), or to bad conditions around the application dates (not taken into account in the balance-sheet method), leading to high losses in some situations. We tested the effect of different levels of threshold values for N losses on the robustness of sequences of N fertilizer application at each NNI at time *t* (data not shown). We observed that increasing the threshold values to 30 or 40 kg N ha^{-1} of losses increased robustness of sequences starting from time t with high NNI (NNI > 1). Yet, there was no effect for sequences starting from time t with low NNI (NNI < 0.7). Thus, for high levels of crop NNI, the low robustness was due to N losses higher than 20 kg N ha^{-1}, whereas, for low levels of crop NNI, the low robustness was due to NNI that falls under the minimum NNI path. For instance, at development stage Z25, the decision rules (based on the minimum and the robust NNI path) suggested that no fertilizer yields maximum robustness, while, for values of crop NNI lower than 0.7, there is a risk that, the NNI would fall under the minimum and robust NNI path by the next development stage Z29. Thus, in practice, we would nevertheless recommend an application of N fertilizer to low values of crop NNI in order to ensure that the crop NNI will be maintained above the NNI path.

As shown by our simulations (Figure 4), losses can be not only far higher with the balance-sheet method, but also more variable. More generally, the method proposed here allows a better adaptation to the inter-year variations than the current balance-sheet method: the NNI-based method is not based on a fixed target yield and on average references (for mineralization), independent of the weather of the year, but it allows to adjust dynamic sequential decisions to the crop evolution, taking into account the effect of the weather and the characteristics of the field. The use of NNI estimations as predictors of the date and rate of fertilizer to be applied requires a precise estimation of this indicator. Numerous indirect indicators have been developed to estimate crop N status, based on hand-held chlorophyll-meter, the Dualex to estimate leaf polyphenolics, nitrate content of stem base extracts, canopy reflectance, remote sensing techniques, or the Green-seeker (Olfs et al., 2005; Samborski et al., 2008; Cartelat et al., 2005; Ravier et al., 2017b). Among them, the development of satellite-based indicators or tractor-roof-mounted sensors provide an opportunity to assess the within-field variability of crop N status, and to value it into variable rates of N application, likely to improve N use efficiency (Basso et al., 2016; Jin et al., 2017).

Finally, as our method results in the delayed and reduced rate of N applications, it could make it possible to reduce the use of other inputs. Decreasing the rate of N fertilizer applied during the tillering period leads to slightly reducing leaf area index and the number of tillers, thus limiting water requirement and use (van Herwaarden et al., 1998). Fungicide use could also be decreased, as the reduction of leaf area index allows a better air circulation within the canopy, thus limiting the development of aerial diseases, and also because the development of fungi is enhanced by N-rich organs (Loyce et al., 2008).

4.2. Benefits and limits of the soil-crop model Azodyn

The Azodyn soil-crop model was well adapted to this implementation of decision rules regarding N fertilization because it gives good account of various N deficiency periods on yield and grain protein content, and of conditions of applications on N losses (David et al., 2004). This model was assessed on numerous and highly diverse agricultural situations, including conventional and organic agricultural systems, in several French regions, with predictive quality for grain yield and protein content similar to other crop models (David and Jeuffroy, 2009). Its use in other European or world regions should benefit from a broader validation.

Based on Jeuffroy and Bouchard (1999), yield loss due to N deficiency was simulated with the indicator IDD, which is the product of the intensity and duration of the N deficiency, characterized with the NNI time-course between end of winter and flowering. To manage N-fertilization, we had to change the indicator, as IDD can be estimated only at the end of the crop cycle, whereas decision rules based on the ongoing monitoring of the N crop status should require to continuously assess the deficiency level, between the end of winter and flowering. Thus, we assumed that N deficiency damages yield only if NNI falls below a minimum dynamic NNI path, which value could vary along the cycle, and we used this minimum NNI path to design decision rules accepting N deficiencies. Whereas Ravier et al. (2017a) identified a minimum NNI-path without detrimental effects on yield, decision-support rules were improved with a robust NNI-path, slightly higher than the minimum NNI-path during tillering and the beginning of stem elongation. Considering this robust NNI-path allowed to reduce the risks of yield loss in the fertilization recommendations, without increasing N losses to the environment.

