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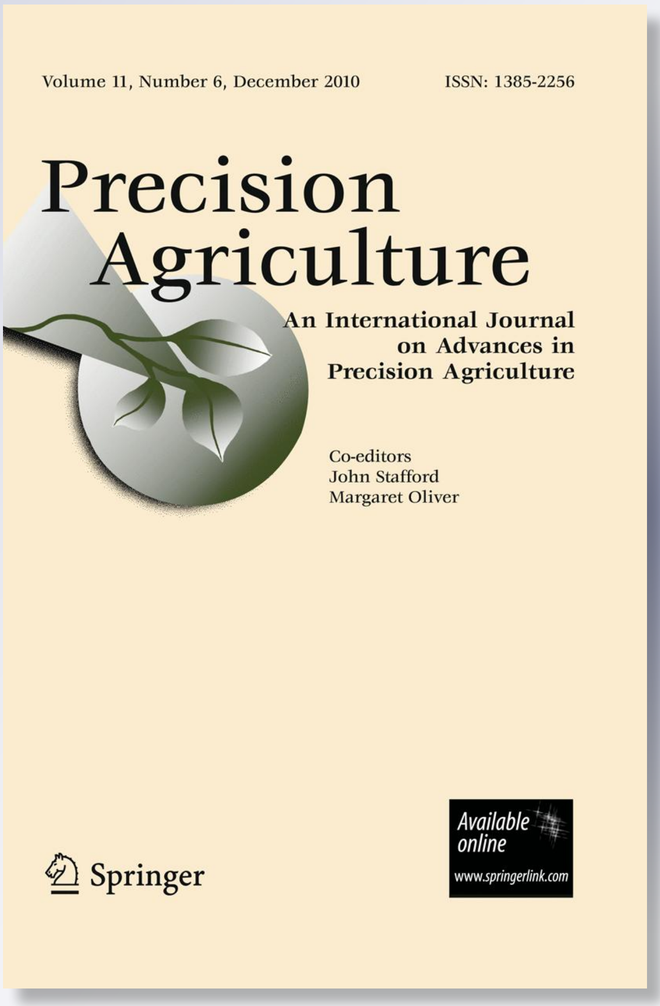

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Development and validation of fuzzy logic inference to determine optimum rates of N for corn on the basis of field and crop features

N. Tremblay · M. Y. Bouroubi · B. Panneton · S. Guillaume · P. Vigneault · C. Bélec

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Abstract A fuzzy inference system (FIS) was developed to generate recommendations for spatially variable applications of N fertilizer. Key soil and plant properties were identified based on experiments with rates ranging from 0 to 250 kg N ha^{-1} conducted over three seasons (2005, 2006 and 2007) on fields with contrasting apparent soil electrical conductivity (EC$_a$), elevation (ELE) and slope (SLP) features. Mid-season growth was assessed from remotely sensed imagery at 1-m^2 resolution. Optimization of N rate by the FIS was defined against maximum corn growth in the weeks following in-season N application. The best mid-season growth was in areas of low EC$_a$, high ELE and low SLP. Under favourable soil conditions, maximum mid-season growth was obtained with low in-season N. Responses to N fertilizer application were better where soil conditions were naturally unfavourable to growth. The N sufficiency index (NSI) was used to judge plant N status just prior to in-season N application. Expert knowledge was formalized as a set of rules involving EC$_a$, ELE, SLP and NSI levels to deliver economically optimal N rates (EONRs). The resulting FIS was tested on an independent set of data (2008). A simulation revealed that using the FIS would have led to an average N saving of 41 kg N ha^{-1} compared to the recommended uniform rate of 170 kg N ha^{-1}, without a loss of yield. The FIS therefore appears to be useful for incorporating expert knowledge into spatially variable N recommendations.

Keywords Precision farming · Variable-rate technology · Fuzzy inference systems · Topography · Apparent electrical conductivity (EC$_a$) · Nitrogen sufficiency index (NSI)

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Introduction

Crop production is a complex system that integrates physical, chemical and biological processes and is managed under increasing economic and ecologic constraints. Under current fertilizer application practices, N use efficiency has been estimated to average only 33% worldwide. Therefore, a large proportion of N is lost as a contaminant into the air, aquifers or surface water (Assimakopoulos et al. 2003; Mullen et al. 2003). Nitrogen management is one of the primary factors affecting crop yield and pollution from agroecosystems. Nitrogen availability to crops is affected by a complex set of interacting edaphic, biological, climatic and management factors. To achieve both economic and environmental objectives, crop production systems must conform to a 'just enough' principle (Schröder et al. 2000).

The uniform application of fertilizer N across fields leads to over- or under-application depending on requirements that are known to vary in space. The spatially variable application of N fertilizers is the only strategy capable of optimizing (both economically and environmentally) the overall use of N (Dharmakeerthi et al. 2006; Kyveryga et al. 2007; Scharf et al. 2006; Welsh et al. 2003). The economically optimum N rate (EONR) is the rate that maximizes profits for producers. The implementation of EONR would require large amounts of data, which are challenging to obtain in a timely manner. An estimate of EONR for in-season application can be obtained by integrating crop and soil information. Vegetation indices (VIs) that assess the biomass or chlorophyll status of a crop can be obtained from a variety of sensors and platforms (Welsh et al. 2003; Doerge 2005; Hawkins et al. 2007) at spatial resolutions suitable for variable-rate N applications. For the assessment of N, VIs can be enhanced by standardization with VIs from reference plots where N supply is not limiting to crop growth in order to determine an N sufficiency index (NSI = normalized difference vegetation index [NDVI] of a crop/NDVI in a rich-N strip). The NSI represents a plant-based relative assessment of N-based limitation of crop growth and is close to one when crop growth is equivalent to growth under a rich-N strip (Doerge 2005; Samborski et al. 2009).

Apparent soil electrical conductivity (EC_a) is affected by soil texture (which links it to soil moisture), the depth of the arable layer and the salinity of the soil (Heiniger et al. 2003). Soil with low EC_a tends to be associated with better plant growth (Kitchen et al. 2003). Topography also influences soil water content and nutrient flow and, as a consequence, plant growth and ultimately crop yield (Dharmakeerthi et al. 2006; Heiniger et al. 2003; Kravchenko 2003).

