Advances in Animal Biosciences: Precision Agriculture (ECPA) 2017, (2017), **8:2**, pp 625–629 © The Animal Consortium 2017. This is a work of the U.S. Government and is not subject to copyright protection in the United States
doi:10.1017/S2040470017000462

advances in animal biosciences

An uncertainty-based comprehensive decision support system for site-specific crop management

V. Adamchuk[1†], R. Lacroix[2], S. Shinde[1], N. Tremblay[3] and H. Huang[1]

[1]*McGill University, Ste-Anne-de-Bellevue, QC, H9X 3V9, Canada;* [2]*Valacta, Ste-Anne-de-Bellevue, QC, H9X 3R4, Canada;* [3]*Agriculture and Agri-Food Canada, Saint-Jean-sur-Richelieu, QC, J3B 3E6, Canada*

This paper presents a framework for the implementation of a decision support system that considers spatial, temporal and managerial factors in assessing the potential impact of crop amendments on the cost of a given production scenario. The proposed system includes a database and a numeric simulation model. The database is linked to previously recorded crop responses for a given agricultural input under different conditions while the numeric simulation model determines the probability of different levels of profit for each decision option. This system then determines the optimal uniform rate of application of an amendment to maximize profits, or to define the range of such rates for a case of variable rate application. Uncertainty-based treatment of each model input allows for a balance between the potential results of under-application or over-application.

Keywords: Crop fertilization, decision support systems, production function, profitability, uncertainty

Introduction

From a control theory point of view, site-specific management of mineral fertilizers and other agricultural inputs follows a two-level control scheme. Understanding the spatial heterogeneity of crop growing conditions within a specific management unit (i.e., agricultural field) allows for application rates of agricultural inputs to be matched with local needs within the acceptable range (Adamchuck *et al.*, 2004; Anselin *et al.*, 2004; Griffin *et al.*, 2008; Holland and Schepers, 2010; Tremblay *et al.*, 2010). This constitutes lower-level control. Higher-level control requires the determination of this range based on past management, weather including prior, current and forecasts, commodity prices, cost and accessibility of input material, risk preference, etc. At both control levels, the uncertainty of spatial and temporal information can be a major impediment to good decision outcomes (McBratney *et al.*, 1997). This paper presents a framework for the implementation of high-level control, conceptualized as a decision support system (DSS) that takes into account spatial, temporal and managerial factors in assessing the potential impact of crop fertilization (or the use of other amendments) on the bottom line of a given production scenario, in the context of uncertain information (Bachmaier, 2012). The concept is illustrated using nitrogen fertilization for corn production in Eastern Canada.

Materials and Methods

A prototype DSS under development (Figure 1) consists of several key components: 1) a user interface, 2) a database, 3) access to public on-line resources, and 4) a numeric simulation engine. The DSS supports users in determining the most profitable fertilization scenario and/or scenario with the lowest expected risk of mismanagement penalties. Nitrogen application for corn in Eastern Canada is used to illustrate the initial structure of this DSS. This means that the system seeks to maximize the net return of the cost of nitrogen fertilization (NRCNF).

Through a mobile interface, the user specifies possible fertilization alternatives with respect to his/her specific crop growth environment, such as soil properties and management practices. These constitute the basic inputs used to construct alternative management scenarios. Complementary input values, such as weather and prices, as well as any additional data that could compensate for missing or limited information (e.g., public soil data), will eventually be retrieved from on-line sources. At the same time, previous observations pertaining to recorded trials will be entered in the database when available (Griffin *et al.*, 2008). The database, currently implemented in PostgreSQL V 9.6.0, already includes 320 records of yield data resulting from an extensive meta-analysis study (Tremblay *et al.*, 2012). Each record is specific to a site and a year and includes corn yield estimates matched to different nitrogen application rates as well as weather data, soil conditions, and management practices.

