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Evaluation of statistical and process-based models as nitrogen recommendation tools in maize production systems

by

Laila Alejandra Puntel

A dissertation submitted to the graduate faculty

in partial fulfillment of the requirements for the degree of

DOCTOR OF PHILOSOPHY

Major: Crop Production and Physiology

Program of Study Committee:
Sotirios V. Archontoulis, Major Professor
John E. Sawyer
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The student author, whose presentation of the scholarship herein was approved by the program of study committee, is solely responsible for the content of this dissertation. The Graduate College will ensure this dissertation is globally accessible and will not permit alterations after a degree is conferred.

Iowa State University
Ames, Iowa
2018

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“Wisdom is not a product of schooling but of the lifelong attempt to acquire it”

Albert Einstein
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ACKNOWLEDGMENTS

I would like to thank my committee chair, Sotirios Archontoulis, and my committee members, Michael Castellano, John Sawyer, Ken Moore, Emily Heaton, and Peter Thorburn, for their guidance and support throughout the course of this research.

In addition, I would also like to thank my family, friends, colleagues, the department faculty, and staff for making my time at Iowa State University a wonderful experience. I want to also offer my appreciation to those farmers who were willing to participate in my field experiments, without whom, the last study of this thesis would not have been possible.
ABSTRACT

Optimizing nitrogen (N) management in maize (Zea mays L.) production systems is critical and essential to ensure profitability, productivity, and environmental sustainability. However, it represents a challenge because N is highly mobile within the soil-plant-atmospheric system. Therefore finding the optimum N rate for maize is a difficult task. The overall goal of this research was to evaluate crop model and statistical-based approaches to making N recommendations for maize and quantify prediction accuracy in two major maize production regions: Iowa, USA and Buenos Aires, Argentina. I addressed three questions: 1) how accurately process-based modeling and statistical based approaches can simulate yields and optimal N rates, 2) how does the accuracy change when models are used as a forecasting tools (with limited input data), and 3) which soil, crop, and atmospheric variables are most important to improve understanding of optimum N rate variability from year-to-year and from field-to-field? Data to test crop model predictions included yield response to N from a 16-year field experiment conducted in central Iowa, USA with two crop rotations totaling 31 N-trials. Data to test statistical models included a 5-year yield response to N from central-west Buenos Aires, Argentina with different rotations, soil properties, and landscape positions totaling 51 trials. The statistical-based approach predicted optimal N rates with higher accuracy than process-based models (root mean square error, RMSE of 42 vs 62 kg N ha\(^{-1}\), respectively). Yields that were predicted at the end of the season had a RMSE that ranged from 1 to 1.3 Mg ha\(^{-1}\). The accuracy of yield predictions at planting decreased more for optimal N rates when using process-based models. Optimal N rate at planting was predicted with similar accuracy to that predicted at the end-of-season (RMSE 60 and 47 kg N ha\(^{-1}\) for process- and statistical-based approach, respectively). Lastly, I found that the spring precipitation (April to June) and the precipitation
events greater than 20 mm accumulated from planting to silking highly explained the variability in optimal N rates in both central Iowa and in central-west Buenos Aires.
CHAPTER 1. OVERVIEW

To meet the food, fuel, and fiber demand of a growing population while proving adequate financial returns to farmers and protecting the environment, modern agriculture will rely on obtaining higher yields per unit of land area over the next few decades (Robertson and Swinton 2005; Tilman et al., 2011). Among production systems, corn (Zea mays L.) is the most important commodity for sustaining the world population. Maize grain production at global scale was 1.04 billion metric tons in 2017/18 (FAO-AMIS), 25% higher than a decade ago and 65% higher than 30 years ago. Due to the importance of maize in food production systems and more recently, because of its use as a biofuel, the global capacity to produce grains will have to further increase to cope with the increasing demand (Bruinsma, 2009; Cassman, 2012; Godfray et al., 2010; Tilman et al., 2002; van Ittersum et al., 2013).

Nitrogen (N) is an essential, and often limited, nutrient in corn production systems. Fertilization with N is critical to achieving high yields and quality (Scharf, 2015). However, because of the highly mobile nature of N in the soil, matching N supply and crop N demand to minimize N losses is difficult to achieve, resulting in environmental issues mostly related with water quality. For example, farmers in developed countries view fertilizer application as a risk-avoidance measure and, in many cases tend to over-fertilize crops (e.g. USA Corn’s Belt). The environmental costs of over applying fertilizer N are highlighted by iconic examples of hypoxia in the Gulf of Mexico and Chesapeake Bay (Ribaudo et al., 2011). In some other countries, such as Argentina, the use of N inputs is limited (mainly due to its cost), producing a negative nutrient balance in the soil contributing to degradation of soil fertility (Townsend and Howarth 2010; Sutton et al., 2013). Thus, N management strategies that could result in a more efficient and optimal use of N sources are central to address the challenges of modern agriculture.
Managing N and estimating optimum N fertilization rate is complex because of multiple interactions that exist in the dynamic soil-plant-atmosphere system and uncertainty in weather (Havlin et al., 2005; Tremblay and Belec, 2006; Brady and Weil, 2008). Although researchers have invested efforts and considerable resources to understand the complexity associated with N management, the uncertainty is still substantial (Scharf, 2015). The problem is further complicated by accounting for spatial variations in soil N contribution, fertilizer losses and crop N uptake from field to field and even place to place within a field. Nitrogen mineralization of soil organic matter may vary because of differences in soil temperature and moisture, or differences in previous crop residues (Scharf, 2015). Nitrogen leaching loss can vary mainly because of difference in topography and soil hydrological properties (Prasad et al., 2015). The crop N fertilizer needs can vary with many factors including cultivars having different yield potential (Mamo et al., 2003), and different seeding rates. Because of these complexities, a fast and accurate diagnostic tool for predicting the optimal N rate for a given field is needed (Ma and Biswas, 2015; Scharf, 2015).

Most of the widely adopted N recommendation tools are static in that they give the same recommendation regardless of yearly weather or crop/fertilizer prices, or evaluate N status after grain crop harvest (e.g. yield goal-based N recommendations, Stanford et al., 1973); soil nitrate test, Bundy and Adraski, 1995). Furthermore, the majority of existing tools also assume field-uniformity, recommending N applications that ignore variation in landscape and edaphic factors such as topography, soil texture, and organic matter (Cassman et al., 2002; Mamo et al., 2003; Scharf, 2015), as well as interactions with plant population and hybrid (Ciampitti and Vyn, 2012).
Existing N management approaches are based on crop models (process based) and statistical approaches. The two approaches have different strengths and weaknesses. Dynamic cropping system simulation models such as Agricultural Production Systems sIMulator (APSIM; Holzworth et al., 2014) are an alternative to static N management approaches. Crop models simulate many processes within the soil-crop system in response to genotype x management x environment across temporal and spatial scales, having the potential to find optimum solutions to better synchronize N fertilizer application with crop N demand (Cassman et al. 2002; Keating et al., 2003; Scharf 2015). Crop models have been used to investigate soil-crop-weather dynamics, to improve our understanding of N dynamics and to answer questions that cannot be addressed with field research due to time and cost constraints (Batchelor et al., 2002). Process-based cropping system models have demonstrated capabilities to explain causes of optimal N rate variability and perform scenario analyses (Gowda et al., 2008; Nangia et al., 2008; Thorp et al., 2007).

While dynamic cropping systems models are promising tools to reduce the uncertainty around optimal N, practical application and scalability of crop models can be limited because models typically require: (a) a large number of input parameters, which are usually not available (Wallach, 2006; Basso et al., 2012); (b) particular skills to develop model specific input parameters and cultivar coefficients from internet databases; (c) intensive training to use effectively, and d) site specific calibration. Furthermore, crop models were not designed for site-specific N management recommendations, even though they are being used for this purpose (Chang et al., 2004; Koch et al., 2004). Therefore, there is a need to evaluate their prediction accuracy when applied across different scales (within fields, regions, and cropping systems) (Kersebaum et al., 2005; Nendel et al., 2013).
As opposed to process-based model approaches, more empirical approaches based on multiple regression have been proposed to estimate spatial and temporal variations of optimal N rate. Initial studies have focused on relating static measurements of soil (change slowly over time; e.g. organic matter) with yield response to N fertilization, but they ignore the temporal interactions of management, soil properties, and environment (Liu et al., 2006; Ruffo et al., 2006). Thus, other studies related optimal N rates with dynamic variables (change rapidly over time; e.g. soil water) to account for temporal interactions (Gregoret et al., 2006). Although these approaches were demonstrated to be successful in explaining variability in yield response to N, the arbitrarily defined variables do little to help us understand the casual influences of such variation. Similar to crop-model-based approaches they have limitations with regard to the adoption of these tools when used outside of the range of variability on which they were calibrated. However, statistical based approaches usually require less input data, thus, facilitating their application and scalability to other locations with much more simplicity than crop simulation models.

Understanding which factors or synergic relationships contribute the most to variability in the optimal N response is complex and still elusive (Scharf 2015). Studies comparing the relative importance of different static and dynamics factors on corn yield and optimal N rates are rare. Some of these variables are being measured on farm or they are available to farmers, however, the accuracy of these variables to predict optimal N rates is still unclear. Identifying the main variables within the complex agronomic system that affect yield most and optimal N response is a necessary step to inform future N studies on scaling up and improving accuracy of crop simulation models. Better N management adapted to the local production environment can
lower N fertilizer rates without yield losses, and thereby reduce N surplus and pollution and its cost to society.

The next three chapters of this dissertation investigate process and statistical approaches to making N management recommendations in two major corn production areas, Iowa (USA) and Central-West Buenos Aires (Argentina, Figure 1.1). I examine the factors controlling the temporal and spatial variability of yields and optimal N rates. By using a long-term experiment from Central Iowa coupled with the APSIM model, I explored how well the cropping system model can simulate crop yield, N dynamics, and economic optimum N rate (EONR). I attempt to answer the question “if the model could predict corn response to N rate, how could this information be used to develop better N rate guidelines (Chapter 2)?” Next, I assessed the prediction accuracy of a well calibrated crop model as an in-season forecast tool (Chapter 3). In Chapter 4, I developed a new recommendation model for central-west Argentina using experimental data with advanced statistical techniques. More specifically, I combined dynamic (change rapidly over time, e.g. soil water) and static (fairly stable, e.g. soil organic matter) variables to explore their relative importance on optimal N rate, and used the most important variables to build a statistical model. In the final chapter, I summarized the main findings of this research and offer concluding remarks (Figure 1.1).
Figure 1.1 Thesis diagram

References


CHAPTER 2. MODELING LONG-TERM CORN YIELD RESPONSE TO NITROGEN RATE AND CROP ROTATION

https://doi.org/10.3389/fpls.2016.01630

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Abstract

Improved prediction of optimal N fertilizer rates for corn (*Zea mays* L.) can reduce N losses and increase profits. We tested the ability of the Agricultural Production Systems iMulator (APSIM) to simulate corn and soybean (*Glycine max* L.) yields, the economic optimum N rate (EONR) using a 16-year field-experiment dataset from central Iowa, USA that included two crop sequences (continuous corn and soybean-corn) and five N fertilizer rates (0, 67, 134, 201, and 268 kg N ha⁻¹) applied to corn. Our objectives were to: (a) quantify model prediction accuracy before and after calibration, and report calibration steps; (b) compare crop model-based techniques in estimating optimal N rate for corn; and (c) utilize the calibrated model to explain factors causing year to year variability in yield and optimal N. Results indicated that the model simulated well long-term crop yields response to N (relative root mean square error, RRMSE of 19.6% before and 12.3% after calibration), which provided strong evidence that important soil and crop processes were accounted for in the model. The prediction of EONR was more complex and had greater uncertainty than the prediction of crop yield (RRMSE of
44.5% before and 36.6% after calibration). For long-term site mean EONR predictions, both calibrated and uncalibrated versions can be used as the 16-year mean differences in EONR’s were within the historical N rate error range (40–50 kg N ha\(^{-1}\)). However, for accurate year-by-year simulation of EONR the calibrated version should be used. Model analysis revealed that higher EONR values in years with above normal spring precipitation were caused by an exponential increase in N loss (denitrification and leaching) with precipitation. We concluded that long-term experimental data were valuable in testing and refining APSIM predictions. The model can be used as a tool to assist N management guidelines in the US Midwest and we identified five avenues on how the model can add value toward agronomic, economic, and environmental sustainability.