Many studies have related plant and soil conditions to EONR, but there are few examples where models have been developed to integrate these effects for estimating EONR. Berntsen et al. (2006) proposed a polynomial model for EONR based on properties such as crop biomass, EC_a and topography. However, such a modeling approach is hardly compatible with datasets characterized by strong variability and weak correlations. It is proposed, therefore, that other strategies that use artificial intelligence are better adapted than deterministic approaches for predicting EONR. Among such strategies, Assimakopoulos et al. (2003) proposed fuzzy logic as the most flexible and comprehensive approach to use in such a context, particularly where expert knowledge can be included (Mertens and Huwe 2002). Jones and Barnes (2000) developed a fuzzy logic-based decision-support system that integrates remote sensing data and plant growth models to manage within-field spatial variation. Panneton et al. (2002) performed a fuzzy classification of a time series of yield maps used for variable management.

Optimal rates of N for corn are difficult to determine because they depend to a great extent on interactions between weather, soil and crop management factors. Nevertheless, the need to optimize N rates is growing as a result of environmental and economic concerns. New tools and strategies must be developed and implemented to optimize N use at the farm level. The crop establishment phase does not require high levels of N availability in the soil, with the consequence that the practice of 'all at sowing' application leads to large soil mineral N concentrations at this early stage, when N is at particular risk of being lost by leaching. The alternative practice, in which a quantity complementary to the amount applied at sowing is saved for 'in-season' application, reduces the likelihood of N losses because most of the N is provided just prior to the period of active uptake by the crop. This practice also allows the plants to be used as indicators of actual local N availability through measurable changes in their chlorophyll, leaf area index and biomass status.

The aim of this study was to develop and validate a fuzzy inference system (FIS) for predicting EONR for corn plots from soil EC_a, elevation (ELE), slope (SLP) and crop information (NSI).

Materials and methods

Field sites and experimental design

The experiments were conducted in 2005, 2006, 2007 and 2008 on corn (*Zea mays* L.) in the Montérégie region of Quebec, Canada. Descriptions of the fields are given in Table 1. The fields used were different each year, but were adjacent to one another. The soil profiles were similar, with mainly heavy clay, loam and clay-loam textures in field areas at low elevation, loam and sandy loam textures in areas at mid-elevation, and sandy loam and loamy sand textures in areas at higher elevation.

Table 1 Description of the experimental fields

Year	Fields for FIS development		Field for validation	
	2005	2006	2007	2008
UTM coordinates	629 589.38 E 4 994 395.04 N	629 781.17 E 4 994 184.80 N	629 598.01 E 4 994 275.43 N	629 788.69 E 4 994 156.51 N
Field size (ha)	8.66	6.52	8.74	12.99
Block dimension (m)	90 × 180	45 × 260	96 × 175	42 × 1100
Plot dimension (m)	22.5 × 180	6.75 × 260	19.5 × 175	N/A
Strip dimension (m)	4.5 × 720	4.5 × 1040	4.5 × 700	6 × 1100
Sowing date	12 May	9 May	3 May	6 May
Early-season plant status observation ($NDVI_1$ used to calculate NSI)	28 June (V7)*	5 July (V6–7)	22 June (V6)	25 June (V5–6)
In-season N application	23 June (V7)	5 July (V6–7)	22 June (V6)	26 June (V5–6)
Mid-season plant-status observation ($NDVI_2$)	12 July (V9)	20 July (V11)	10 July (V8)	N/A
Harvest date	14 November	2 November	31 October	23–24 October
Variety	DKC4627 Bt 2950		Pioneer 37Y13 (bt_RR) 2950 CHU	

* Growth stage as defined by Ritchie et al. (1992)

Nitrogen treatments for development of the fuzzy inference system

Four in-season N-rate treatments plots were randomized within four blocks during the development years (Table 1). Strips with no N fertilizer for the whole season (Nil-N) and with non-limiting N fertilizer applications (rich-N strips) were also laid out. At sowing, all plots received 30 kg N ha^{-1} broadcast, and the rich-N strips received 250 kg N ha^{-1}. At the time of in-season N application (Table 1), the following N-rate treatments were applied in plots: 0, 158 kg N ha^{-1} (2005 and 2006) and 0, 135 kg N ha^{-1} (2007). These rates were determined each year on the basis of the expected N contribution of the preceding crop. Figure 1a shows an example of how the treatments were laid out. All trials were under conventional tillage with a row spacing of 0.75 m.

Measurements and data pre-processing

Soil EC_a was measured on bare soil in the spring before sowing (2005 and 2006) or after harvest (2007). Measurements were taken with a Veris model 3100 sensor cart system (Veris Technologies, Inc., Salina, KS) for shallow (about 0–30 cm) and deep (about 60–90 cm) readings. Apparent electrical conductivity was recorded along transects approximately 10 m apart as a simple mono-directional scan or a bidirectional scan depending on the complexity of the terrain features. Elevation was determined along transects approximately 9 m apart with a differential GPS receiver (Pathfinder Pro XRB,

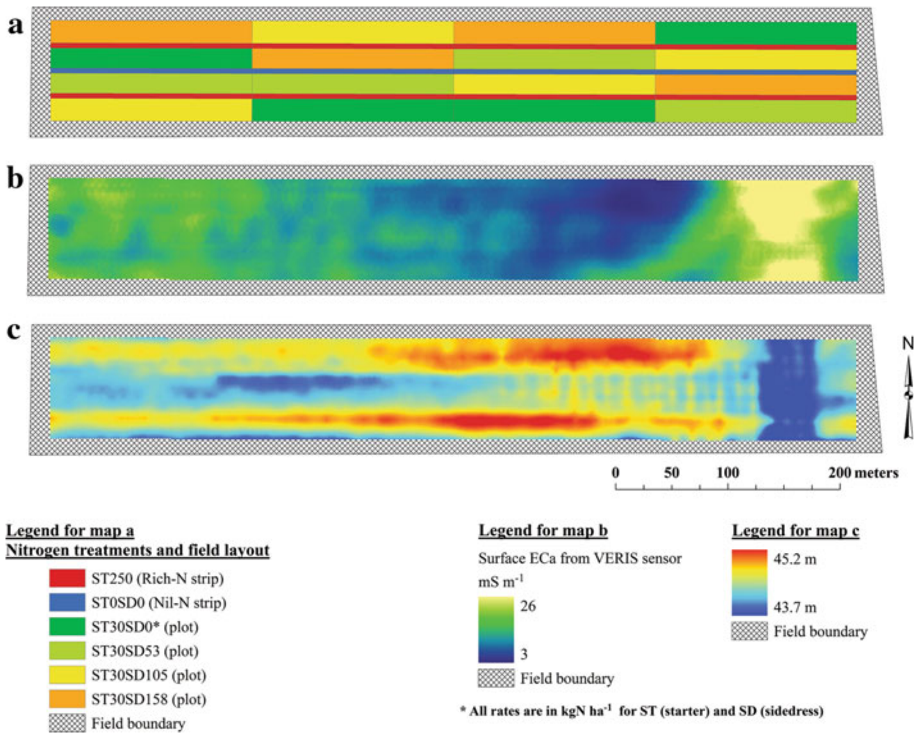

Fig. 1 Maps of N treatments, EC_a measured by the Veris sensors and ELE measured by the differential GPS receiver in 2005