The heart of the DSS is composed of a record retrieval mechanism, an expected production function composer and an engine for the numeric computation of profits. The function of the record retrieval is to identify production records that are 'similar' in terms of context to the specific one defined by the user. As part of the specifications for development of the DSS, the

† E-mail: viacheslav.adamchuk@mcgill.ca

https://doi.org/10.1017/S2040470017000462 Published online by Cambridge University Press

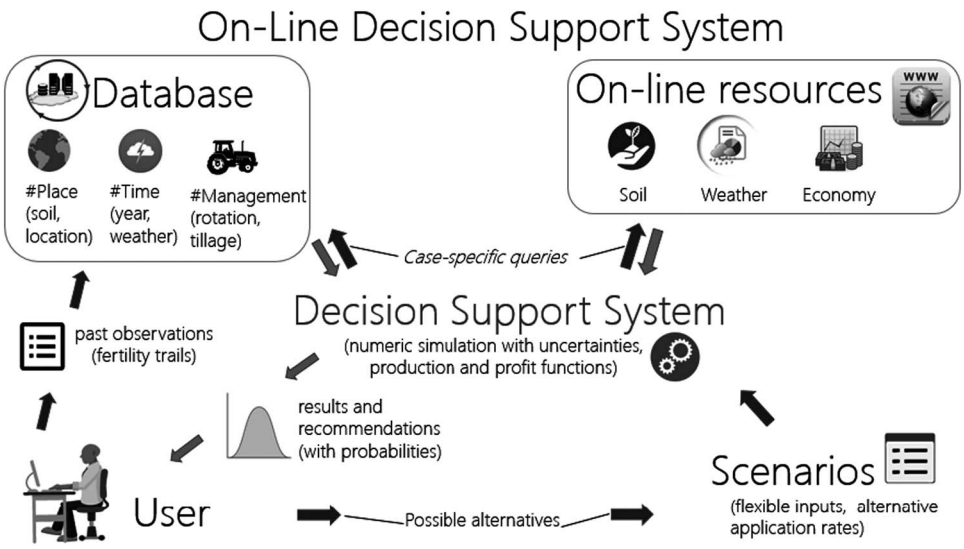


Figure 1 Architecture of the proposed decision support system.

retrieval of similar records has to be possible even in the absence of certain input information. In the current version of the prototype, records can be retrieved with SQL statements, based on soil texture, rain amount data class (i.e., 0–50 mm, 50–100 mm and 100 + mm) based on the concept of abundant and well distributed rainfall (AWDR) proposed by Tremblay *et al.* (2012) as well as tillage practices (i.e., till or no-till) and N contribution of preceding cultivar (e.g., weak, medium, strong).

Although the decision support system is able to accommodate different production function models, in the current version, the production function was modeled using a quadratic-plateau (QP) approach, which is known to be a good fit with biological response (Bullock and Bullock, 1994; Bongiovanni and Lowenberg-DeBoer, 2000; Adamchuck, 2013). Thus, yield response to nitrogen fertilization was defined as:

$$Y = \begin{cases} a_0 + a_1 N + a_2 N^2 & for \quad N < N_{Y\,max} \\ a_0 + a_1 N_{Y\,max} + a_2 N_{Y\,max}^2 & for \quad N \geq N_{Y\,max} \end{cases} \quad (1)$$

where Y is the crop yield (t ha^{-1}), N is the specified fertilizer application rate (kg ha^{-1}), N_{Ymax} is the minimum fertilizer application rate resulting in the maximum yield, and a_0, a_1 and a_2 are the coefficients of a second-order polynomial representation of yield response to N application rates below N_{Ymax}.

As shown in Figure 2, to define this production function in terms of yield response to fertilization from Y_0 (yield with no fertilization) to Y_{max} (maximum achievable yield), the coefficients of the second-order polynomial can be rewritten as:

$$a_0 = Y_0 \quad (2)$$

$$a_1 = \frac{2(Y_{max} - Y_0)}{N_{Y\,max}} \quad (3)$$

$$a_2 = \frac{Y_0 - Y_{max}}{N_{Y\,max}^2} \quad (4)$$

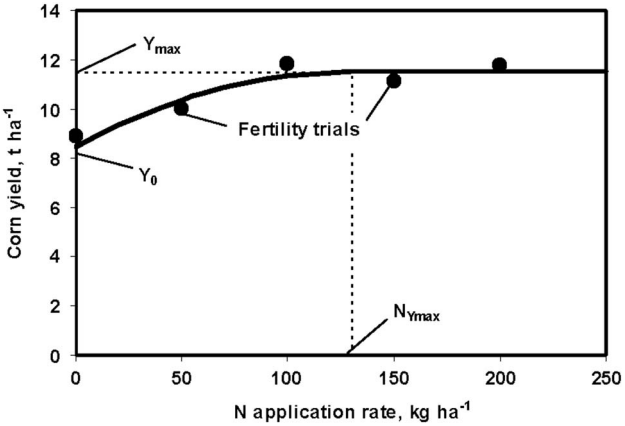


Figure 2 Example of a quadratic-plateau yield response model.