**Introduction**

The economic optimum nitrogen (N) rate (EONR) is the fertilizer rate at which crop yield increase is not large enough to pay for additional N application, and therefore more N would only result in unnecessary costs (Sawyer et al., 2006). Optimal N input needs to be considered when making N recommendations since it has the potential to improve N use efficiency, crop yield, and profitability as well as to reduce environmental impacts (Wang et al., 2003; Lawlor et al., 2008; Kyveryga et al., 2009; Basso et al., 2016). Nitrogen losses by leaching are proportional to the N rate applied and tend to increase rapidly at rates greater than optimal for crop use (Haghiri et al., 1978; Cooper and Cooke, 1984; Andraski et al., 2000; Randall et al., 2000).

There is tremendous uncertainty and risk associated with prediction of the EONR in corn–based systems, both at the field and sub-field scale (Paz et al., 1999; Scharf et al., 2005; Tremblay et al., 2012). Farmers may attempt to protect corn yield potential with high fertilizer N inputs, which leads to decreased profitability (Lambert et al., 2006) and increased likelihood of
environmental contamination (Andraski et al., 2000; Jaynes et al., 2001; Robertson and Groffman, 2007).

A number of approaches have been developed to predict optimal N application rates. These include yield goal-based N recommendations and N budgets (Stanford, 1973, 1982; Stanford and Legg, 1984), pre-plant and pre-sidedress soil nitrate test (PPNT and PSNT, Bundy and Andraski, 1995; Shapiro et al., 2008), Illinois soil nitrogen test (ISNT, Mulvaney et al., 2001), crop canopy sensing (NDVI, Schmidt et al., 2009 and chlorophyll meter, Blackmer and Schepers, 1995; Varvel et al., 1997), and economic maximum return to N (MRTN, Sawyer et al., 2006). Some of these tools are static in that they give the same recommendation regardless of yearly weather or crop/fertilizer prices, or evaluate N status after grain crop harvest. Soil tests or hand-held crop meters are often time consuming, expensive, and/or require periodic and intense sampling (Blackmer et al., 1997; Ma and Dwyer, 1999; Grove and Schwab, 2006; van Es et al., 2007; Lemaire et al., 2008; Franzen et al., 2016). Most current and widely adopted N management practices also assume field-uniformity, recommending N applications that ignore variation in landscape factors such as topography, soil texture, and organic matter (Cassman et al., 2002; Mamo et al., 2003; Scharf et al., 2005), as well as interactions with plant population and hybrid (Ciampitti and Vyn, 2012). Use of precision agriculture technologies (real-time remote sensing, unmanned aerial images, soil mapping, etc.) combined with variable N application have the potential to increase N use efficiency by matching the N requirements within field zones (Dobermann and Cassman, 2002; Ferguson et al., 2002; Mamo et al., 2003; Mulla, 2013). However, the selection of a site-specific optimum N rate is difficult to predict based on the large temporal and spatial variability of the N supply and demand (van Es et al., 2007; Setiyono et al., 2011). Unfortunately, the above approaches have not fully resolved needed
improvements from N management and gains in N use efficiency (Raun and Johnson, 1999; Fageria and Baligar, 2005) since N losses from corn-based systems are still high with negative environment impacts (Jaynes et al., 2001; Mitsch et al., 2001).

The challenge in managing N and estimating the optimum N fertilization rate comes from the complex interactions that exist in the dynamic soil-plant-atmosphere system and uncertainty in weather (Havlin et al., 2005; Tremblay and Belec, 2006; Brady and Weil, 2008). Soil N mineralization from SOC and crop N uptake, and N losses are three important components defining the optimum N rate, however, these processes are dynamic and difficult to predict (Cassman et al., 2002). Therefore N management tools that simultaneously consider dynamics in soil organic carbon mineralization, crop growth, weather conditions, and agronomic practices may greatly improve site- and year-specific EONR estimates (Basso et al., 2012, 2016; Dumont et al., 2016). Dynamic cropping system simulation models such as Agricultural Production Systems sIMulator (APSIM; Holzworth et al., 2014), DSSAT (Jones et al., 2003), RZWQM (Ahuja et al., 2000), CropSyst (Stockle et al., 2003), SALUS (Basso et al., 2006), and others have been used to investigate soil-crop-weather dynamics, however, model use has been limited to address long-term optimum N rates (Ma et al., 2007; Basso et al., 2010). The scientific literature is also rich with examples of model applications to improve our understanding of N dynamics and to answer questions that cannot be addressed with field research due to time and cost constraints (Batchelor et al., 2002; Schnebelen et al., 2004; Fountas et al., 2006; Malone et al., 2010; Basso et al., 2012, 2016; Anapalli et al., 2014). However, use of models in practical applications to assist real-life challenges such as N rate guidance is limited because models typically require: (a) a large number of input parameters, which are usually not available
(Wallach, 2006; Basso et al., 2012); (b) particular skills to develop model specific input parameters and cultivar coefficients from internet databases; and (c) intensive training for use.

Over the last few years web-applications have been developed to simplify the use of models (e.g., Yield Prophet, Carberry et al., 2009). Furthermore, digital soil and weather databases such as web soil survey1 (Soil Survey Staff, 2006) and daymet (Daymet, 1980–2008; Thornton et al., 2012) provide free access to high-resolution input parameters. As a result, the potential of using simulation models to assist with real-life practical problems and especially to predict the risk associated with selecting specific N fertilizer rates has received strong industrial interest (Thorp et al., 2007; Gowda et al., 2008; Nangia et al., 2008). The next challenge to applying models across different scales (within fields, regions, and cropping systems) is to determine prediction accuracy; e.g., how well cropping system models can predict crop yield, N dynamics, and EONR. And if they can predict corn response to N rate, how can this information be used to develop better N rate guidelines.

In this study we used a 16-year field research dataset from a site in central Iowa, USA that included five N rates and two crop sequences to test the ability of the APSIM model (Holzworth et al., 2014) to predict crop yields and optimal N rate for corn.

Objectives

Our specific objectives were to: (a) quantify model prediction accuracy before and after calibration, and report calibration steps; (b) compare crop model-based techniques in estimating optimal N rate for corn; and (c) utilize the calibrated model to explain factors causing year to year variability in yield and optimal N.
Materials and Methods

Site, Weather, and Experimental Datasets

The field-experiment was conducted at the Agricultural Engineering and Agronomy Research Farm near Ames, Iowa, USA (42° 0′37.50″N, 93°47′22.98″W) on a Clarion loam soil (fine-loamy, mixed, superactive, mesic Typic Hapludoll). The experiment was initiated in 1999 and continuous to the present. For this study we used data from 1999 to 2014 (16-years). The climate at the site is humid continental (warm, rainy summers) with annual precipitation of 900 mm and a mean temperature of 9°C (Supplementary Figure S1). Over the 16-year experimental period, crops experienced warm and wet conditions (3 years), cool and wet conditions (3 years), warm and dry conditions (5 years), and cool and dry conditions (5 years; Supplementary Figure S1). Years 2008, 2010, and 2014 were the wettest and years 2000, 2011, 2012, and 2013 the driest. Mean annual air temperatures were 16 and 23°C for spring and summer, respectively. Year 2012 was the warmest and year 2008 the coolest (Supplementary Figure S1).

The long-term experiment was designed to study the effect of five N fertilizer rates (0, 67, 134, 201, and 268 kg N ha$^{-1}$; hereafter N0, N67, N134, N201, and N268, respectively) on corn yield in continuous corn (CC) and soybean-corn rotation (SC). The experimental design was a randomized complete block design with four replications. Nitrogen fertilizer was applied near planting (± 10–15 days). Specific information on the fertilizer type and application dates are provided in Supplementary Table S1. Within the SC rotation, corn and soybean phases were present each year in the rotation: thus a simulation starting with corn in year one and another simulation starting with soybeans on year one were set up. Hereafter SC when the rotation starts with corn in year one (odd numbered years) and a validation set (SC_val) when the rotation starts with soybean in year 1 (even numbered years). Each treatment had four replications. Nitrogen fertilizer was only applied to corn. Supplementary Table S1 provides management information
by year and rotation. Measurements included corn and soybean grain yields each year (expressed at 15.5 and 13% moisture content, respectively). Soil organic carbon measurements were available at 0–15 cm in 1999, 2009, and 2014, and at 0–30 cm in 2009 for CC (Brown et al., 2014; Poffenbarger et al., unpublished).

**The APSIM Modeling Platform**

The APSIM (Keating et al., 2003; Holzworth et al., 2014) is an open-source advanced simulator of agricultural systems that combines several process-based models in a modular design. APSIM is a field-scale model that operates mainly on a daily time step. The APSIM model was selected for use in this study because of its flexibility and easy use in specifying crop rotations via the user interface, capability in simulating long-term dynamics in both soil and crop processes, advanced flexibility in simulating the effect of shallow water table dynamics that are important in this geographic region (Helmers et al., 2012) and previously determined good performance in this geographic region (Malone et al., 2007; Hammer et al., 2009; Lobell et al., 2013; Archontoulis et al., 2014a,b, 2016; Basche et al., 2016; Dietzel et al., 2016; Martinez-Feria et al., 2016). Details about APSIM and its performance across a range of studies can be found at http://www.apsim.info.

**APSIM Configuration and Calibration**

Two rounds of APSIM model evaluations were performed; a blind phase (uncalibrated model) where management and cultivar information were used, and a calibrated phase (calibrated model) where crop yield and SOC data were provided into the model. Similar protocols have been used in the AgMIP project (Agricultural Model Inter-Comparison and Improvement Project; Rosenzweig et al., 2013).
**Blind-Phase Model Parameters and Set-Up**

For the blind phase, we first incorporated available management information into APSIM (Supplementary Table S1). When required management information was unavailable, we used typical values from the literature relevant to the research site (Abendroth et al., 2011; Pedersen and Licht, 2014). The following input parameters were held constant across the 16-years: planting depth of 5 cm for both crops, plant populations of 8 and 38 plants m$^{-2}$ for corn and soybean, respectively, and November 10th and April 10th dates for fall and spring tillage operations; and corn hybrid (106-day) and soybean variety (2.5 maturity group) values derived from previous studies in the region (Archontoulis et al., 2014a,b; Supplementary Table S2). Daily weather data were obtained from the Iowa Environmental Mesonet (2014). Soil profile information was taken from Web Soil Survey (Soil Survey Staff, 2006) and soil-root related parameters were developed following the methodology described in Archontoulis et al. (2014a). The maximum rooting depths for corn and soybean were set to 1.5 and 1.2 m, respectively.