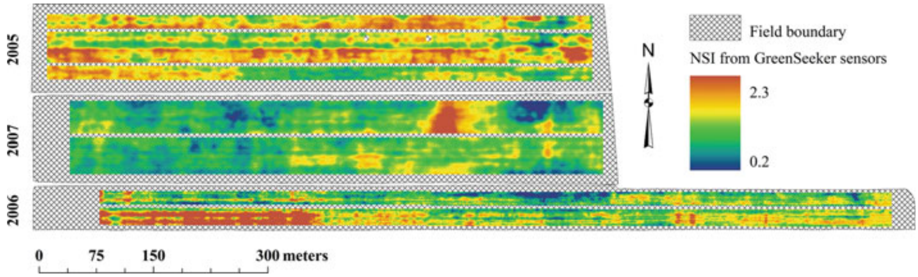

Fig. 2 Maps of NSI measured by the GreenSeeker sensors before in-season N application in 2005, 2006 and 2007

Trimble Navigation Ltd., Sunnyvale, CA; accuracy ± 15 cm) mounted on an all-terrain vehicle. The sampling density for both variables was one point per 6–12 m along the transects. All the datasets were first checked for normality. Experimental variograms were computed from the EC_a and GPS ELE data with GS + software (Gamma Design Software, LLC, Plainwell, MI). Geostatistical models were fitted to the variograms and the model parameters were used for kriging. The SLP features were calculated with the 3D Analyst extension in ArcGIS software (ESRI, Inc., Redlands, CA). Figure 1b and c shows the maps of kriged EC_a and ELE for the 2005 field.

The NDVI measurements were obtained before the application of N ($NDVI_1$; Table 1) from five GreenSeeker sensors (NTech Industries Inc., Ukiah, CA). For the mid-season plant-status observation, NDVI was recorded again (defined as $NDVI_2$; Table 1) with a Compact Airborne Spectrographic Imager (CASI; ITRES Research Ltd., Calgary, AB) to assess plant response to N fertilizer application and terrain features. The NSI for every point was calculated from $NDVI_1$, with the $NDVI_1$ from the rich-N strips (defined as $NDVI_{1S}$) used as a reference. The $NDVI_{1S}$ was arbitrarily set at the 90th percentile of the $NDVI_1$ value of the 20 nearest neighbours in the rich-N strip. The NSI maps for 2005–2007 are shown in Fig. 2.

The indicator used to quantify crop growth in the weeks after in-season N application was dNDVI, defined as the difference between $NDVI_2$, which was measured mid-season, and $NDVI_1$, which was measured at in-season fertilizer application (Table 1). Since $NDVI_1$ and $NDVI_2$ were not measured at the same points, a nearest neighbour procedure was used to find the $NDVI_2$ value corresponding to each $NDVI_1$ measurement.

The relationship between dNDVI and N rate was analyzed for different soil conditions (represented by EC_a, ELE and SLP properties) and different status of the plant (measured by NSI).

Principles of fuzzy inference systems

Fuzzy logic is widely used as an interface between symbolic and numerical spaces, allowing the implementation of human reasoning in computers. Fuzzy inference systems deal with linguistic variables, which are variables whose values are linguistic terms. For example, the *ELE* variable can be handled by means of three linguistic terms: *Low*, *Medium* and *High*. The linguistic concepts are implemented using fuzzy sets, which usually overlap. A fuzzy set is defined by its membership function (MF). A point, **x**, in the universe, such as a given ELE (i.e. a real value), belongs to a fuzzy set, *A*, with the

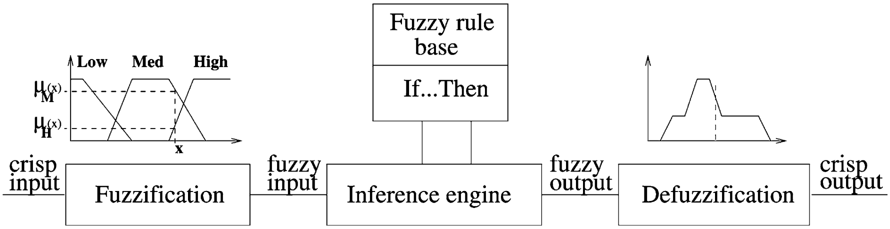

Fig. 3 Principles of the FIS

membership degree $0 \leq \mu_A(\mathbf{x}) \leq 1$. On the left side of Fig. 3, the value belongs to the *Medium* set with a degree of $\mu_M(\mathbf{x})$ and to the *High* set with a degree of $\mu_H(\mathbf{x})$. These degrees can be interpreted as the level to which the **x** *ELE* should be considered *Medium* or *High*. In this case, it cannot be considered *Low* at all.

The core of the fuzzy system is a set of fuzzy 'if–then' rules stated in the form 'If Elevation is High then….' When several variables are involved in the rule description, the membership degrees can be combined using an 'AND' operator (the most common are the minimum and the product) or an 'OR' operator (maximum or bounded sum; the sum is limited to one) to give the weight of a rule when conclusions from a set of rules are aggregated to infer an output. As a consequence of overlap in the fuzzy partition, several rules are likely to be called by the same input data. The inferred output is the result of the aggregation of all these weighted conclusions.

The design of a fuzzy system involves two main steps: definition of the input and output variables, and rule description. In this study, both steps were carried out on the basis of expert knowledge and experimental results, as discussed below. Generally, simulations of output values corresponding to combinations of inputs are used to observe the behaviour of the model that was designed. An example showing the details of calculating EONR output from EC_a, ELE, SLP and NSI inputs for an FIS similar to the one presented here is given in Tremblay et al. (2010).

Validation process

An independent set of data was used to validate the FIS during the 2008 season. The data were obtained from a field that was adjacent to those used for model development (Table 1) and that had been subjected to comparable N treatments. Similar to the FIS development years, soil EC_a was measured on bare soil in the spring before sowing, and the NDVI measurements were obtained before N application ($NDVI_1$; Table 1). Figure 4a and b shows the maps of the kriged EC_a and NSI. The 2008 field used for the validation was sown with a different cultivar from that used for development of the FIS (Table 1). Seven rates of N application strips (including the nil-N and rich-N strips) were established along the east–west axis of the plot (Fig. 4c). In each N-treatment strip, 12 sampling points were selected randomly but were scattered to encompass spatial variation in the soil observed along the east–west axis. A radius of at least 2 m was left between two sampling points and between these points and any treatment zone boundary. Grain yields (on a 14% grain humidity basis) were obtained from 168 sampling points (Fig. 4d).