In its simple form, the objective function *NRCNF* (\$ ha^{-1}) can be defined using linear cost structure according to:

$$NRCNF = Y \cdot c_Y - N \cdot c_N \quad (5)$$

where c_Y is the price of harvested crop (\$ t^{-1}) and c_N is the cost of fertilization (\$ kg^{-1}).

The piecewise model described by equation (1) can be fitted using non-linear procedures like nlin in SAS (Tumusiime *et al.*, 2011) or nls in R (Rossiter, 2016). However, with these procedures, convergence is not always guaranteed, and a brute-force numerical approach constitutes an appealing alternative since it always leads to a best-fit model. This is computationally intensive and the approach that follows was used to accelerate the development of the current version of the DSS prototype. Parameters Y_0, Y_{max} and N_{Ymax} were first calculated in R using a brute-force approach for each fertility trial observation. Then, the probability distribution of each of these parameters for a given subset of observations has been used as the input for the numeric simulation. In this case, the discrepancies between the model parameter estimates have been treated as DSS input uncertainties. Similarly, costs c_Y and c_N were assumed to be

https://doi.org/10.1017/S2040470017000462 Published online by Cambridge University Press

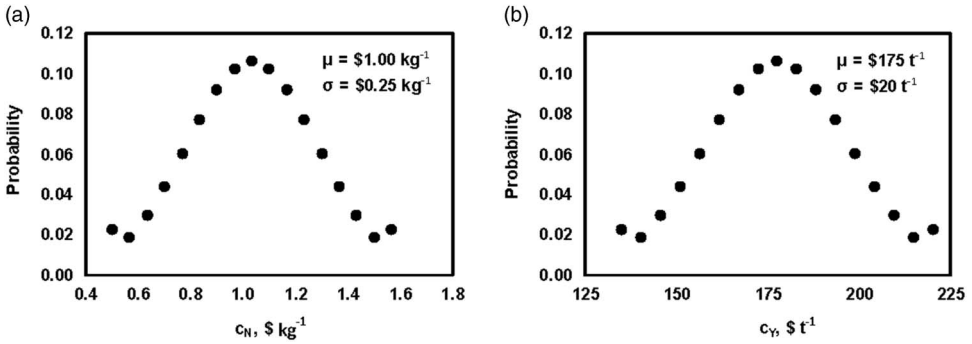


Figure 3 Distributions of the price of yield (a) and cost of fertilization (b) model inputs.

uncertain and based on historical data and/or economic forecasts.

As a result, the NRCNF was calculated for every potential N rate and every potential combination of values Y_0, Y_{max}, N_{Ymax}, c_Y and c_N. Assuming partial independence among these five inputs and estimated level of probability for each input value, the following equation has been used to calculate the expected NRCNF:

$$NRCNF_{est} = \sum_{i=1}^{N} (NRCNF_i \cdot p(NRCNF_i)) \qquad (6)$$

where N is the total number of combinations of discrete values of Y_0, Y_{max}, N_{Ymax}, c_Y and c_N. The individual $NRCNF_i$ and its probability $p(NRCNF_i)$ have been calculated using:

$$NRCNF_i = Y(Y_{0i}, Y_{\max i}, N_{Y\max i}, N) \cdot c_{Yi} - N \cdot c_{N_i} \qquad (7)$$

$$p(NRCNF_i) = p(Y_{0i}) \cdot p(Y_{\max i}) \cdot p(N_{Y\max i}) \cdot p(c_{Yi}) \cdot p(c_{Ni}) \qquad (8)$$

where $Y(Y_{0i}, Y_{maxi}, N_{Ymaxi}, N)$ is the yield function derived by combining equations (1) through (4), and $p(Y_{0i})$, $p(Y_{maxi})$, $p(N_{Ymaxi})$, $p(c_{Yi})$ and $p(c_{Ni})$ are the probabilities of each individual value of model parameter. Naturally, it should be noted that:

$$\sum_{i=1}^{N} p(NRCNF_i) = 1 \qquad (9)$$

To illustrate DSS performance, a set of input parameter distributions have been arbitrarily selected using the initial database and cost estimates. While assuming a normal distribution of input parameters, Figure 3 illustrates the probabilities associated with 17 different discrete values of c_Y and c_N. Similarly, yield response parameters (Y_0, Y_{max}, N_{Ymax}) were estimated using two distinct groups of fertility trials (fine-textured soil and coarse-textured soil) with relatively high levels of uncertainty. Figure 4 shows the probabilities associated with 17 different discrete values of each parameter for both types of soil conditions. With 17 values (15 intervals plus two distribution tails) for each of the five input variables, the total of N = 1 419,857 input combinations were calculated for every possible N application rate (from 0 to 200 kg ha^{-1} with 10 kg ha^{-1} increment). The always positive parameter Y_0 was constrained to be less then or equal to Y_{max} and the range for N_{Ymax} was restricted between 0 and 300 kg ha^{-1}.