We set up APSIM by connecting the following models: corn and soybean crop models (Keating et al., 2003), Soil N (soil N and C cycling model with default soil temperature model; Probert et al., 1998), SoilWat (a tipping bucket soil water model; Probert et al., 1998); SURFACEOM (residue model; Probert et al., 1998; Thorburn et al., 2001, 2005), and the following management rules: planting, harvesting, fertilizer, tillage, and rotations (Keating et al., 2003). In addition we implemented within the MANAGER module an N deposition rule that simulates atmospheric N deposition as a function of daily precipitation (N deposition in kg N ha$^{-1}$ d$^{-1}$ = 0.01 * precipitation in mm; Holland et al., 2005). On average, this added about 7 kg N ha$^{-1}$ year$^{-1}$ into the system. Initial model conditions such as root mass, surface residue mass, soil water, soil nitrate, and SOC pool partitioning were obtained by starting the model 6 years prior to the start of the experiment (Supplementary Table S3). Experience using APSIM in this
geographic region for simulating corn-soybean production systems has indicated that the fast microbial SOC pool (BIOM) of APSIM requires at least 4 years to stabilize (Basche et al., 2016; Dietzel et al., 2016; Martinez-Feria et al., 2016). Having this pool stabilized is important to remove confounding effects of microbial SOC buildup or decline which affects N dynamics. The APSIM version 7.6 was used on a daily time step. The simulation process was consecutive to account for carry-over effects from year to year, such as soil inorganic nitrogen, soil moisture, root and residue carbon and nitrogen inputs from previous crops.

Model Calibration and Testing

In the calibration and testing phase, we used end-of-season grain yields and SOC data to improve predictions. The long-term (end-of-season) data are powerful in detecting weakness in the model (i.e., years with low prediction accuracy), but do not provide guidance on which of the model’s processes or parameters needed to be improved. Therefore, to inform the calibration process, additional information was used: knowledge gained from other APSIM calibration studies in Iowa (Archontoulis et al., 2014a, 2016; Basche et al., 2016; Dietzel et al., 2016), sensitivity techniques, and model behavior analysis coupled with expert judgment (Supplementary Figure S2). The odd-numbered years (for CC and SC) were used for calibration and even numbered years for validation (SC_val dataset).

During calibration the following changes in APSIM were made: first, we replaced the default APSIM soil temperature model that uses EPIC model equations (Williams et al., 1984) with a more mechanistic soil temperature model (Campbell, 1985) available in APSIM (soiltemp2). The reason was twofold: (a) soiltemp2 has been found to perform better in Iowa (Archontoulis et al., 2014a; Basche et al., 2016; Dietzel et al., 2016); and (b) soiltemp2 better represents reality than the default model as it accounts for soil temperature changes due to tillage, residue cover, and management practices. Second, we replaced SoilWat with the SWIM
soil water model (Huth et al., 2012) available in APSIM. This model allowed simulation of fluctuating shallow groundwater tables, which in this region varies from about 80 to 200 cm (Groundwater, USGS, Iowa Water Science Center). Third, we improved the simulation of soybean residue C:N ratio at harvest because the simulated C:N ratio was low when compared to published data (Johnson et al., 2007) and caused an over-prediction of corn yields in the SC rotation with no N applied. We improved soybean C:N ratio by decreasing the critical N concentration of different plant tissues at physiological maturity by about 20% (Supplementary Table S2). Additionally, we decreased the potential N fixation rate (Supplementary Table S2) to better match seasonal N fixation estimates to those observed in the literature for this region (Salvagiotti et al., 2008). No changes were made in the corn crop model, although various options were explored via sensitivity analysis. Given all these changes we re-initialized conditions at the start of the simulation on year 1999 (Supplementary Table S3).

**Data Analysis**

**Estimation of the Annual Economic Optimum Nitrogen Rate**

The relationship between observed or simulated yield and N rate was fit using the quadratic

Equation 1  \[ y = a + bx + cx^2 \]

or the quadratic-plus-plateau,

Equation 2  \[ y = a + bx + cx^2, \quad x < x_0 \]

Equation 3  \[ y = a + bx_0 + cx_0^2, \quad x \geq x_0 \]

In these equations, \( y \) represents corn yield (either observed or simulated), \( x \) is the fertilizer N rate, \( a \) is the intercept, \( b \) is the linear coefficient, \( c \) is the quadratic coefficient, and \( x_0 \) is the N rate at the join point. The PROC NLIN procedure in SAS (Version 9.4, SAS, 2013).
Equations were deemed significant at $p < 0.05$ and the equations with the smallest sums of squares and largest $R^2$ were selected.

Corn EONR and the yield at the EONR (YEONR) were calculated from the N response equations by setting the first derivative of the fitted response curve equal to the historical price ratio of 5.6:1 N:corn grain price (US$ kg$^{-1} N:US$kg$^{-1} grain) ratio (Cerrato and Blackmer, 1990; Bullock and Bullock, 1994). The impact of the N:corn grain price ratio on EONR has been well documented in the literature (Cerrato and Blackmer, 1990; Sawyer et al., 2006). In this study, we used a fixed ratio across years similarly to other modeling studies (Basso et al., 2012). Using this approach, we calculated EONR and YEONR values for: (a) the observed data (EONR-Obs, YEONR-Obs); (b) the simulated data from the uncalibrated model (EONR-APSIM-Unc, YEONR-APSIM-Unc); and (c) the simulated data from the calibrated model (EONR-APSIM-Cal, YEONR-Cal).

Additionally, a different technique to calculate an optimal N rate was used (Basso et al., 2016). The calibrated APSIM model was ran for every 5 kg N ha$^{-1}$ increments from 0 to 350 kg N ha$^{-1}$ to simulate corn yields. Then the N rate at which the economic return on N was maximized [hereafter RTN (return to N approach)-APSIM] was estimated by difference: simulated yield times corn price minus fertilizer rate times N cost between two levels of N rate. A value of zero (or near zero) corresponds to the optimum N rate. Same prices for corn grain and N fertilizer was used as with the EONR technique.

The RTN-APSIM technique differs from the EONR-APSIM-Cal in the following way: EONR-APSIM-Cal estimates the economic optimum N rate through regression equations (Equation 1-3) fitted to five simulated corn yields at 0, 68, 134, 200, and 268 kg N ha$^{-1}$. The RTN-APSIM uses the ability of APSIM to run on any desired N rate increment to predict corn
yield (every 5 kg N, from 0 to 350 kg N ha\(^{-1}\)) and therefore the economic optimum N rate can be identified without use of regression equations. The RTN approach follows a similar methodology to that is currently used for corn N rate recommendations in the USA Midwest (known as the MRTN approach; Sawyer et al., 2006). The difference between RTN-APSIM and MRTN is that the regression equations for MRTN are within a database with extensive N rate response trials and associated regression equations, while RTN-APSIM generates a synthetic database, which depends on the accuracy of the model to predict yields and N response.

**Estimation of Site Mean Economic Optimum Nitrogen Rate**

Two methods were used to estimate the site mean EONR and YEONR: (a) we first averaged individual annual estimates of EONR and YEONR for each rotation, and then calculated the associated standard deviation (SD; across years mean); and (b) we averaged corn yields across years for each rotation and then we estimated EONR and YEONR using regression equation fitting and EONR calculation, which is an approach used for N recommendations (pooled mean, Sawyer et al., 2006). The same methods were used for RTN-APSIM, except no regression equation fitting was required.

**Statistical Evaluation of Model Performance**

To evaluate APSIM model goodness of fit, we used graphical and statistical methods. For the statistical evaluation, we computed the root mean square error (RMSE),

\[
RMSE = \sqrt{\frac{\sum_{i=1}^{n} (S_i - O_i)^2}{n}}
\]

and RRMSE,
Equation 5

$$\text{RRMSE} = \frac{\text{RMSE}}{\hat{\text{O}}} \times 100$$

where $\hat{\text{O}}$ is the mean observed value, $S_i$ is the model estimated value, $O_i$ is the observed value, and $n$ is the number of data pairs. The RMSE summarizes the average difference between observed and predicted values, while RRMSE provides the relative difference. In both cases, the lower the value of the index the better the model performance. In this study, we considered RRMSE $\leq 15\%$ as “good” agreement; $15\%$–$30\%$ as “moderate” agreement; and $\geq 30\%$ as “poor” agreement (Liu et al., 2013; Yang et al., 2014).

Factors Affecting Optimal Nitrogen Rate Inter-Annual Variability

Regression analysis was performed to identify statistical significant relationships between simulated EONR and explanatory factors. We considered three explanatory factors: yield at optimum N rate, time of N application rate relative to corn planting date, and precipitation sums over different time periods. We used $R^2$ to evaluate predictability of optimum N rate based on the factors mentioned above.

Results

Observed Corn and Soybean Yield Response to N Fertilizer, and Crop Rotation

Observed corn yield varied across years, N rates, and crop sequences (Figure 2.1, Figure 2.2). Yearly variability CC, corn yield averages across years ranged from 4.2 (N0) to 11.6 (N268) Mg ha$^{-1}$ with a maximum yield response to N (difference between N0 and N268 treatment) of 7.6 Mg ha$^{-1}$ (Figure 2.3). In SC, corn yield averages were greater for all N treatments compared to CC, and varied from 7.8 (N0) to 12.9 (N268) Mg ha$^{-1}$ with a maximum yield response to N of 5.1 Mg ha$^{-1}$. At N0, for individual years the largest yield difference between CC and SC was 3.6 Mg ha$^{-1}$. Greater yearly variability in corn yield was observed in CC (coefficient of variation, CV = 17.8%) than in SC (CV = 12.9%). The CV decreased with increasing N rate in CC (from 24.8 to 15.4%), but was consistent across N rate in SC. Across
rotations, high corn yields under non-limited N condition were obtained in wet years (precipitation above 1100 mm, e.g., 2008 and 2010; Figure 2.1, Figure 2.2, Figure 2.3) and low corn yields in dry years (precipitation below 600 mm precipitation, e.g., 2000, 2012, and 2013). Observed soybean yields varied from 2.1 to 4.8 Mg ha\(^{-1}\) across years and N rates (Figure 2.4; Supplementary Figure S2). The yearly variability in soybean yield had a CV of 19.5%. Soybean yields were not affected by N rates applied to corn (Figure 2.3; Supplementary Figure S2).

**Model Accuracy before and after Calibration**

**Simulation of Corn Yields**

Overall, across years, N rates and crop sequences, APSIM explained from 50–69% (before calibration) to 67–88% (after calibration) of the observed variability in corn yield (Figure 2.3). The model agreement improved during calibration from moderate (RRMSE = 19.6%, uncalibrated) to good (RRMSE = 12.3%, calibrated) for corn yield prediction (Figure 3). In CC, the uncalibrated model simulated corn yield response to N well in 7 years (RRMSE < 15%), moderately well in 6 years (RRMSE 15–30%), and poorly in 3 years (RRMSE > 30%); while after calibration the model simulated yields well in 14 years and moderately well in 3 years (Figure 2.1).