The validation process comprised two parts. The first part involved a comparison of the EONR given by the FIS ($EONR_{FIS}$) with the actual EONR extracted from the relationship

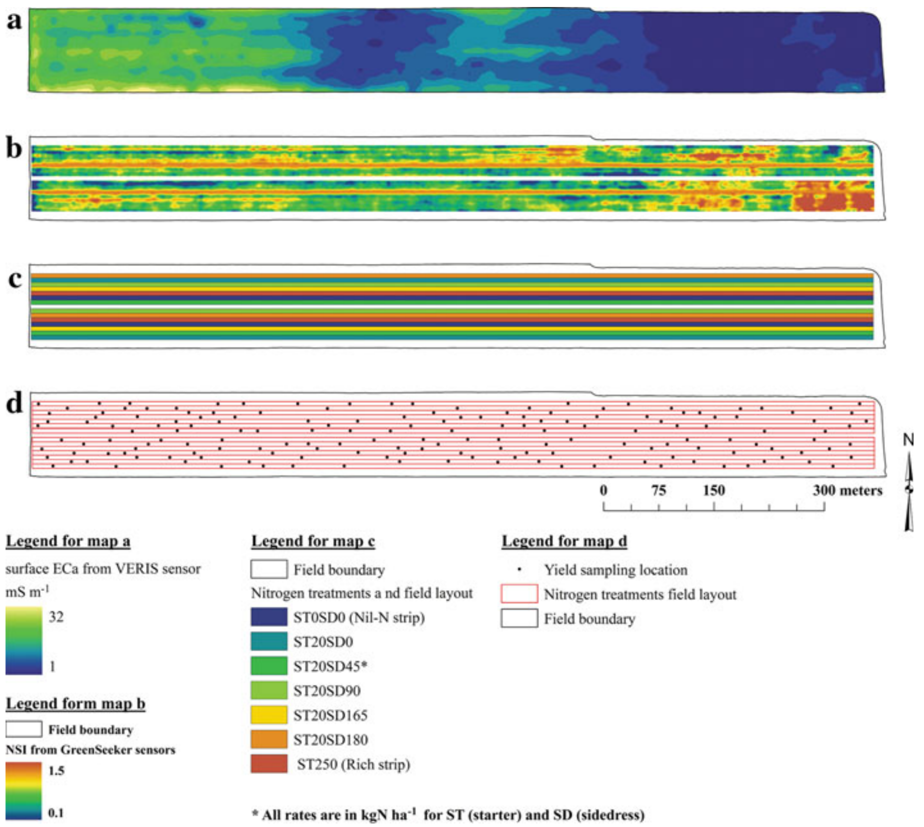

Fig. 4 Maps of the validation data in 2008 showing: **a** the EC_a classification, **b** the spatial variation in NSI, **c** the N treatments and field layout and **d** the sampling locations for yield measurements

between yield and N rate obtained in the 2008 experiment ($EONR_{val}$) and with two other fixed rates, namely the official recommendation from the Centre de Référence en Agriculture et Agroalimentaire du Québec (CRAAQ), for the province of Quebec (CRAAQ 2003), and the recommendation of the grower's agronomist, who considered the cropping history of the field (identified as Grower). The $EONR_{FIS}$ was calculated with soil and plant status properties measured in 2008 as inputs for the FIS. The experimental $EONR_{val}$ was determined by linear-plateau modelling of the relationship between yield and N rate, as in Schmidt et al. (2002). The linear-plateau model gives the minimum N rate (in the intersection of the slope and the plateau) required to reach the maximum yield. The four fertilizer rate recommendations for N ($EONR_{FIS}$, $EONR_{val}$, CRAAQ and Grower) were compared for different soil conditions and plant status.

The second part consisted of the comparison of the simulated yields resulting from the four N recommendation strategies. The yield corresponding to any N rate was calculated by inverting the linear-plateau model for the relationship between yield and N rate. Comparison of the yields obtained from the four N recommendations made it possible to determine the ability of the variable-rate FIS model to maintain high yield with minimal fertilizer input.

Results and discussion

Expert knowledge about optimum nitrogen rate

The desired outcome of the FIS was an EONR obtained through the analysis of the growth indicator dNDVI, which is the difference between NDVI measured mid-season (at stage V8–V10, 15–20 days after in-season fertilizer application) by the CASI sensor and NDVI measured just prior to in-season fertilizer application (at stage V5–V7) by the GreenSeeker sensors.

To determine EONR requires prior knowledge of soil textural and landscape characteristics, as well as plant N status. Tremblay et al. (2007) found, for the 2005 and 2006 data used here, that better growing conditions for corn were found in areas of low EC_a, low SLP and high ELE. Among those three soil properties, EC_a is recognized as the one most correlated (negatively) to plant growth (Kravchenko et al. 2003). Figure 5 shows plant growth (represented by dNDVI) in relation to N rate for three classes of EC_a, three classes of ELE and three classes of SLP. These classes were determined by means of the histogram segmentation method developed by Otsu (1979). The classes were: (1) for EC_a, low from 0 to 8 mS m^{-1}, medium from 8 to 17 mS m^{-1} and high above 17 mS m^{-1}, (2) for ELE,