The summary of probabilities associated with every possible value of NRCNF at any given application rate constitutes the basis for the model output. Report of $NRCNF_{est}$ for every application rate is a traditional way to determine optimum application rates. However, to assess the risk affiliated with different management scenarios, one can analyze the probability of profit being above a certain threshold and select the rate that is related to the anticipated profit with an acceptable level of probability.

Results and discussion

Based on the numeric simulation model parameters shown in Figures 3 and 4, the estimated NRCNF ($NRCNF_{est}$) is shown in Figure 5. Apparently, N = 150 kg ha^{-1} and N = 180 kg ha^{-1} were found to be the most profitable for fine- and coarse-textured soil, respectively. However, Figure 6 illustrates the probability for every combination of NRCNF and N application rate.

Apparently, according to Figure 6, higher application rates tend to increase NRCNF estimates with more uncertainty as compared to low application rates, when relatively low expected NRCNF is certain. Figure 7 interprets these NRCNF probability distributions in terms of probabilities to achieve a specific level of NRCNF. Thus, a relatively moderate rate of 100 kg ha^{-1} will result in NRCNF \$2000 ha^{-1} in approximately one out of three cases in the fine-textured soil. However, similar certainty to realize only \$1500 ha^{-1} NRCNF can be achieved with about 150 kg ha^{-1} application rate when managing coarse-textured soil.

As one would imagine, these examples illustrate results for very uncertain scenarios and more definite answers are expected once the model inputs are more accurately defined. As with many agricultural inputs, nitrogen fertilization has an asymmetrical negative impact on profit for applying higher and lower application rates than the estimated optimum. Under uncertain conditions and the current level of cost parameters, the probability of NRCNF reduction is higher when a lower than optimum nitrogen application rate is accepted and vice versa; the probability of severe economic loss for over-application is rather small.

https://doi.org/10.1017/S2040470017000462 Published online by Cambridge University Press