In SC, the uncalibrated model simulated corn yield response to N well in 10 years, moderately well in 3 years, and poorly in 2 years; while after calibration the model simulated yields well in 11 years and poorly in 4 years (Figure 2.2). In general the calibrated model captured the trends in the observed variability in corn yields across years (Supplementary Figure S4A) as well as the annual yield response to N rates (Figure 2.1 and Figure 2.2).
Figure 2.1 Corn yield response to N fertilizer for the continuous corn (CC) cropping system. The blue points with standard errors (n = 4) indicate the observations. The gray and red points are Agricultural Production Systems sIMulator (APSIM) simulations before and after calibration, respectively. Continuous lines are regression fits from Eqs. 1–3. When lines are not shown it means that Eqs. 1–3 did not converge. Relative root mean square error for both calibrated (RRMSE) and uncalibrated model (RRMSE_un) are shown for each year.
Figure 2.2 Corn yield response to N fertilizer for the soybean-corn (SC) cropping system. The blue points with standard errors (n = 4) indicate the observations. The gray, red, and green points indicate uncalibrated, calibrated and validated simulations from the Agricultural Production Systems sIMulator (APSIM) model. Continuous lines are regression fits from Eqs. 1–3. When lines are not shown it means that Eqs. 1–3 did not converge. Relative root mean square error for both calibrated (RRMSE) and uncalibrated model (RRMSE_un) are shown for each year.
Figure 2.3 Sixteen year mean crop yield response to N fertilizer rate (A, D, and G panels), and observed versus simulated crop yields across years and N rate (B, C, E, F, H, and I). Points are observations or simulations, continuous lines are regression fits from Eqs. 1–3, and broken lines show 1:1 relationship.
Figure 2.4 Economic optimum N rate (EONR) and corn yield at the EONR (YEONR) for every year in CC and SC. The EONR and YEONR estimates from observations using Eqs. 1-3 are shown as bars. Different color symbols show Agricultural Production Systems sIMulator (APSIM) model simulations: red points calibrated model, gray points uncalibrated model, and green points return to N approach (RTN) from the calibrated model.

Simulation of Soybean Yields

Given that the simulation setup was sequential and soybean was part of the CS rotation, the ability of APSIM in simulating soybean yields was also tested. The model simulated no response to N rate applied to the previous corn crop, which agrees with the observed data (Figure 4; for individual years see Supplementary Figure S3). The agreement in simulated soybean yields was moderate before and after calibration (calibrated RRMSE = 19%; Figure 2.3).
Simulation of Optimum N Rate and Methods Comparison

Site Mean Optimum N Rate

The calibration process improved the prediction of the site mean EONR in the SC but not in CC (Table 2.1; Figure 2.3) Sixteen year mean crop yield response to N fertilizer rate (A, D, and G panels), and observed versus simulated crop yields across years and N rate (B, C, E, F, H, and I). Points are observations or simulations, continuous lines are regression fits from Eqs. 1–3, and broken lines show 1:1 relationship.). The simulated EONR (both calibrated and uncalibrated versions) was overestimated in CC and underestimated in SC (Table 2.1). The absolute difference in site mean EONR between simulated and observed values was smaller in SC; -39 and 18 kg N ha\(^{-1}\) for CC and SC, respectively, before calibration and -41 and 10 kg N ha\(^{-1}\) for CC and SC, respectively, after calibration (Table 2.1). In addition, the simulated EONR SD was high with the APSIM-Unc, largely due to mis-estimation of some years as non-N responsive.

Table 2.1 Mean economic optimum N rate (EONR, kg N ha\(^{-1}\)) across 16-years for: observed, Obs; un-calibrated Agricultural Production Systems iMulator (APSIM) model, Unc; calibrated model, Cal; and the return to N approach from the calibrated model, RTN.

<table>
<thead>
<tr>
<th>Rotation</th>
<th>Obs</th>
<th>Unc</th>
<th>Cal</th>
<th>RTN</th>
<th>Obs-Unc</th>
<th>Obs-Cal</th>
<th>Obs-RTN</th>
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<td>Average</td>
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<tr>
<td>CC</td>
<td>188 ± 42</td>
<td>190 ± 82</td>
<td>225 ± 33</td>
<td>176 ± 21</td>
<td>-2</td>
<td>-37</td>
<td>12</td>
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<tr>
<td>SC</td>
<td>149 ± 48</td>
<td>99 ± 71</td>
<td>137 ± 43</td>
<td>118 ± 30</td>
<td>50</td>
<td>12</td>
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<td>Pooled(^2)</td>
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<td>228</td>
<td>195</td>
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<tr>
<td>SC</td>
<td>158</td>
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<td>147</td>
<td>140</td>
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</table>

\(^1\) Individual annual optimum N rate estimates were averaged across 16-years and the standard deviation (SD) calculated

\(^2\) Individual annual corn yield values were first averaged across years and then the optimum N rates estimated
Annual Optimum N Rate

The calculated EONR-Obs (from observations) was highly variable from year to year and ranged from 123 to 268 kg N ha$^{-1}$ in CC and from 42 to 241 kg N ha$^{-1}$ in SC (Figure 2.4). The inter-annual variability in EONR-Obs was greater in SC than in CC (CV of 32 vs. 22%, respectively).

The calculated EONR from the APSIM model followed some of the observed annual trends (Figure 2.4), with the prediction error to be larger in SC than CC (Supplementary Figure S7). In CC, the RMSE ranged from 63 kg N ha$^{-1}$ before calibration to 56 kg N ha$^{-1}$ after calibration. In SC, the RMSE ranged from 83 kg N ha$^{-1}$ before calibration to 68 kg N ha$^{-1}$ after calibration. Interestingly, the two methods of calculating EONR from modeled yields (via regression Eqs. 1–3 or via the RTN approach) had similar RMSE and RRMSE values across years, but the annual predictions of optimum N using the RTN approach were less variable across years (Figure 2.4). These results show that for year-to-year simulation of EONR, the calibrated version should be used either via Eqs. 1–3 with regression analysis or the RTN approach. Overall the calibration process reduced the RRMSE in annual EONR predictions by 14.2% in CC and 10.3% in SC (Supplementary Figure S8).

The calculated yearly YEONR-Obs (from observation) was less variable compared to the EONR variability (CV of 17 and 12% for CC and SC, respectively, Figure 2.4). The simulated YEONR followed the observed annual trends well (Figure 4; RMSE of 1.88 Mg ha$^{-1}$ before calibration and 1.41 Mg ha$^{-1}$ after calibration). The model simulated YEONR was more accurate than EONR. In relative terms, the error in YEONR prediction was about four times lower than the error in EONR prediction (Supplementary Figures S6 and S7). However, there was no correlation between these errors (Supplementary Figure S6).
Use of the RTN approach to compute the optimum N rate, and compared to the simulated calibrated values (Table 2.1), produced a closer EONR in CC to the observed EONR (-8 kg N ha\(^{-1}\)), but a greater difference in SC (18 kg N ha\(^{-1}\)). Unlike the APSIM-Cal and APSIM-Unc simulations, the RTN-APSIM did not over-estimate EONR in CC, but underestimated in SC (Table 2.1).

**Factors Causing Yearly Variability in Optimal Nitrogen Rate**

The YEONR-Obs (Supplementary Figure S5), precipitation (Figure 2.5), and the time of N application (Supplementary Figure S8) were explored as possible factors to explain inter-annual variability in EONR. There was a significant positive relationship between spring precipitation and EONR-Obs but the relationship had low predictive power (\(p < 0.05; R^2 = 0.27–0.45\); Figure 2.5). Spring precipitation, defined here as precipitation accumulated from April 1 to June 31, was selected from among many other precipitation intervals explored in this study as the best predictor of inter-annual EONR variability (Supplementary Figure S8). The YEONR, time of N rate application, the July precipitation (15 days window around corn silking), and combinations of those factors (including spring precipitation) via multi-factor regression modeling did not result in any significant correlation.
Figure 2.5 Cumulative spring precipitation from April 1st to June 30th (every year) versus economic optimum N rate (observed and simulated EONR, circles and squares, respectively; top panels), simulated spring soil N supply (from soil organic carbon mineralization; middle panels), and simulated spring N loss (denitrification and leaching; lower panels) for CC and SC crop sequences.

The calibrated APSIM version showed a similar relationship between EONR and spring precipitation as with EONR-Obs (Figure 2.5) and therefore the model was used to provide insights into factors causing this relationship. Soil net N mineralization (simulated N supply), and the sum of denitrification and N leaching below 1 m depth (simulated N loss) were used as explanatory variables. The model indicated that the relationship between EONR and spring precipitation was primarily caused by an exponential increase in simulated N loss and to some
extent by a reduction in simulated N supply with increasing spring precipitation (Figure 2.5). The model also showed that the rate of the simulated N supply reduction with increased precipitation was similar between rotations. Furthermore model analysis showed that the level of simulated N supply was 50% higher in SC than CC, which explains the lower EONR values typically found in SC systems (Figure 2.3).

**Discussion**

**Calibration Strategy and Steps**

Evaluating a model against long-term data is critical when the model is to be used for N management. This is because processes such as N mineralization, require several years to be sufficiently evaluated (Jenkinson et al., 1994; Leigh et al., 1994; Körschens, 2006) and can differentially affect N response among years. Our study is among a few in the literature that tests a process-based model in the long-term (Ma et al., 2007). The long-term data were powerful in detecting weakness in the model, but did not provide guidance on which of the model’s processes or parameters needed to be improved (Kersebaum et al., 2015). Therefore, during calibration we aimed to improve the overall representation of the system based on previous knowledge of the site (for example, C:N ratio of soybean and corn residue, phenology, etc.) rather than just optimizing cultivar parameters by year to better fit the observed data within the study range. This strategy is robust and allows the calibrated model to be used outside the study period (future years) with confidence at this site.

During calibration we implemented the alternate soil water (SWIM) and temperature (soiltemp) models available in the framework, and changed parameters influencing soybean residue C:N ratio (Table 2.2; Figure 2.3). Among changes made in the model, the activation of fluctuating water table via the SWIM soil water model was found to be the most important (e.g., see improvements in yield prediction from 2012 drought in Figure 2.2 and Figure 2.3). Yet, few
models have this capability, despite the great importance of water table depth on water balance, N dynamics, and crop growth (Kalita and Kanwar, 1992; Varvel et al., 1997; Hefting et al., 2004; Kahlown et al., 2005; Nosetto et al., 2009; Portela et al., 2009). Simulations of the groundwater table depth (Supplementary Figure S2I) were reasonable judging measurements in nearby sites (Hatfield et al., 1999; Helmers et al., 2012; Archontoulis et al., 2016).

The simulated soybean residue C:N ratio was initially low (∼20, Supplementary Figure S2) compared to literature values (25–40; Al-Kaisi et al., 2005; Bichel, 2013; Li et al., 2013). The low C:N ratio occurred mainly because APSIM supplies enough N through fixation to ensure non-N limiting soybean growth, and thus no response of soybean yield to prior-year N application to corn (potential residual inorganic-N (Figure 2.4; Supplementary Figure S2). This effect resulted in simulated luxurious N uptake in plant tissues and therefore low C:N ratio of the soybean residue. After calibration, the soybean residue C:N ratio increased to reasonable values (around 30; Supplementary Figure S2D), the simulation of the annual N fixation decreased to realistic estimates (around 180 kg N ha⁻¹ year⁻¹, Salvagiotti et al., 2008; Christianson et al., 2012), while the model maintained good performance in terms of N fixation and yield response to prior-year corn N fertilization (Figure 2.4; Supplementary Figures S2G and S3).

We believe these changes improve the representation of N fixation (Chen et al., 2016) and soybean residue in the model. However, more experimental work is needed to verify these changes and improve the simulation of soybean rotation effects in APSIM.
### Table 2.2  
Statistical evaluation of the uncalibrated and calibrated APSIM model performance in simulating corn and soybean yields by N rate across 16-years.