Based on simple and easily measurable functions and parameters, Azodyn was already easily adapted to several crops (pea, Biarnès et al., 2009; barley, Beillouin et al., 2018; oilseed rape, Valantin-Morison et al., 2003; pea-wheat intercrop, Malagoli et al., 2020). Moreover, it simulates in a consistent way, the main outputs (yield, grain quality, N losses) that farmers use to manage the fertilization of their crops. Thus, it could be easily used to adapt the dynamic method of N fertilization, proposed here, to other crops, assuming improved performance and assessment in a larger range of situations. Improvements concerning the way N losses are simulated could be beneficial to fertilization-N management. In the current version of Azodyn, N losses due to N-fertilizer are globally simulated as the unrecovered Nitrogen from N-fertilizer, as proposed by Meynard et al. (1997), which allows to easily quantify them in a large range of situations. Nevertheless, mixing all types of losses (NH_3, NO_2, N_2) does not allow to learn about how to reduce them, as these different types partly depend on various processes and conditions.

4.3. Putting into practice the new way of managing N-fertilization

According to our simulations, mean grain yield did not differ significantly between N sequences resulting from current recommendations and from the NNI-based method, whereas these N sequences highly differed in timing and rates. The decision rules developed in this study to implement the NNI-based method led to delay N fertilizer applications, compared to current recommendations. If the comparison with these current recommendations highlighted promising results regarding yield, grain quality and N losses, such strategies, where N fertilizer applications are delayed, are perceived by farmers as particularly risky. As they consider the drought risk as high after the beginning of stem elongation, farmers tend to apply N fertilizer before this stage, as soon as the weather forecast announces rain, regardless of crop N requirement (Ravier et al., 2018), in order to avoid drought risks during spring, thus leading to higher N losses. Given farmers' perception about drought risks, they might be unwilling to delay the first fertilizer application after the beginning of stem elongation. Climate frequency analyses should thus be performed to adapt the decision rules to each region, taking into account this specific risk.

Secondly, we can put forward that the NNI-based method can be more relevant compared to methods proposed previously to improve N timing and rate. Indeed, Limaux et al. (2001) developed a decision rule to trigger the 1st N application, based on the yellowing of a small strip sown at double-density within the field. The change in color of this double-density strip indicates that a N deficiency would soon occur on the normal density plot. Yet this method was not widely adopted because farmers considered the visual interpretation of the indicator to be too subjective. Here, the decision rules are based on a specific indicator of N deficiency, as NNI varied only with N nutrition (Lemaire and Meynard, 1997). Moreover, the minimum NNI path was defined as a sensitive and specific indicator (Ravier et al., 2017a), which are relevant qualities for an activation rule (Makowski et al., 2009). Furthermore, as suggested by Toffolini et al. (2016), to support farmers' actions, indicators should be learning-oriented, facilitating understanding and interpretation. In this sense, Ravier et al. (2018) showed that regular monitoring of NNI provides opportunities for farmers to learn: as soon as NNI can be estimated regularly during the crop cycle, it may 1) provides real-time information about crop N status, reassuring farmers about the fact that N is not limiting for yield, 2) be used to control the efficiency of past applications, and 3) be a means to interpret N dynamics in the plant and in the soil. The NNI-based method offers this opportunity to enhance learning from farmers as they themselves measure and monitor the NNI of their crop, and as NNI is both an indicator of the past functioning of the crop and an indicator of its future evolution.

The NNI-based method relies on the regular monitoring of crop N status, at times of optimal weather conditions for N fertilizer absorption. In France, based on empirical observations, advisors recommend applying fertilizer when at least 15 mm of rainfall is expected within the following 15 days (Cohan and Bouthier, 2010). However, weather forecasts are often too unreliable to provide accurate rainfall predictions for the next fortnight (Kusunose and Mahmood, 2016). Moreover, this high threshold of 15 mm frequently results in too early fertilizer applications, to escape later dry periods (Ravier et al., 2016). There is no scientific consensus on the definition of optimal weather conditions for fertilizer application. Nevertheless, applying N fertilizer during a rainfall event strongly limits N losses by volatilization (Meyer et al., 1961; Powlson et al., 1992; Campbell et al., 1995; Jones et al., 2013), the process responsible for the largest amount of N losses (Limaux et al., 1999). Considering as sufficient a cumulative rainfall of 10 mm in the three days following the fertilizer application seemed to be relevant (Jones et al., 2013). Furthermore, fertilizer use varies with fertilizer type: solid N fertilizers tend to lead to higher levels of N volatilization than liquid fertilizers, for N applications on humid soils (Meyer et al., 1961; Jones et al., 2013), and the reverse when applied on dry soils (Jones et al., 2013). Azodyn was refined to take into account the form of the N-fertilizer applied (proportion of urea, ammonia (NH_4) and nitrate (NO_3)), soil moisture and rainfall after N application (Beillouin et al., 2018), to estimate N losses.