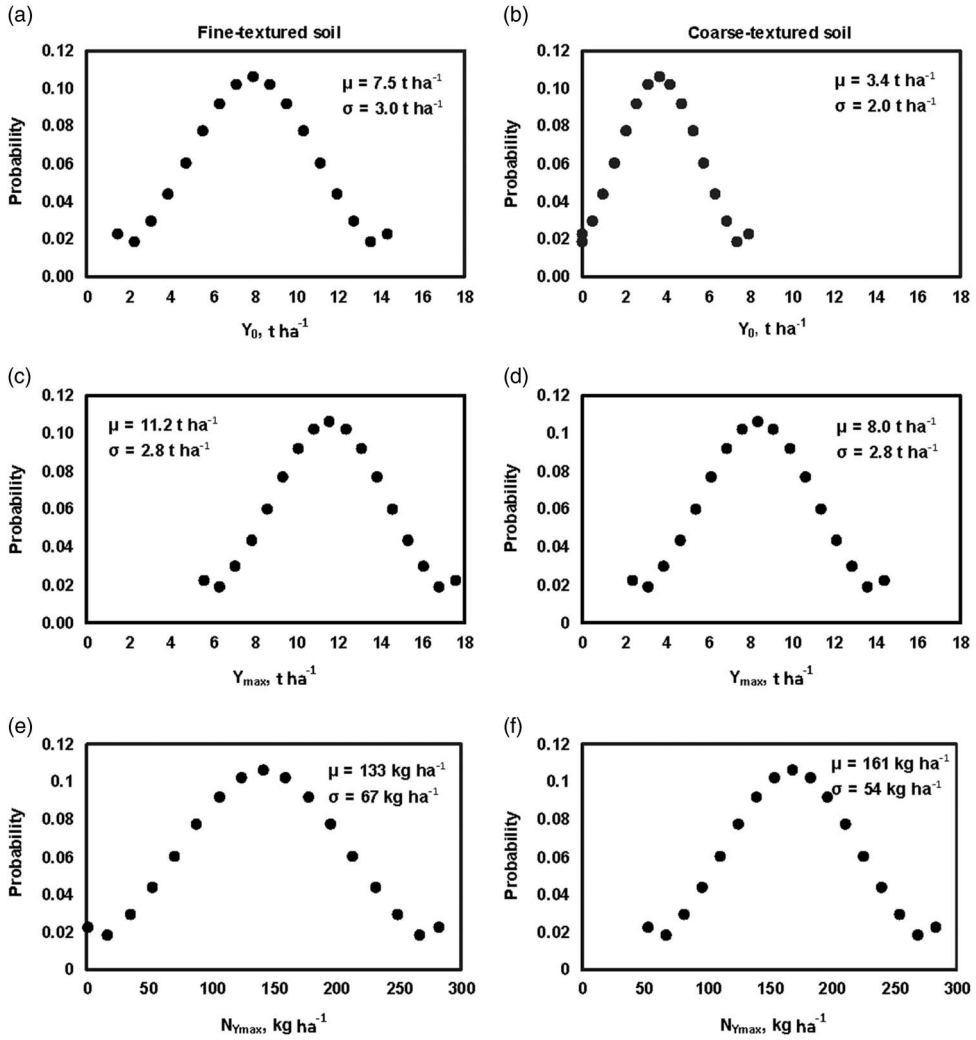


Figure 4 Distributions of zero fertilization yield (a and b), maximum yield (c and d) and minimum N application rate to achieve maximum yield (e and d) for fine-textured (a, c, and e) and coarse-textured (b, d, and f) soil production scenarios.

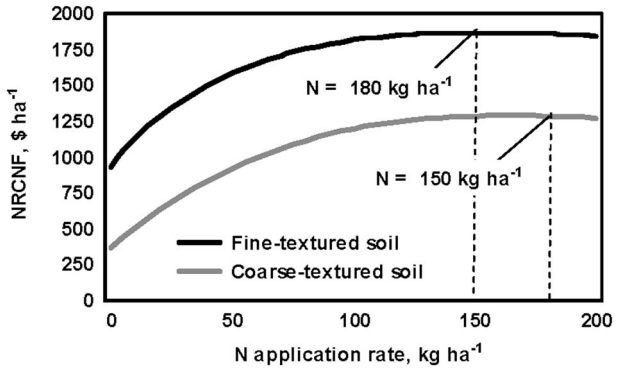


Figure 5 Expected NRCNF for two different soil conditions.

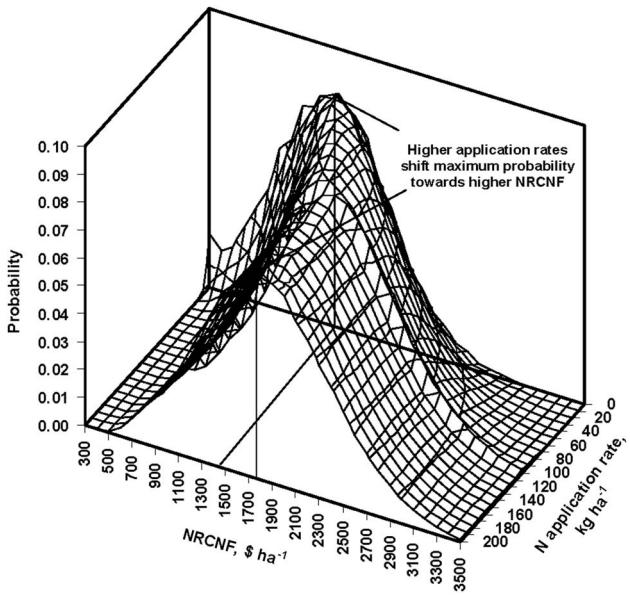


Figure 6 NRCNF probability for an array of possible application rates and a specific management scenario.

Conclusion

The proposed decision support system enables the determination of the optimum average application rate that maximizes expected profits (net return over cost of fertilization) or to define the range of such rates for a case of variable rate application. Uncertainty-based treatment of each model input and dynamic

https://doi.org/10.1017/S2040470017000462 Published online by Cambridge University Press