<table>
<thead>
<tr>
<th>N rate</th>
<th>Uncalibrated</th>
<th></th>
<th>Calibrated/Validated</th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Corn</td>
<td>Soybean</td>
<td></td>
<td>Corn</td>
<td>Soybean</td>
</tr>
<tr>
<td></td>
<td>CC</td>
<td>SC</td>
<td>SC_val</td>
<td>SC</td>
<td>SC_val</td>
</tr>
<tr>
<td>0</td>
<td>1412</td>
<td>946</td>
<td>1365</td>
<td>631</td>
<td>1337</td>
</tr>
<tr>
<td>67</td>
<td>1255</td>
<td>806</td>
<td>1996</td>
<td>689</td>
<td>1275</td>
</tr>
<tr>
<td>134</td>
<td>1627</td>
<td>1324</td>
<td>2269</td>
<td>672</td>
<td>1264</td>
</tr>
<tr>
<td>201</td>
<td>1870</td>
<td>1586</td>
<td>2528</td>
<td>726</td>
<td>1320</td>
</tr>
<tr>
<td>268</td>
<td>1806</td>
<td>1611</td>
<td>2353</td>
<td>723</td>
<td>1288</td>
</tr>
<tr>
<td>Mean</td>
<td>1611</td>
<td>1287</td>
<td>2019</td>
<td>689</td>
<td>1297</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th></th>
<th>RMSE (kg ha⁻¹)</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>RRMS%</td>
</tr>
<tr>
<td>0</td>
<td>1283</td>
<td>920</td>
</tr>
<tr>
<td>67</td>
<td>1284</td>
<td>718</td>
</tr>
<tr>
<td>134</td>
<td>1085</td>
<td>1466</td>
</tr>
<tr>
<td>201</td>
<td>1084</td>
<td>1365</td>
</tr>
<tr>
<td>268</td>
<td>946</td>
<td>1387</td>
</tr>
<tr>
<td>Mean</td>
<td>1136</td>
<td>1171</td>
</tr>
</tbody>
</table>

### APSIM Performance in Simulating Yields before and after Calibration

This study quantified accuracy of both calibrated and uncalibrated versions in order to show the degree of improvement possible with the use of long-term data. The ability of a model to predict crop yield in any environment depends on the given inputs (soil, weather, and management), how well the model structure represents reality, and the model parameters. To evaluate and test APSIM model performance, we used a system approach that explicitly considered available experimental data (corn and soybean yield, and SOC measurements) and also using literature information to evaluate additional model processes such as N fixation, root/shoot ratio, N concentrations, phenology, and others (Supplementary Figures S3 and S4). Interestingly, the model simulated long-term SOC change equally before and after calibration.

---

3 Dataset used for model validation
(RRMSE < 5%). The reason is likely that for modeling SOC, the cumulative carbon input change over time is most important (e.g., Luo et al., 2011). Annual over- and under-prediction of yields and corresponding carbon input are compensated over time if the long-term site mean yield prediction is similar before and after calibration.

The fact that APSIM simulated well yields and crop yield response to N (Figure 2.1, Figure 2.2, Figure 2.3), provided strong evidence that important soil and crop processes were being accounted for in the model. Otherwise, the model would consistently produce large under- or over-estimated yields values, resulting in different patterns across time compared to the observations (Supplementary Figure S4A). It is important to note the good simulation of grain yield with no N fertilizer input across the 16-years (Supplementary Figure S4A), which provides evidence that soil N supply and N uptake were well simulated by the model. Furthermore, the model simulated greater net soil N mineralization in the SC rotation than in CC, which is in line with literature reports (Bundy et al., 1993; Schoessow et al., 2010). Difference in net soil N mineralization (caused by residue amount and C:N ratio) was the main cause of EONR difference between CC and SC as the simulated N loss was found to be about the same in both rotations (Figure 2.5).

As expected, APSIM performance in simulating crop yields improved after calibration: RRMSE decreased from 15–30% to below 15%; Figure 2.3, Table 2.2). These performance evaluation results for crop yields are comparable to those reported in the literature for other models (Ahmed et al., 2007; Thorp et al., 2008; Liu et al., 2011; Yang et al., 2014). For a fair judgment of model performance, we should also mention the following assumptions, and those unknowns that may have an impact on model results: (a) we used a fixed cultivar focused on representing well the phenology across the 16-years (Supplementary Figure S2); however,
different cultivars were used in the experiment (Supplementary Table S1) and some probably
had different physiological characteristics; (b) there were unknowns in plant population at
harvest, tillage date, and depth; (c) there was likely to be abiotic stresses in some years, hail
storm damage (2013, Figure 2.2), and lodging issues (2002 and 2004 in CC, Figure 2.1) that
were not considered within the model.

Corn yield predictability with calibrated APSIM (in particular for CC) increased at high
N rates in particular for CC (see RMSE, Table 2.2). This occurred mainly because at high N
rates the model has to account for only water limitations to crop growth, while at low N rates
both water and N (and their interactions) become limiting factors to crop growth. This is also in
accordance with published results from other crop models (Timsina and Humphreys, 2006; Liu
et al., 2011; Yang et al., 2013; Li et al., 2015a,b).

**Modeling Optimal Nitrogen Rate**

Simulating EONR was more sensitive and complex, and had more associated uncertainty,
than simulating yields (Supplementary Figures S6 and S7). This occurred because identification
of the optimum N rate and associated yield in the yield-N response relationship – were quite
dependent on the small incremental change (slope) in yield as N rate approached the maximum
response. Over- or under-estimation of simulated yields around the optimum N rate resulted in
deviations in model-derived EONR values (Equation 1Equation 2Equation 3). For example, in
year 2002 the RRMSE for CC yield predictions by the calibrated model across N rates was 8.6%
(Figure 2.1). This variation resulted in a 50% RRMSE in EONR prediction and in a 9.3%
RRMSE in YEONR prediction. The difficulty in accurately predicting EONR from five
simulated yield points is no different than uncertainties associated with the selection of
regression equations to describe yield response to N with observed yields, and thus can affect
APSIM estimation of the agronomic and economic optimum N rate (Waugh et al., 1973; Cerrato and Blackmer, 1990; Kyveryga, 2005; Scharf et al., 2005; Hernandez and Mulla, 2008).

However, the RTN-APSIM technique that did not use regression fitted equations had similar RMSE and RRMSE values as with EONR-APSIM-Cal, and was in close agreement with the across years mean (pooled) EONR-Obs (Table 2.2). A main difference between the two techniques was that the RTN-APSIM was less variable from year to year, especially for CC (Figure 2.4). The lower inter-annual variability in optimum N estimates from the RTN-APSIM method could be attributed to the N rate increments used in the calculations (5 kg vs. 67 kg N increments) and computation method differences, which can affect the identification of the optimum N point in yield response to N rate (Bachmaier, 2012). We concluded that the differences between simulated and observed annual optimum N rate values (Supplementary Figure S7) are due to over- and under-estimates of corn yields, especially surrounding the N rate inflection point, and to a smaller extent, due to the sensitivity of Equation 1Equation 2Equation 3 used to estimate EONR.

The 16-year mean differences in EONRs, especially for RTN-APSIM (Table 2.1), which could be called estimated errors, are acceptable within historical and current N rate ranges (46–56 kg N ha\(^{-1}\); ± 23–28 kg N ha\(^{-1}\)) suggested for corn (Voss and Shrader, 1979; Sawyer et al., 2006) that includes uncertainty in estimation of optimal N (note that the range also depends on the fertilizer: corn price ratio). This means that the APSIM model can be used as a tool to assist optimum N rate recommendations in this USA region.

An important question is how the model can be used to add value within existing N rate guidelines. The main problem with EONR estimation is that the determination is made after crop harvest when yields are known. However, rate guidance is needed before N application in the fall
or spring before and after planting. Thus, farmers and crop advisers use guidelines based on extensive numbers of N rate research trials (MRTN; Sawyer et al., 2006). This makes the estimation of the site mean EONR very important in this study, given also that a large portion of Midwestern farmers apply N before crop planting. The APSIM model can assist N rate decisions via the following pathways. First, if the objective of long-term experiments is to derive site mean EONR recommendations, then the model can assist in this task (Figure 2.3). Given that the calibration processes improved more the yearly EONR prediction (14.2 and 10.3% reduction in the RRMSE for CC and SC, respectively, see Supplementary Figure S7) than site mean EONR prediction (no improvement for CC and 5% reduction in the RRMSE for SC rotation using the pooled mean), this study provides an encouraging result for model usability if only minimum site-information is available.

Second, APSIM has the potential to predict in real-time soil nitrate dynamics within the soil profile and this information could be used to adjust early-to-mid season N application rates (Archontoulis et al., 2016). This approach is currently being used by commercial companies. Third, since APSIM can predict grain yields early in the season using a range of possible weather conditions (actual, historical, future; Archontoulis et al., 2016), it could also predict needed N rates based on yield predictions as it is currently being applied in Australia as decision-support tool (Yield Prophet; Carberry et al., 2009). Nitrogen rate accuracy from yield prediction would be highly dependent on model yield predictability, and needs to be confirmed with an additional study. The value added by models and the accuracy in predicting needed N rates will always be greater when models are supported by local experimental data to periodically check performance and allow updates in the model algorithms or parameters to deal with new genetics and changes in soil and weather over time (Ahuja et al., 2014).
Causes of Optimal Nitrogen Rate Variability

In addition to predictability, deeper understanding of the factors causing EONR inter-annual variability is important for optimizing agronomic, economic, and environmental outcomes. Among three factors explored with data available for this study (time of N application, optimum yield, and precipitation periods), the cumulative May to June (spring) precipitation explained yearly EONR variability (Figure 2.5). However, the relatively low predictability of this relationship might be due to other confounding factors such as time of N application and planting date, which were not constant over the 16-year period in this study. The relationship between spring precipitation and EONR found in this study agreed with other studies conducted in rainfed environments (Vanotti and Bundy, 1994; Piekielek et al., 1995; Kachanoski et al., 1996; Bundy, 2000; Lory and Scharf, 2003; Sawyer et al., 2006; Scharf et al., 2006), but not with studies conducted in irrigated regions where yield level (optimum yield) was the main driver for the inter-annual variability in EONR (Dobermann et al., 2003; Gehl et al., 2005). Interestingly, the July precipitation which reflects the ± 15 day period around corn silking (see APSIM diagnostics Supplementary Figure S2) was not correlated with EONR yearly variability ($R^2 < 0.25$, $p < 0.05$; Supplementary Figure S9) despite the great importance of this period for kernel number determination and corn grain yields (Edmeades et al., 2000; Andrade et al., 2002; Calviño et al., 2003). This would be attributed to high soil moisture capacity of the soil and shallow groundwater tables in this region that can compensate for period of water stress and also due to the fact that corn takes up about 70% of its total N uptake by silking (Ciampitti and Vyn, 2012; Woli et al., 2016).

Variability in EONR and its relationship with spring precipitation in the US Midwest has typically been associated in previous research with an increase in N loss with high spring precipitation but previous studies lacked comprehensive measurements (Meisinger, 1984;
Eghball and Varvel, 1997; Kay et al., 2006; Lawlor et al., 2008). The APSIM model analysis explicitly quantified the shape and magnitude of N loss per mm of precipitation and indicated that the shape of the relationship is similar in CC and SC systems (Figure 2.5).