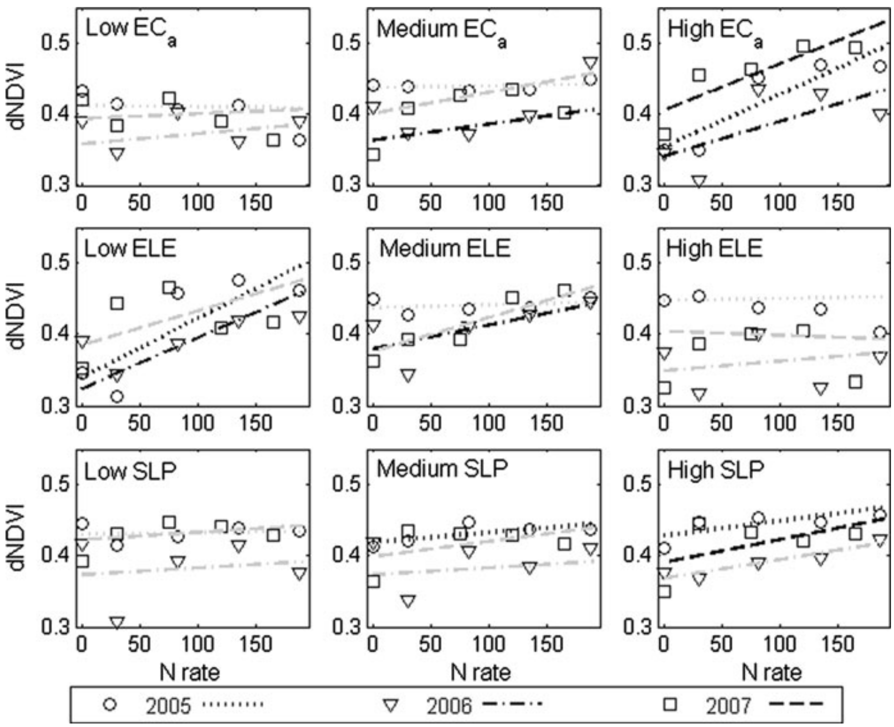

Fig. 5 The effect of soil properties on growth from in-season N application to mid-season crop observation (dNDVI, averages and linear fitting), for different rates of N application (in kg N ha^{-1}) and for three classes of EC_a, ELE and SLP. Dark and light lines represent significant and non-significant (at 90% confidence level) relationships between dNDVI and N rates, respectively

low, medium and high (absolute values were different among the 3 years) and (3) for SLP, low from 0 to 0.65°, medium from 0.65° to 1.45° and high above 1.45°.

These classes reveal the different behaviour of dNDVI as a function of N rate. For low EC_a, dNDVI is mostly independent of N rate. At high EC_a, dNDVI responds to increasing N. Indeed, the slopes of the dNDVI-N rate relationships are significant for the 3 years 2005, 2006 and 2007 (Fig. 5). For medium EC_a, moderate responses to N rate are observed and the slope of the relationship is significant in 2006 only. Responses to N rate are also more apparent for low ELE (significant in 2005 and 2006) and, to a lesser extent, medium ELE (significant only in 2006). These terrain conditions represent areas that are less favourable to plant growth and can apparently be improved by higher rates of N. In more-elevated areas (high ELE), maximum dNDVI is often reached at low N rates (30–87 kg N ha^{-1}). Nitrogen rates are generally more effective in situations of high SLP (significant in 2005 and 2007) which correspond to drier soil conditions. However, the impact of SLP on the response of dNDVI to N rate is less clear; the slopes of the regressions are smaller for high SLP than for low ELE or high EC_a.

The slopes of dNDVI as a function of NSI are negative (Fig. 6). When NSI is high, dNDVI is low because crop growth was excellent early in the season (at topdressing) before in-season application of N for all N rates compared to a situation of non-limiting N supply. In this case (high NSI), NDVI increased from the topdress stage (when $NDVI_1$ was acquired) to mid-season stage (when $NDVI_2$ was acquired) by only 0.3–0.4 and almost independently of applied N rate and of soil conditions. When NSI is low, indicating a small

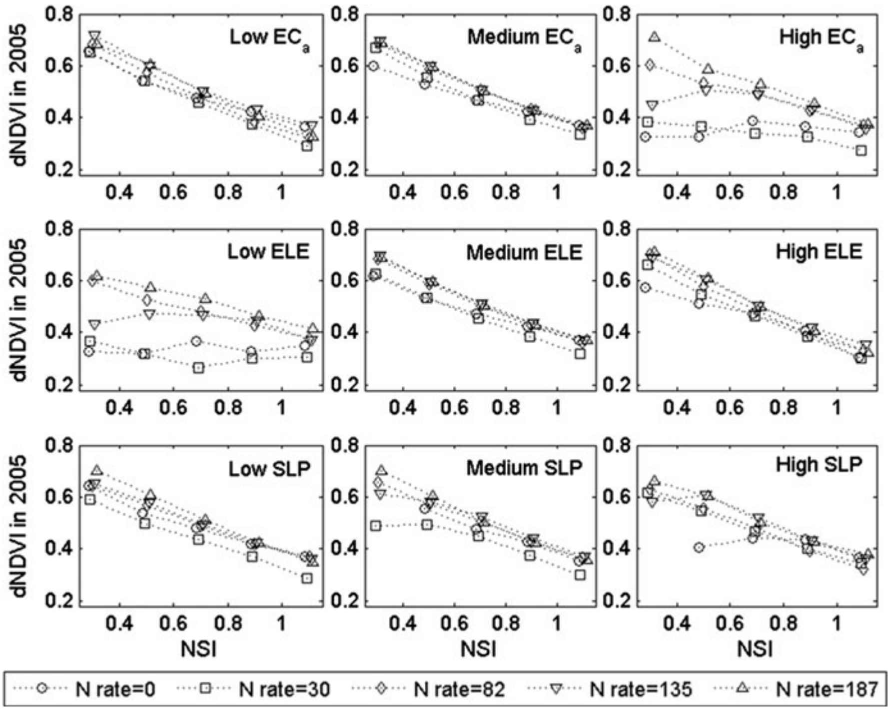

Fig. 6 The effect of NSI on growth (represented by dNDVI) for different rates of N application (in kg N ha^{-1}) and for three classes of EC_a, ELE and SLP (2005 year)

growth level at the topdress stage, dNDVI is high (0.6–0.7) in good soil conditions (low EC_a, high ELE or low SLP) for almost all applied rates of N. However, in a situation of low NSI combined with poor soil conditions (high EC_a or low ELE), the response to N is considerable and dNDVI increases from 0.3 for low N rate (0 or 30 kg ha^{-1}) to 0.7 for high N rate (187 kg ha^{-1}). It follows that crop growth can be enhanced by in-season N applications in areas of high EC_a and low ELE, corresponding to unfavourable soil conditions when a small growth is observed at the topdress stage.

Fuzzy sets and inference rules from expert knowledge

The proposed FIS used the variables EC_a, SLP, ELE and NSI to determine EONR. Trapezoidal shapes and three fuzzy sets (low, medium and high levels) for soil variables (EC_a, SLP and ELE) were used. For NSI, two fuzzy sets (low and high) were used. The EONR was also fuzzified with trapezoidal MFs into three sets, low, medium or high, to allow more possibilities for rule definition and more precise EONR recommendations.

The limits of the fuzzy sets were determined in accordance with the three classes obtained by Otsu segmentation, as shown below. The fuzzy sets representing soil properties were defined as follows (Fig. 7): EC_a was completely low from 0 to 5 mS m^{-1}, medium from 11 to 14 mS m^{-1}, high up to 20 mS m^{-1}, and fuzzy between 5 and 11 mS m^{-1} and between 14 and 20 mS m^{-1}; for ELE, intervals are not given because they can differ greatly between fields; and SLP was low from 0 to 0.4°, medium from 0.9° to 1.2°, high up to 1.7°, and fuzzy between 0.4° and 0.9° and between 1.2° and 1.7°.