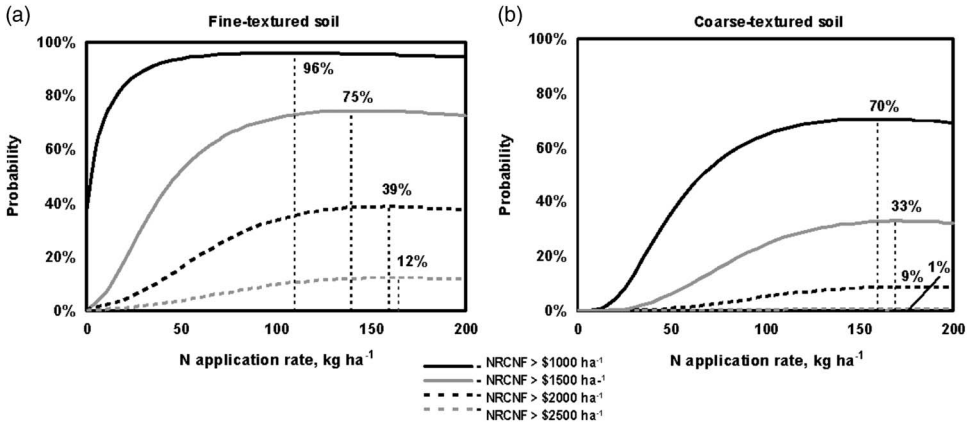


Figure 7 Probabilities of classes of profits for fine and coarse texture soils.

data exchange with the underlying production function database constitute the unique features of this algorithm. Its implementation has the potential to provide a balance between expected profit losses from potential under-application and over-application errors when it comes to the economics of modern crop production systems.

Acknowledgements

This research was supported in part through Agriculture and Agri-Food Canada and Fertilizer Canada Agri-Innovation Program 'A Canadian Research Network to Improve 4R Nutrient Stewardship for Environmental Health and Crop Production.'

References

Adamchuck VI 2013. Theoretical basis for sensor-based in-season nitrogen management. In: Precision Agriculture: Papers from the 9th European Conference on Precision Agriculture, ed. J. Stafford, Wageningen Academic Publishing, Wageningen, The Netherlands, pp. 403–410.

Adamchuck VI, Morgan MT and Lowenberg-Deboer J 2004. A model for agro-economic analysis of soil pH mapping. Precision Agriculture 5 (2), 111–129.

Anselin L, Bongiovanni R and Lowenberg-DeBoer J 2004. A spatial econometric approach to the economics of site-specific nitrogen management in corn production. American Journal of Agricultural Economics 86 (3), 675–687.

Bachmaier M 2012. Sources of inaccuracy when estimating economically optimum N fertilizer rates. Agricultural Sciences 3 (3), 331–338.

Bongiovanni R and Lowenberg-DeBoer J 2000. Economics of variable rate lime in Indiana. Precision Agriculture 2 (1), 55–70.

Bullock G and Bullock DD 1994. Quadratic and quadratic-plus-plateau models for predicting optimal nitrogen rate of corn: a comparison. Agronomy Journal 86, 191–195.

Griffin T, Dobbins C, Vyn T, Florax R and Lowenberg-DeBoer J 2008. Spatial analysis of yield monitor data: Case studies of on-farm trials and farm management decision making. Precision Agriculture 9 (5), 269–283.

Holland KH and Schepers JS 2010. Derivation of a variable rate nitrogen application model for in-season fertilization of corn. Agronomy Journal 102 (5), 1415–1424.

McBratney AB, Whelan BM and Shatar TM 1997. Variability and uncertainty in spatial, temporal and spatiotemporal crop-yield and related data. In: Novartis Foundation Symposium, Ciba Foundation, pp. 141–160.

Rossiter DG 2016. Technical note: Curve fitting with the R environment for statistical computing. http://www.css.cornell.edu/faculty/dgr2/teach/R/R_CurveFit.pdf (accessed on November 11, 2016).

Samborski SM, Tremblay N and Fallon E 2009. Strategies to make use of plant sensors-based diagnostic information for nitrogen recommendations. Agronomy Journal 101 (4), 800–816.

Tremblay N, Bouroubi YM, Bélec C, Mullen RW, Kitchen NR and Thomason WE 2012. Corn response to nitrogen is influenced by soil texture and weather. Agronomy Journal 104 (6), 1658–1671.

Tremblay N, Bouroubi YM, Panneton B, Guillaume S, Vigneault P and Bélec C 2010. Development and validation of fuzzy logic inference to determine optimum rates of N for corn on the basis of field and crop features. Precision Agriculture 11 (6), 621–635.

Tumusiime E, Brorsen BW, Mosali J, Johnson J, Locke J and Biermacher JT. 2011. Determining optimal levels of nitrogen fertilizer using random parameter models. Journal of Agricultural and Applied Economics 43 (4), 541–552.

https://doi.org/10.1017/S2040470017000462 Published online by Cambridge University Press