The ability of APSIM and other mechanistic process-based models to simulate and explain the effect of precipitation on simulated N loss and supply, and thus, the impact on N response (Figure 2.5) becomes even more relevant with future climate change scenarios. For the US Midwest several studies have predicted higher frequency of both drought and flood events (Schoof et al., 2010; Kunkel et al., 2013; Dai et al., 2015). In this context, long-term simulations with different weather allow to capture the ranges of yield responses to N rates and choose the optimal rate that more frequently provides the best outcomes in terms of higher yield and lower nitrate leaching (Basso et al., 2016). Furthermore, the APSIM model can generate predictions across different weather scenarios that could be used to inform potential need for changes in future N management decisions.

Conclusion

Model analysis of a 16-year field-experiment dataset that included crop yields and SOC values with five N fertilizer rates and two crop sequences revealed the following main findings:

1. The fact that APSIM simulated well crop yields and crop yield response to N rate, provided strong evidence that important soil and crop processes were being accounted for in the model;

2. Model calibration (implementation of SWIM soil water model with activation of soil water table, use of soil temperature 2 model, and improvements in soybean residue C:N ratio) reduced the simulation error (RRMSE) in crop yield prediction by 9% and the annual EONR prediction by 12%. We also found that SOC prediction was insensitive to calibration when long-term mean crop yield was simulated well;
(3) The optimum N rate was higher for CC than SC and according to the model analysis this is associated with higher SOC net mineralization in the SC rotation.

(4) Simulation of EONR was more sensitive and complex than simulating crop yield. Results suggest that for long-term site mean EONR predictions both versions (calibrated and uncalibrated) can be used, while for accurate year-by-year simulation of EONR the calibrated version should be used. Use of the RTN-APSIM approach (small N rate increment with no regression fit) for optimal rate estimation had similar performance compared to EONR-APSIM-Cal approach (five N rate-points and regression fit). A main difference in optimal N rate estimation between the two techniques was that the RTN-APSIM output was less variable from year to year.

(5) Five potential applications were identified where the model could assist N management: (a) estimation of long-term mean EONR; (b) simulation of N dynamics (soil N available and crop N demand); (c) prediction of optimal N using a range of possible weather conditions; (d) simulation of climate change impact on optimal N need;

(6) The APSIM model can be used to explore and explain factors causing inter-annual variability in EONR. For example, the model showed that in rainfed corn-based systems in Iowa, the higher the spring precipitation (April to June) the higher the EONR because simulated N loss via denitrification and leaching increased exponentially while simulated N supply via mineralization tended to decrease.

Finally, for rainfed corn-based systems in the USA Midwest, a combination of process-based modeling, coupled with existing N rate recommendation methods and field data, may be the best approach to fine tune optimal N rate guidance for corn and to develop future
management-based strategies under climate change scenarios for maximizing agronomic, economic, and environmental outcomes.

References


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## Appendix

### Table S1. Corn and soybean management practices available at the time of simulation: planting date, date of N application, N source, hybrid, relative maturity and seed planting density for corn-corn and corn-soybean rotation from 1999 to 2014.

<table>
<thead>
<tr>
<th>Year</th>
<th>Corn planting date</th>
<th>Date of N application in corn</th>
<th>N source</th>
<th>Corn relative maturity</th>
<th>Soybean planting date</th>
</tr>
</thead>
<tbody>
<tr>
<td>1999</td>
<td>19-May</td>
<td>3-May</td>
<td>urea</td>
<td>107</td>
<td>19-May</td>
</tr>
<tr>
<td>2000</td>
<td>5-May</td>
<td>2-May</td>
<td>urea</td>
<td>107</td>
<td>5-May</td>
</tr>
<tr>
<td>2001</td>
<td>9-May</td>
<td>1-May</td>
<td>urea</td>
<td>104</td>
<td>9-May</td>
</tr>
<tr>
<td>2002</td>
<td>3-May</td>
<td>26-Apr</td>
<td>urea</td>
<td>105</td>
<td>3-May</td>
</tr>
<tr>
<td>2003</td>
<td>29-Apr</td>
<td>22-Apr</td>
<td>urea</td>
<td>108</td>
<td>29-Apr</td>
</tr>
<tr>
<td>2004</td>
<td>27-Apr</td>
<td>15-Apr</td>
<td>urea</td>
<td>107</td>
<td>11-May</td>
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<tr>
<td>2005</td>
<td>10-May</td>
<td>3-May</td>
<td>urea</td>
<td>105</td>
<td>10-May</td>
</tr>
<tr>
<td>2006</td>
<td>9-May</td>
<td>4-May</td>
<td>urea</td>
<td>106</td>
<td>18-May</td>
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<tr>
<td>2007</td>
<td>13-May</td>
<td>1-May</td>
<td>urea</td>
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<td>18-May</td>
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<td>urea</td>
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<td>2009</td>
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<td>12-May</td>
<td>32% UAN</td>
<td>105</td>
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<td>2010</td>
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<td>6-May</td>
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<td>2011</td>
<td>11-May</td>
<td>19-May</td>
<td>32% UAN</td>
<td>106</td>
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<td>2012</td>
<td>10-May</td>
<td>10-May</td>
<td>32% UAN</td>
<td>105</td>
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<td>2013</td>
<td>24-May</td>
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<td>32% UAN</td>
<td>104</td>
<td>13-Jun</td>
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<td>2014</td>
<td>7-May</td>
<td>6-May</td>
<td>urea</td>
<td>105</td>
<td>20-May</td>
</tr>
</tbody>
</table>
Table S2. APSIM corn and soybean cultivar and crop model specific parameter values used in this study. When more than one value is given (see soybean), this means that there is an array of values for the specific parameter.

<table>
<thead>
<tr>
<th>Acronym</th>
<th>Value</th>
<th>Unit</th>
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<td><strong>Corn</strong></td>
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<td></td>
</tr>
<tr>
<td>tt_emerg_to_endjuv (thermal time from emergence to end juvenile)</td>
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<td>°C-days</td>
</tr>
<tr>
<td>tt_flower_to_maturity (thermal time from flowering to phys maturity)</td>
<td>812</td>
<td>°C-days</td>
</tr>
<tr>
<td>head_grain_no (potential kernel number per ear)</td>
<td>800</td>
<td>#</td>
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<tr>
<td>grain_gth_rate (grain growth rate)</td>
<td>9.17</td>
<td>mg/rain/day</td>
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<tr>
<td>tt_flower_to_start_grain (thermal time from flowering to start grain fill)</td>
<td>170</td>
<td>°C-days</td>
</tr>
<tr>
<td>tt_maturity_to_ripe (thermal time from maturity to harvest)</td>
<td>150</td>
<td>°C-days</td>
</tr>
<tr>
<td><strong>Soybean</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>x_pp_hi_incr (photoperiod)</td>
<td>1, 24</td>
<td>Hours</td>
</tr>
<tr>
<td>y_hi_incr (daily rate of harvest index)</td>
<td>0.01, 0.01</td>
<td>1/days</td>
</tr>
<tr>
<td>x_hi_max_pot_stress (stress index)</td>
<td>0.0, 1.0</td>
<td>(-)</td>
</tr>
<tr>
<td>y_hi_max_pot (maximum value for harvest index)</td>
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<td>(-)</td>
</tr>
<tr>
<td>tt_emergence (thermal time to emergence)</td>
<td>100, 100</td>
<td>°C-days</td>
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<tr>
<td>x_pp (photoperiod levels)</td>
<td>13.59, 14.6, 15.6, 16.6</td>
<td>Hour</td>
</tr>
<tr>
<td>y_tt_end_of_juvenile (thermal time to juvenile)</td>
<td>100, 133, 200, 400</td>
<td>°C-days</td>
</tr>
<tr>
<td>y_tt_floral_initiation (thermal time from end of juv to floral initiation)</td>
<td>128, 171, 256, 512</td>
<td>°C-days</td>
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<tr>
<td>y_tt_flowering (thermal time from flowering to start grain fill)</td>
<td>246, 328, 492, 1312</td>
<td>°C-days</td>
</tr>
<tr>
<td>y_tt_start_grain_fill (thermal time from start to end of grain fill)</td>
<td>499, 666, 999, 2664</td>
<td>°C-days</td>
</tr>
<tr>
<td>tt_end_grain_fill (thermal time from end grain fill to maturity)</td>
<td>20</td>
<td>°C-days</td>
</tr>
<tr>
<td>tt_maturity (thermal time from maturity to harvest)</td>
<td>70</td>
<td>°C-days</td>
</tr>
<tr>
<td>node_sen_rate (node senescence rate)</td>
<td>95</td>
<td>°C-days node⁻¹</td>
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<tr>
<td>Twilight (twilight)</td>
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<td>(-)</td>
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<tr>
<td>x_stage for N fixation (crop stage number)</td>
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<td>stage #</td>
</tr>
<tr>
<td>N_fix_rate (Nn fixation rate)</td>
<td>0.0006, 0.0016, 0.0016,</td>
<td>gN/gDM</td>
</tr>
<tr>
<td>x_stage for N concentration (crop stage number)</td>
<td>0.0009</td>
<td>gN/gDM</td>
</tr>
<tr>
<td>y_n_conc_min_leaf (minimum N concentration in leaves)</td>
<td>3, 6, 9</td>
<td>stage #</td>
</tr>
<tr>
<td>y_n_conc_crit_leaf (critical N concentration in leaves)</td>
<td>0.02, 0.01, 0.0085</td>
<td>gN/gDM</td>
</tr>
<tr>
<td>y_n_conc_max_leaf (maximum N concentration in leaves)</td>
<td>0.06, 0.05, 0.02</td>
<td>gN/gDM</td>
</tr>
<tr>
<td>y_n_conc_crit_stem (critical N concentration in stems)</td>
<td>0.03, 0.02, 0.008</td>
<td>gN/gDM</td>
</tr>
<tr>
<td>y_n_conc_max_stem (minimum N concentration in stems)</td>
<td>0.03, 0.02, 0.008</td>
<td>gN/Gdm</td>
</tr>
<tr>
<td>y_n_conc_crit_pod (critical N concentration in pods)</td>
<td>0.03, 0.02, 0.008</td>
<td>gN/Gdm</td>
</tr>
<tr>
<td>y_n_conc_max_pod (maximum N concentration in pod)</td>
<td>0.06, 0.06, 0.008</td>
<td>gN/Gdm</td>
</tr>
</tbody>
</table>
**Table S3.** Soil profile values from the initialization period (1993 to 1999). The values refer to the start of the simulation on 1/1/1999. BD, bulk density; LL, lower limit; DUL, drained upper limit; SAT, saturated volumetric water content; SW, soil water; Corn and Soy KL, parameters defining capacity to extract water per day; OC, soil organic carbon; Finert, inert of soil organic C (not decomposing); Fbiom, microbial SOC (fast decomposing); Hum, humic SOC (medium decomposing); and NO$_3$-N, soil nitrate.