The NSI was considered low below 0.6, high up to 1.0 and fuzzy between those two values. The MFs of EONR were also of trapezoidal shape and were defined as low between 0 and 30 kg N ha^{-1}, medium between 80 and 120 kg N ha^{-1}, high up to 170 kg N ha^{-1}, and fuzzy between 30 and 80 kg N ha^{-1} and between 120 and 170 kg N ha^{-1}.

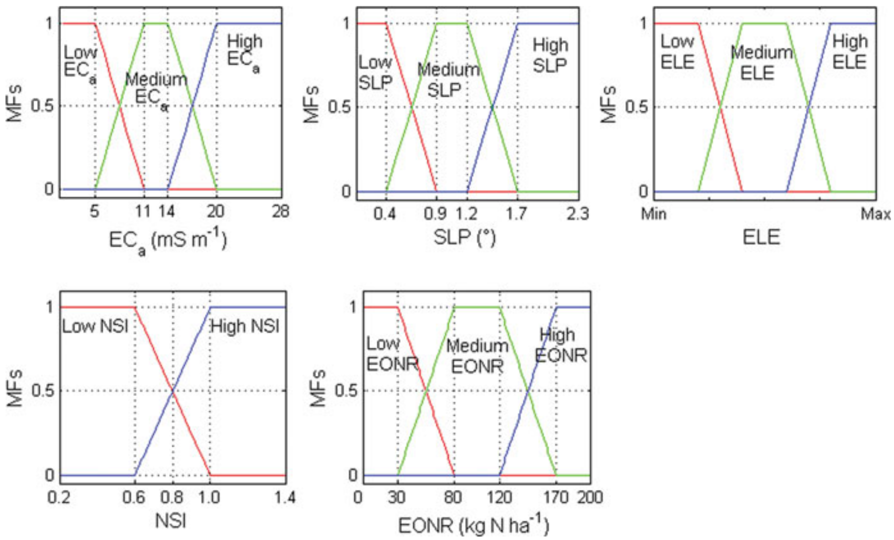

Fig. 7 Membership functions for FIS input (EC_a, ELE, SLP and NSI) and output (EONR) variables

On the basis of the expert knowledge gathered from the three seasons (2005, 2006 and 2007) through the analysis of the relationship between growth (represented by dNDVI) and soil conditions (EC_a, ELE and SLP) or plant status (measured by NSI), the following rules are proposed:

- **IF** (EC_a is high **OR** ELE is low **OR** SLP is high) **AND** (NSI is low) **THEN** (EONR is high).
- **IF** (EC_a is high **OR** ELE is low **OR** SLP is high) **AND** (NSI is high) **THEN** (EONR is med).
- **IF** (EC_a is low **OR** ELE is high **OR** SLP is low) **THEN** (EONR is low).
- **IF** (EC_a is med **OR** ELE is med **OR** SLP is med) **AND** (NSI is low) **THEN** (EONR is med).
- **IF** (EC_a is med **OR** ELE is med **OR** SLP is med) **AND** (NSI is high) **THEN** (EONR is low).

These rules can be updated to include local knowledge or new experimental results.

Economically optimum nitrogen rate as predicted by the fuzzy inference system

To observe the behaviour of the FIS output, EONR was generated for combinations of EC_a (ranging from 2 to 25 mS m^{-1}) and NSI (ranging from 0.35 to 1.2) and for two topographic conditions, namely favourable conditions corresponding to high ELE ($ELE = ELE_{max}$) and low SLP ($SLP = 0$), and unfavourable conditions corresponding to low ELE ($ELE = ELE_{min}$) and high SLP ($SLP = 2°$). The results of the EONR simulations as a function of the input parameters are illustrated in Fig. 8a and b. As expected, the general surface responses of EONR to EC_a and NSI are similar for favourable and unfavourable topographic conditions. In the latter case, however, EONRs that are higher by about 60 kg N ha^{-1} or more are proposed, as compared to favourable topographic conditions. For unfavourable soil conditions (high EC_a, low ELE and high SLP), a maximum of 180 kg N ha^{-1} is recommended if the NSI is low (high deficiency), but only 100 kg N ha^{-1} is recommended if NSI is high (low deficiency). For favourable soil conditions (low EC_a, high ELE and low SLP), the model recommends 50 kg N ha^{-1}, regardless of NSI status. According to the FIS rules, a low NSI becomes important only where the soil is unfavourable. In this case, the FIS recommends a supplement of 40 kg N ha^{-1} for low NSI compared to high NSI (Fig. 8b). The model accounts for the effect of EC_a, with a difference about 80 kg N ha^{-1} between the extremes of EC_a.

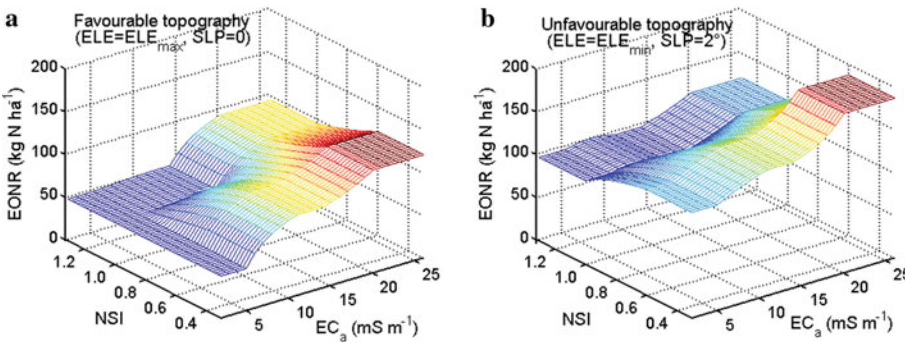

Fig. 8 Simulation of EONR using the FIS developed for different situations of input values under conditions of: **a** favourable topography and **b** unfavourable topography

Validation with an independent dataset

The model was validated for different soil and plant status conditions. Although each N rate was covered to some extent under all terrain conditions, the 168 data points that were harvested in 2008 were not enough to represent all cases of the FIS input property (EC_a, ELE, SLP and NSI) combinations ($3 \times 3 \times 3 \times 2 = 54$). Therefore, the two most important properties, namely ECa and NSI, were selected for further validation of the FIS. The 168 yield measurements were attributed to seven N rates, two EC_a values and two NSI levels (28 groups). Each group comprised at least three samples, allowing for consistency in the yield average in each group.