4.4. Extrapolation to other agronomic situations

This work, considered as a proof of concept, concerned a single agronomic situation (i.e. for one soil type, one preceding crop, one climate, etc…), simulated across 20 weather scenarios. The decision rules proposed in the manuscript are applicable in the agricultural situations of the studied region, with similar soil types, whatever the type of fertilizer. We assume that changing cultivar will not require adapting the decision rules, as cultivars differ more on the dynamics of N uptake and NNI than on the yield response to NNI (Le Gouis et al., 2000). We also assume that decision rules should be changed for other soil types, to better take into account the local dynamics of inorganic N availability. Decision rules should also differ among regions, to be adapted to the specific local weather conditions. Based on the proposed method, it will be possible to build decision rules for a larger range of agronomic situations. This would require different steps: (1) setting Azodyn input data (Table 1) for the new situations considered, (2) identifying days with optimal weather conditions for N fertilizer application (Table 2) for each weather scenario, (3) building a simulation plan with all possible N fertilizer rates at each time with optimal conditions, (4) characterizing each stimulation in terms of whether the NNI and N-loss thresholds are respected, (5) calculating the robustness of sequences of N fertilizer application timing and rates, and the robustness of N rates at each level of crop NNI at each time. Decision rules are assumed to differ slightly between agronomic situations and weather conditions, because: (i) soil type and previous crop strongly influences soil N dynamics and, thus, N availability to the crop during the growing season, which is taken into account in the NNI monitoring ; (ii) successive crop stages may occur on different dates, modifying the daily minimum NNI values to be respected on particular calendar dates; (iii) weather conditions may strongly influence application dates, and thus optimal N rates. Finally, the robustness of N rates will probably also be dependent on agronomic situations.

5. Conclusion

We developed here a set of decision rules to determine, in real time and as a function of instantaneous crop N status, the rate of N fertilizer most likely to keep crop NNI above a minimum NNI path, whatever the next possible time to apply N fertilizer. Resulting most often in the delay of N applications, this new method makes it possible to achieve maximum yields and to prevent N losses of more than 20 kg N ha^{-1}. Viability theory provides an original framework, never used before for the development of a decision support system for N fertilizer management based on a soil-crop model, such as Azodyn, and resulting in higher performance in terms of grain protein content and gaseous N losses, without yield reduction. The proposed method shows the interest of the NNI indicator to efficiently manage the dynamics of N fertilization. This approach could also be applied to other crops, such as rapeseed or fruit trees, where N fertilization also requires improvement, and to other agricultural practices for which real-time decisions are based on the monitoring of indicators, such as pest or water irrigation management. The analysis of the robustness of management options showed that a distinction should be made between physiological and management thresholds. Field experiments are now required to determine whether the NNI-based method can actually support farmers' change in N fertilizer management. This will require a convenient way to measure NNI without the need for time-consuming and destructive plant sampling, and an adaptation of the decision rules to diverse agronomic situations. Such trials should also assess if yields are similar to or better than those achieved with current recommendations, whilst decreasing the total amount of N fertilizer applied and N losses. If this method proves effective, it would be particularly suitable for use in precision agriculture, in which farmers are equipped to automatically measure plant indicators and could even adjust N application rates within fields on the basis of NNI estimation with onboard sensors.

Acknowledgments:

We thank *Arvalis-Institut-du-végétal*, and the ADEME (*Agence de l'Environment et de la Maîtrise de l'Energie*) for funding this study. This study was part of the REACCTIF project. We thank Julie Sappa (Alex Edelman & Associates) for reviewing the English, and Bertrand Omon for proving the data to set Azodyn parameter for the studied situation.

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