<table>
<thead>
<tr>
<th>Soil layer</th>
<th>BD (Mg m$^{-3}$)</th>
<th>LL (mm)</th>
<th>DUL (mm)</th>
<th>SAT (mm)</th>
<th>SW (d$^{-1}$)</th>
<th>Corn KL (d$^{-1}$)</th>
<th>Soy KL (d$^{-1}$)</th>
<th>OC (g 100g$^{-1}$)</th>
<th>Finert (kg C ha$^{-1}$)</th>
<th>Fbiom (kg C ha$^{-1}$)</th>
<th>Hum (Kg ha$^{-1}$)</th>
<th>NO$_3$-N (Kg ha$^{-1}$)</th>
</tr>
</thead>
<tbody>
<tr>
<td>0 to 8</td>
<td>1.300</td>
<td>0.164</td>
<td>0.299</td>
<td>0.459</td>
<td>0.275</td>
<td>0.080</td>
<td>0.080</td>
<td>2.00</td>
<td>8008</td>
<td>1183</td>
<td>11609</td>
<td>0.25</td>
</tr>
<tr>
<td>8 to 16</td>
<td>1.300</td>
<td>0.164</td>
<td>0.299</td>
<td>0.459</td>
<td>0.263</td>
<td>0.075</td>
<td>0.075</td>
<td>1.98</td>
<td>8442</td>
<td>741</td>
<td>11345</td>
<td>0.30</td>
</tr>
<tr>
<td>16 to 31</td>
<td>1.367</td>
<td>0.159</td>
<td>0.296</td>
<td>0.434</td>
<td>0.276</td>
<td>0.070</td>
<td>0.070</td>
<td>1.66</td>
<td>16851</td>
<td>1004</td>
<td>16054</td>
<td>0.60</td>
</tr>
<tr>
<td>31 to 54</td>
<td>1.425</td>
<td>0.145</td>
<td>0.286</td>
<td>0.413</td>
<td>0.283</td>
<td>0.060</td>
<td>0.060</td>
<td>1.39</td>
<td>29835</td>
<td>293</td>
<td>14911</td>
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</tr>
<tr>
<td>54 to 74</td>
<td>1.450</td>
<td>0.133</td>
<td>0.278</td>
<td>0.403</td>
<td>0.278</td>
<td>0.050</td>
<td>0.050</td>
<td>1.15</td>
<td>26784</td>
<td>171</td>
<td>6395</td>
<td>1.20</td>
</tr>
<tr>
<td>74 to 102</td>
<td>1.550</td>
<td>0.132</td>
<td>0.277</td>
<td>0.365</td>
<td>0.277</td>
<td>0.043</td>
<td>0.043</td>
<td>0.43</td>
<td>15020</td>
<td>169</td>
<td>3631</td>
<td>0.40</td>
</tr>
<tr>
<td>102 to 120</td>
<td>1.600</td>
<td>0.132</td>
<td>0.276</td>
<td>0.346</td>
<td>0.276</td>
<td>0.035</td>
<td>0.035</td>
<td>0.15</td>
<td>3417</td>
<td>73</td>
<td>830</td>
<td>0.05</td>
</tr>
<tr>
<td>120 to 150</td>
<td>1.600</td>
<td>0.132</td>
<td>0.276</td>
<td>0.346</td>
<td>0.323</td>
<td>0.030</td>
<td>0.000</td>
<td>0.15</td>
<td>6178</td>
<td>64</td>
<td>959</td>
<td>0.05</td>
</tr>
<tr>
<td>150 to 199</td>
<td>1.600</td>
<td>0.132</td>
<td>0.276</td>
<td>0.346</td>
<td>0.346</td>
<td>0.000</td>
<td>0.000</td>
<td>0.15</td>
<td>11416</td>
<td>20</td>
<td>324</td>
<td>0.00</td>
</tr>
</tbody>
</table>
Figure S1. Cumulative annual precipitation and mean temperature in Ames, Iowa, USA. The long term average cumulative precipitation and temperature across years (1980–2014) are shown with the vertical and horizontal lines, respectively. These average values were used as classification criteria to separate years into warm, cool, dry, and wet. Years shown in red represent the years used in this study (1999–2014).

APSIM diagnostics

One of the major goals in testing model performance is to evaluate the behavior of the model. Figure S1 illustrates simulated results (1999–2014) from the calibrated model for key model variables. In the absence of specific measurements, these results were judged by experts and literature information and found to be reasonable. The simulated grain harvest index ranged from 0.43 to 0.55 and was affected by N rate in corn. The root to shoot ratio at harvest showed a small decline with N application rate and was about 0.13 and 0.16 for corn and soybean, respectively. The grain N concentration was different between corn and soybean crops (1.5 vs. 6.5%, respectively) and it showed a positive response to N rate. Stover (above ground biomass minus grain), stem, and root N concentration and C:N ratios were different between crops, showed a response to N-rate while their simulated values were within the range of values reported in the literature (Ciampitti and Vyn, 2012; Al-Kaisi et al., 2005; Salvagiotti et al., 2008). The simulated soybean N fixation was on average 180 kg N/ha and showed a strong response to residual N,
Figure S2. Simulation of grain harvest index at harvest (a), root to shoot ratio at harvest (b), grain N concentration at harvest (c), stover (above ground biomass minus grain), stem and root C to N ratio at harvest (d, e, and f, respectively), soybean N fixation (g), time to flowering and maturity (h) and year to year fluctuation of groundwater table at harvest (i, average trend across cropping systems and N-rates). The points (squares, cycles and triangles) are average values across experimental years (1999-2014) and the corresponding vertical bars represent the standard deviation. CC: continuous corn, SC: soybean-corn rotation, and SC_val: soybean-corn rotation data set used for validation.

Line with literature findings (Salvagiotti et al., 2008). Simulation of flowering and physiological maturity for both crops reflected very well what is usually observed in this region. Finally, the groundwater table varied from year to year and was shallower in wetter years such as 2008, 2010 and 2014 (Fig. S1i, and Figure 2.1).
Figure S3. Soybean grain yield versus N rate applied to the previous year corn in the soybean-corn rotation. The blue points with standard errors (n=4) indicate the measurements. The grey, red, and green connected points indicate uncalibrated, calibrated and validated simulations from the APISM model.
Figure S4. Temporal variability in corn yield (A) and soil organic carbon (SOC) changes at 0-15 cm (B) and at 0-30 cm (C) for the continuous corn system. Continuous lines are simulations from the calibrated APSIM model and points are observations. Color blue and red refers to 0 and 268 kg N ha-1 treatments, respectively. Vertical bars represent the standard error of the observed mean.
Figure S5. Relationship between yield at the economic optimum N rate (YEONR) and the optimum N-rate for continuous corn and soybean-corn rotation. Dashed lines indicate non-significant trends.

Figure S6. Relative difference between predicted and observed economic optimum N rate (EONR, x-axis) and between simulated and observed yield at optimum N rate (YEONR, y-axis).
Figure S7. Annual difference between simulated and observed economic optimum N rate (EONR) and yield at the EONR (YEONR). The first part of each acronym within a panel heading refers to the crop sequences (CC, continuous corn and SC, soybean-corn). The second part refers to the differences being shown; for example Obs minus APSIM_cal = EONR-Obs minus EONR-APSIM_cal, and RTN refers to return to N approach from the calibrated model.
Figure S8. Economic optimum N rate (EONR) from observations versus time of N application relative to corn planting date. Dotted lines indicate non-significant trends.

Figure S9. The R-square values derived from linear regression between observed economic optimum N rate (EONR-Obs) and precipitation for different months or a combination of months. A: April, M: May, J: June, Jul: July, A: August, S: September, O: October, AM: April to May, MJ: May to June, AMJ: April to June, AMJJ: April to July and MJJAS: May to September. Red box indicates the selected period used for further analysis.
References


CHAPTER 3. A SYSTEMS MODELING APPROACH TO FORECAST CORN ECONOMIC OPTIMUM NITROGEN RATE

Modified from a paper published in Frontiers in Plant Science, 13 April 2018 | https://doi.org/10.3389/fpls.2018.00436

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Abstract

Historically crop models have been used to evaluate crop yield responses to nitrogen (N) rates after harvest when it is too late for the farmers to make in-season adjustments. We hypothesize that the use of a crop model as an in-season forecast tool will improve current N decision-making. To explore this, we used the Agricultural Production Systems sIMulator (APSIM) calibrated with long-term experimental data for central Iowa, USA (16-years in continuous corn and 15-years in soybean-corn rotation) combined with actual weather data up to a specific crop stage and historical weather data thereafter. The objectives were to: (1) evaluate the accuracy and uncertainty of corn yield and economic optimum N rate (EONR) predictions at four forecast times (planting time, 6th and 12th leaf, and silking phenological stages); (2) determine whether the use of analogous historical weather years based on precipitation and temperature patterns as opposed to using a 35-year dataset could improve the accuracy of the forecast; and (3) quantify the value added by the crop model in predicting annual EONR and yields using the site-mean EONR and the yield at the EONR to benchmark predicted values.

Results indicated that the mean corn yield predictions at planting time ($R^2 = 0.77$) using 35-years
of historical weather was close to the observed and predicted yield at maturity ($R^2 = 0.81$).

Across all forecasting times, the EONR predictions were more accurate in corn-corn than soybean-corn rotation (relative root mean square error, RRMSE, of 25 vs. 45%, respectively). At planting time, the APSIM model predicted the direction of optimum N rates (above, below or at average site-mean EONR) in 62% of the cases examined ($n = 31$) with an average error range of $\pm 38$ kg N ha$^{-1}$ (22% of the average N rate). Across all forecast times, prediction error of EONR was about three times higher than yield predictions. The use of the 35-year weather record was better than using selected historical weather years to forecast (RRMSE was on average 3% lower). Overall, the proposed approach of using the crop model as a forecasting tool could improve year-to-year predictability of corn yields and optimum N rates. Further improvements in modeling and set-up protocols are needed toward more accurate forecast, especially for extreme weather years with the most significant economic and environmental cost.

**Introduction**

Over and under fertilization of nitrogen (N) in corn production affects the farmer's profitability and the environment (Shanahan et al., 2008). Predicting the economic optimum N rate (EONR) before crop planting is an ongoing research effort. The challenge persists because of multiple dynamic factors influencing the EONR. In brief, genotypic inputs (cultivars), environment (soil $\times$ weather, especially rainfall and its distribution), and management choices (tillage, N application time, etc.) affect soil and crop processes in various ways. The result of all these dynamic processes and their interactions (soil supply vs. crop demand) determine the yield at any N fertilization level (Figure 3.1). There are several examples in the literature where a single component of the system was studied in detail without acknowledging other system's components and their inherent feedbacks (effect of tillage, effect of residue removal, Kwaw-Mensah and Al-Kaisi, 2006; Coulter and Nafziger, 2008). Several tools and methodologies have
been developed over time to assist farmers with N rate decisions (e.g., yield goal approach, Stanford, 1973; soil nitrate test, Bundy and Andraski, 1995; Shapiro et al., 2008), while other new tools such as sensor technologies and simulation models are currently being developed and tested (Scharf, 2015; Banger et al., 2017).

![Economic Optimum Nitrogen Rate (EONR)](image)

**Figure 3.1** Overview of the main factors influencing the economic optimum nitrogen fertilizer (EONR) rate and their interactions. Soil organic matter (SOM).

Most of today's N-rate decision tools focus on a single component of the soil-plant system to predict EONR rather than utilizing all of the N dynamics and interactions that occur among processes in the system (**Figure 3.1**; Arbuckle and Lasley, 2013). For example, the single time soil testing approach around corn at 6th leaf stage provides an estimate of soil N supply (Magdoff et al., 1984; Blackmer et al., 1989; Binford et al., 1992). However, the prediction accuracy and usage of this approach is low because the soil nitrate varies greatly in time and space, especially in rainfed production regions with unpredictable rain events (Jemison and
Lytle, 1996; Ma et al., 2007; Arbuckle and Lasley, 2013). Other examples are crop sensors and remote sensing technologies that provide an estimate of crop N status during the season (Yuan et al., 2016). Although promising as a N diagnostic tool this approach has not yet been widely adopted by farmers (Mamo et al., 2003; Scharf et al., 2005; Hawkins et al., 2007) because they typically delay N application until the plant N status can be reliably determined. That requirement increases the risk of not being able to apply N or adds extra application costs (Van Es et al., 2006; Tremblay et al., 2012; Franzen et al., 2016).