The actual EONRs for the 2008 experiment ($EONR_{val}$) were calculated with linear-plateau regressions for each combination of the two EC_a and two NSI levels (low or high) (Fig. 9). The $EONR_{val}$ was 91 or 100 kg N ha^{-1} in the 'high NSI' group (depending on the EC_a group). The $EONR_{val}$ was established as 155 kg N ha^{-1} for the 'low EC_a–low NSI' group and 200 kg N ha^{-1} for the 'high EC_a–low NSI' group (Fig. 9). These $EONR_{val}$ values indicate the rates against which the N rate recommendations should be gauged. The rates calculated by the FIS ($EONR_{FIS}$) are relatively close to the actual ones ($EONR_{val}$) for four selected combinations of soil and growth status (high or low EC_a and NSI) (Table 2). The FIS was able to use soil properties (EC_a) and early season plant status (NSI) to determine the optimal N rates that maximized final yields in 2008.

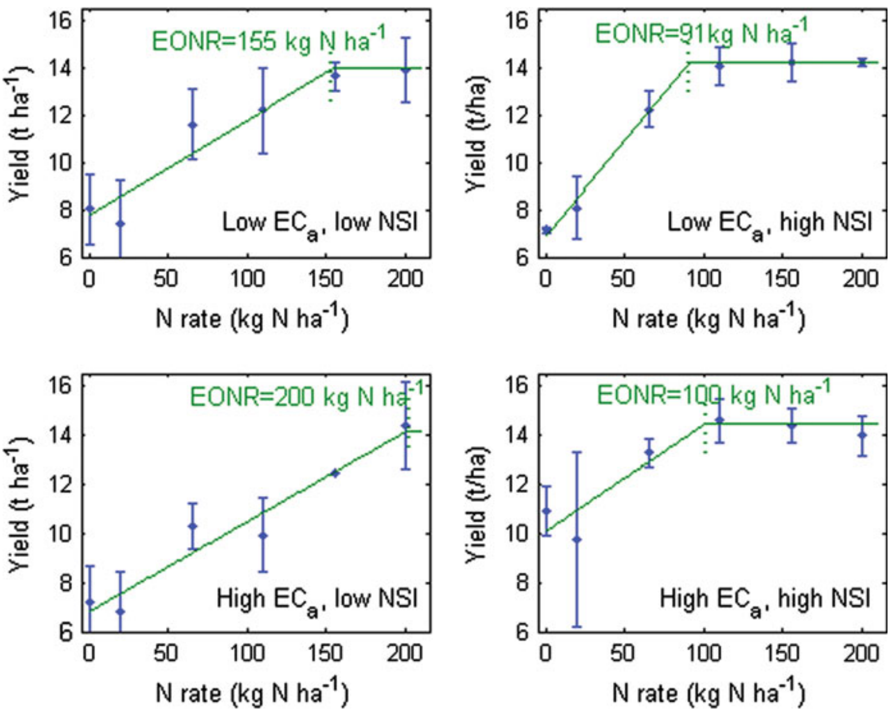

Fig. 9 Actual EONR in 2008 ($EONR_{val}$) from a linear-plateau model according to four combinations of EC_a and NSI levels (low or high)

Table 2 Nitrogen rates recommended for the validation (2008) field by the FIS model (FIS = $EONR_{FIS}$), the provincial guidelines (CRAAQ) and the grower's agronomist (Grower), together with actual EONR for each of the four EC_a–NSI combinations (Val = $EONR_{val}$)

EC_a–NSI combination	N rate (kg N ha^{-1})				Grain yield (t ha^{-1})			
	FIS	CRAAQ	Grower	Val	FIS	CRAAQ	Grower	Val
Low EC_a–low NSI	160	170	135	155	13.9	14.0	13.1	14.0
Low EC_a–high NSI	99	170	135	91	14.1	14.2	14.2	14.2
High EC_a–low NSI	190	170	135	200	13.6	13.0	11.3	14.1
High EC_a–high NSI	112	170	135	100	14.4	14.4	14.4	14.4
Global (all cases)	129	170	135	–	14.0	14.0	13.2	–

In addition, simulated grain yield performances of the three scenarios (FIS, CRAAQ and Grower) and actual yield performance of the FIS (Val) are given

The FIS recommendations can also be compared to uniform applications of N rates established according to two other recommendation systems: (1) the official general recommendation (170 kg N ha^{-1}) for the province of Quebec, as established by the CRAAQ (2003); and (2) the expert advice (135 kg N ha^{-1}) of the grower's agronomist, who considered the cropping history of the field and the contribution of previous crop residues (the preceding crops in 2007 were sweet pea for processing and then soybean). The recommendation systems were compared on the basis of their capacity to maintain high yield with minimal fertilizer input.

The rates generated by the FIS were 160, 99, 190 and 112 kg N ha^{-1} for the four corresponding EC_a–NSI classes (Table 2). The rate recommendations from the FIS ($EONR_{FIS}$) were less than the CRAAQ recommendation under conditions of high NSI or low EC_a levels, which corresponded to 88% of the field area. The $EONR_{FIS}$ was higher than the CRAAQ recommendation only when NSI was low and EC_a was high. The grower's rate was higher than the $EONR_{FIS}$ where NSI was high, but was otherwise insufficient. The average N rate recommended by the FIS was 41 kg N ha^{-1} less than the CRAAQ rate and 6 kg N ha^{-1} less than the grower's rate.

The yields expected from the rates of all three recommendation systems were calculated for the four EC_a–NSI classes by inverting the linear-plateau relationships (Fig. 9). With 41 kg N ha^{-1} less, the FIS recommendation would have resulted in a yield loss of only 0.09 t ha^{-1} (or 0.06%) against what would have been achieved with the CRAAQ rate. The grower's rate, even though it was 6 kg N ha^{-1} higher on average than the FIS rate, would have led to an average yield loss of 0.82 t ha^{-1} (5.9%), mostly because uniform N application results in suboptimal rates in conditions of high EC_a and low NSI.

Although the FIS was developed by optimizing dNDVI, which was derived from remotely sensed information obtained prior to and after the N side-dressing was applied, the system performed well when tested against actual grain yield response to fertilizer N. The dNDVI parameter therefore appears to be appropriate for developing spatially detailed knowledge about the effect of treatments applied in-season to a growing crop. In situations other than the ones in this study, the FIS that was developed must be used with care. First, the MFs established here have to be adapted to other regions or to other sources providing EC_a, ELE or NDVI, and the MF related to EONR must also take into account the minimum and maximum rates that can be reasonably applied in the new situations. Second, the fuzzy rules developed for the Montérégie region of Quebec are likely to be valid for similar areas, but the relationship between growth and soil properties could be very different in other regions, such as arid ones (Kitchen et al. 2003).

Conclusion

The spatially variable nature of optimal N fertilizer application requirements within fields justifies the development of systems that rely on the remote assessment of crop chlorophyll or biomass status (with NDVI as a surrogate variable) to promote variable-rate applications. Reports on the performance of current variable-rate N application systems have shown room for improvement based on complementary information such as soil conditions. Fuzzy inference systems can combine crucial plant- and soil-based spatial information to provide N fertilizer recommendations adapted to the conditions at different locations within fields. Nitrogen fertilizer applications can be reduced where soil conditions are favourable to growth and increased where soil conditions are naturally unfavourable. In the present study in the field tested in Quebec, it was shown that this approach would have led to an overall reduction in fertilizer use of 25% relative to provincial recommendations without any detrimental effect on crop productivity. The variable-rate N applications recommended by the FIS would also have enhanced yield by 6% compared to a well-adapted uniform N rate. The FIS developed for this purpose could be adapted to other conditions by adjusting the MFs to the ranges of prevailing input and output variables and, eventually, by adapting fuzzy rules from complementary expert knowledge.

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References

Assimakopoulos, J. H., Kalivas, D. P., & Kollias, V. J. (2003). A GIS-based fuzzy classification for mapping the agricultural soils for N-fertilizers use. *Science of the Total Environment, 309*, 19–33.

Berntsen, J., Thomsen, A., Schelde, K., Hansen, O. M., Knudsen, L., Broge, N., et al. (2006). Algorithms for sensor-based redistribution of nitrogen fertilizer in winter wheat. *Precision Agriculture, 7*, 65–83.

CRAAQ (Centre de Références en Agriculture et Agroalimentaire du Québec). (2003). *Fertilisation reference guide* (In French). Ste-Foy, QC, Canada: CRAAQ.

Dharmakeerthi, R. S., Kay, B. D., & Beauchamp, E. G. (2006). Spatial variability of in-season nitrogen uptake by corn across a variable landscape as affected by management. *Agronomy Journal, 98*, 255–264.

Doerge, T. A. (2005). Nitrogen measurement for variable-rate N management in maize. *Communications in Soil Science and Plant Analysis, 36*, 23–32.

Hawkins, J. A., Sawyer, J. E., Barker, D. W., & Lundvall, J. P. (2007). Using relative chlorophyll meter values to determine nitrogen application rates for corn. *Agronomy Journal, 99*, 1034–1040.

Heiniger, R. W., McBride, R. G., & Clay, D. E. (2003). Using soil electrical conductivity to improve nutrient management. *Agronomy Journal, 95*, 508–519.

Jones, D., & Barnes, E. M. (2000). Fuzzy composite programming to combine remote sensing and crop models for decision support in precision crop management. *Agricultural Systems, 65*, 137–158.

Kitchen, N. R., Drummond, S. T., Lund, E. D., Sudduth, K. A., & Buchleiter, G. W. (2003). Soil electrical conductivity and topography related to yield for three contrasting soil-crop systems. *Agronomy Journal, 95*, 483–495.

Kravchenko, A. N., Thelen, K. D., Bullock, D. G., & Miller, N. R. (2003). Relationship among crop grain yield, topography, and soil electrical conductivity studied with cross-correlograms. *Agronomy Journal, 95*, 1132–1139.

Kyveryga, P. M., Blackmer, A. M., & Morris, T. F. (2007). Disaggregating model bias and variability when calculating economic optimum rates of nitrogen fertilization for corn. *Agronomy Journal, 99*, 1048–1056.

Mertens, M., & Huwe, B. (2002). FuN-balance: A fuzzy balance approach for the calculation of nitrate leaching with incorporation of data imprecision. *Geoderma, 109*, 269–287.

Mullen, R. W., Freeman, K. W., Raun, W. R., Johnson, G. V., Stone, M. L., & Solie, J. B. (2003). Identifying an in-season response index and the potential to increase wheat yield with nitrogen. *Agronomy Journal, 95*, 347–351.

Otsu, N. (1979). A threshold selection method from gray-level histograms. *IEEE Transactions on Systems, Man, and Cybernetics, 9*, 62–66.

Panneton, B., Brouillard, M., & Piekutowski, T. (2002). Gestion de séries pluriannuelles de cartes de rendement. *Canadian Biosystems Engineering, 44*, 7.23–7.29.

Ritchie, S. W., Hanway, J. J., & Benson, G. O. (1992). *How a Corn Plant Grows*. Special Report No. 48. Ames, IA: Cooperative Extension Service, Iowa State University of Science and Technology.

Samborski, S. M., Tremblay, N., & Fallon, E. (2009). Strategies to make use of plant sensors-based diagnostic information for nitrogen recommendations. *Agronomy Journal, 101*, 800–816.

Scharf, P. C., Kitchen, N. R., Sudduth, K. A., & Davis, J. G. (2006). Spatially variable corn yield is a weak predictor of optimal nitrogen rate. *Soil Science Society of American Journal, 70*, 2154–2160.

Schmidt, J. P., DeJoia, A. J., Ferguson, R. B., Taylor, R. K., Young, R. K., & Havlin, J. L. (2002). Corn yield response to nitrogen at multiple in-field locations. *Agronomy Journal, 94*, 798–806.

Schröder, J. J., Neeteson, J. J., Oenema, O., & Struik, P. C. (2000). Does the crop or the soil indicate how to save nitrogen in maize production?: Reviewing the state of the art. *Field Crops Research, 66*, 151–164.

Tremblay, N., Bouroubi, M. Y., Panneton, B., Vigneault, P., & Guillaume, S. (2010). Space, time, remote sensing and optimal nitrogen fertilization rates—A fuzzy logic approach. In D. Clay, (Ed.), *GIS Applications in Agriculture*. Boca Raton, FL: Taylor & Francis Group. In press.

Tremblay, N., Bouroubi, M. Y., Vigneault, P., Bélec, C., & Wang, Z. (2007). Responsible decision-support system for corn nitrogen management using remote sensing and geographic information system technologies. In C. Zhao (Ed.), *Proceedings of the 4th International Symposium on Intelligent Information Technology in Agriculture (ISIITA)* (pp. 80–93). Beijing, China: China Agricultural Science & Technology Press.

Welsh, J. P., Wood, G. A., Godwin, R. J., Taylor, J. C., Earl, R., Blackmore, S., et al. (2003). Developing strategies for spatially variable nitrogen application in cereals part II: Wheat. *Biosystems Engineering Special Issue: Precision Agriculture–Managing Soil and Crop Variability for Cereals, 84*, 495–511.