Another N tool, the yield goal (Stanford, 1973; Stanford and Legg, 1984), requires inputs such as grain yield, N concentration, nitrogen use efficiency, and N credits coming from manure, legume crops, and soil organic matter to determine corn N rates. These inputs are difficult to estimate because they are derived properties (outputs) of many interactive processes occurring simultaneously within the soil-plant-atmosphere system (Figure 3.1). Thus, farmers use prior knowledge or guesswork to provide these inputs. According to Lory and Scharf (2003) and Shanahan (2011), the yield goal approach usually results in over fertilization as a form of “insurance” against uncertain soil N supply. In contrast, the Maximum Return To Nitrogen approach (MRTN; Sawyer et al., 2006) requires simple inputs such as location, rotation, crop and fertilizer prices. By using an extensive experimental network of derived N-response datasets across the USA Midwest, it provides farmers with a N-rate recommendation per geographical areas (Sawyer et al., 2006).

In contrast to the aforementioned tools, process-based cropping system models that account for different soil-crop processes, and their interactions with management, cultivar and environmental conditions (Figure 3.1), have demonstrated capabilities explaining causes of EONR variability and perform scenario analyses (Thorpe et al., 2007; Gowda et al., 2008; Nangia
et al., 2008; Puntel et al., 2016). However, most of the model applications in N research have been applied ex-post (after harvest), which is of limited use to farmers (Kersebaum et al., 2005; Nendel et al., 2013).

Successful crop yield forecasting approaches using process-based models and historical weather in the USA (Morell et al., 2016; Togliatti et al., 2017) and Australia (Carberry et al., 2009), have indicated the potential to complement the explanatory power of cropping system models with the forecasting component that is needed for N decisions. Theoretically, by running a process-based model for different N rates using actual and historical weather, data the model can provide end-of-season yields (the yield-N response curve) at any time during the growing season. Thus, the EONR could be estimated as early as planting time, providing a new approach to make N rate decisions and supporting information on crop yields, N supply, and N demand (Figure 3.1). To our knowledge, the validity of this approach and the uncertainty around the year-by-year (annual) EONR prediction at planting and during the growing season have not been previously investigated.

A critical aspect in crop yield forecasting (and ultimately N-forecasting) is the use of weather information to drive model simulations. Traditionally, historical weather data is used to fill the unknown weather for the remainder of the growing season and calculate yield probabilities (Hammer et al., 1996; Quiring and Legates, 2008). Thus, forecasting yield and optimal N-rate at planting time is a challenge given the uncertainty in weather. As weather information becomes available during the season, the uncertainty around crop yield prediction decreases, but it follows different patterns from year to year and cropping systems (Archontoulis et al., 2016; Togliatti et al., 2017). Furthermore, use of analogous historical weather years (i.e., weather with similar precipitation or temperature patterns as the year to be forecasted) instead of
using 35-year record has been used as an approach to improve yield forecast (i.e., Hammer et al., 2001; Hansen et al., 2004). The time of the forecast may also affect yield and EONR predictions and uncertainty patterns.

In this study, we tested the hypothesis that the use of a calibrated cropping system model coupled with an assembly of actual and historical weather datasets can predict EONR as early as planting time with similar accuracy as the prediction at harvest with known weather (ex-post).

We build upon Puntel et al. (2016) in which the APSIM model was calibrated using 16 years of corn yield response to N data from two crop rotation systems at a site in central Iowa, USA.

**Objectives**

(1) evaluate the accuracy and uncertainty of corn yield and EONR predictions at four forecast times (planting time, 6th and 12th leaf, and silking crop physiological stages) compared with the observed and simulated values at harvest;

(2) investigate whether the use of selective historical weather records (e.g., years with similar precipitation) will increase accuracy of yield and EONR predictions as opposed to the 35-year historical record; and

(3) quantify value added by the crop model in predicting annual EONR and yields using the site-mean EONR and the yield at the EONR (average of yearly values) to benchmark predicted values.

**Materials and Methods**

**Experimental Data and Site Description**

We used 16 years (1999–2014) of corn yield response to N fertilizer rate data from a field experiment conducted in central Iowa, USA (details in Puntel et al., 2016). The experiment was designed to study the effect of five N fertilizer rates (0, 67, 134, 201, and 268 kg N ha⁻¹) on corn yield in continuous corn (CC) and corn following soybean (SC) cropping systems.
Application of N was either pre-plant or side-dress; see details in Puntel et al. (2016). Corn grain yield was reported at 15.5% moisture content. The corresponding EONR values per year and rotation were calculated using measured yields (see section Estimation of the Annual Economic Optimum Nitrogen Rate). The weather at the experimental site is humid continental with warm rainy summers with an average annual precipitation of 900 mm and annual temperature of 9°C. Over the 16-year experimental period, crops experienced warm and wet conditions (3 years), cool and wet conditions (3 years), warm and dry conditions (5 years), and cool and dry conditions (5 years; Figure S1a). The soil at the site is a deep fertile loamy (Clarion soil series) with topsoil organic matter of 3.4% and profile plant available water of 250 mm.

The APSIM Modeling Platform, Set Up, and Calibration

The APSIM model is an open-source advanced simulator of agricultural systems that combines several process-based models in a modular design (Holzworth et al., 2014). In this study, we used the recently calibrated version of the model for this site with no additional changes (see Puntel et al., 2016 for detailed calibration information). Model performance is also provided in this study (see yield predictions at maturity, results section). The simulation process was continuous, starting in 1999 and ending in 2014 without annual re-initialization of inputs to capture carryover effects on soil N, water, residue, and soil organic matter dynamics from 1 year to the next. The following APSIM models were used: corn and soybean crop models (Keating et al., 2003), Soil N (soil N and C cycling model; Probert et al., 1998), SWIM (soil water model using the Richard equation and fluctuated water tables; Huth et al., 2012); SURFACEOM (residue model; Probert et al., 1998; Thorburn et al., 2001; Thorp et al., 2005), soil temperature (Campbell, 1985), and the following management rules: planting, harvesting, fertilizer, tillage, and rotations (Keating et al., 2003).
Forecasting Yields and EONR

To forecast yields and EONR in each study year (1999–2014) we combined actual weather data up to a specific crop stage and historical weather data thereafter (Figure S2). The following forecast times were considered in this study: planting, 6th leaf (V6), 12th leaf (V12), and silking (R1; Abendroth et al., 2011). We selected these times because farmers in rainfed production regions can make delayed N applications during vegetative and early reproductive stages (R1) without a significant negative effect on yield (Scharf et al., 2002). In this environment, there is not much evidence of yield response to N fertilizer application after corn silking, thus we did not explore yield and N forecasts during grain filling period.

Except for planting time, which only includes observed weather data until the planting date, the rest of the forecast times used observed in-season weather data until the forecast time (Figure S2). Historical daily weather data from 1980 to 2015 (35 years, maximum available for this site) was obtained from the Iowa Environmental Mesonet (2014) to fill the unknown weather. The combination of 35 years of simulations, four forecast times, 16 study years, five N rates, and two crop rotations resulted in more than 22,000 simulations. We calculated the yearly mean and standard deviation of yield and EONR from the 35 simulated values per year and forecasting time similar to Togliatti et al. (2017). The simulated site-mean EONR was calculated by averaging individual annual estimates of EONR and yield at EONR (YEONR) for each rotation, and then calculating the associated standard deviation (SD; across years mean).

Once the simulations were completed, we grouped the data to represent the following five weather scenarios and quantify the impact on yield and EONR forecasts:

- Use simulated yields from calendar years with similar annual precipitation and temperature patterns as the year of interest (e.g., 2010 and 1984). These groups of years can be found in Figure S1a.
• Use simulated yields from calendar years with similar summer (June to August) precipitation and temperature patterns as the year of interest. These groups of years can be found in Figure S1b.

• Use simulated yields from the five calendar years prior to the study year (e.g., for 2010 we used 2005–2009 years).

• Use simulated yields from the 10 calendar years prior to the study year.

• Use simulated yields from the 20 calendar years prior to the study year.

Scenarios I and II were investigated because previous findings showed that the used of analogous weather years instead of the full weather record could increase accuracy of yield predictions and thus, derived EONR predictions (Hammer et al., 2001; Hansen et al., 2004). Scenarios III to V were investigated to quantify the impact of using limited amount of weather data because long term (35-years) weather data are not available in every location (Hansen et al., 2004; Grassini et al., 2015).

Data Analysis

Estimation of the Annual Economic Optimum Nitrogen Rate

The relationship between observed or simulated yield and the five N rates was fit using the quadratic and quadratic-plus-plateau model following the methodology described in Puntel et al. (2016). Models were deemed significant at p < 0.05 and the equations with the smallest sums of squares and largest R² were selected. The EONR and YEONR was calculated from the N response equations by setting the first derivative of the fitted response curve equal to a common price ratio of 5.6:1 N: corn grain price (US$ kg⁻¹ N: US$ kg⁻¹ grain) ratio during the study years (Cerrato and Blackmer, 1990; Bullock and Bullock, 1994). Variations in N: grain price ratios during the period of this study (1999–2014) were not taken into consideration because of its
potential confounding effect on the simulated EONR and YEORN evaluation. Different price ratios will need to be considered for historical evaluation (Amatya et al., 2008; Sawyer, 2015).

Both the observed EONR and YEONR for each year are presented in Puntel et al. (2016).

**Statistical Evaluation of Model Performance**

To evaluate the APSIM model simulations goodness of fit, we used graphical and statistical methods. For the statistical evaluation, we computed the root mean square error (RMSE), and the relative root mean square error (RRMSE; see equations in Archontoulis and Miguez, 2015) between observed and predicted values. The lower the value of RMSE and RRMSE the better the model performed. In this study, we considered RRMSE ≤15% as “good” agreement; 15–30% as “moderate” agreement; and ≥30% as “poor” agreement (Liu et al., 2013; Yang et al., 2014).

We quantified the accuracy of yield and EONR predictions by comparing the closeness agreement between the simulated and observed means. The accuracy of EONR prediction was considered good when the error was < ± 30 kg N ha⁻¹. This threshold represents the historical and current suggested N fertilization rate range for corn (Voss and Shrader, 1979; Sawyer et al., 2006).

The uncertainty around the simulated yields and EONR was calculated as the standard deviation of the 35 estimates (Togliatti et al., 2017). The standard deviation characterized the range of values within which the mean prediction is asserted to lie. We used the standard deviation among forecasting times to evaluate the impact of known weather on the uncertainty around the mean prediction for EONR and yield. Finally, we evaluated the proximity of the observed EONR and yield values to the acceptable range within the standard deviation.

To calculate the site-mean EONR and YEONR, we averaged annually observed values for each rotation similar to Puntel et al. (2016). These site-mean values were used to benchmark
model predictions, i.e., above, below or at average. We then counted the number of years in which the model correctly predicted the direction being above, below or at average of EONR and YEONR values at planting time. In each year, we calculated the absolute differences between the observed and the predicted EONR and we counted the years with an average difference of ± 30 kg N ha⁻¹.

We also examined APSIM predictions of EONR in extreme N rate years defined as years where the observed EONR is at least 30 kg N ha⁻¹ above or below the site-mean EONR. We specified three categories: (1) 30 kg N ha⁻¹ greater than the site-mean EONR (high N need), (2) within ± 30 kg N ha⁻¹ of the site-mean EONR, and (3) 30 kg N ha⁻¹ lower than the site-mean EONR (low N need). In addition, we explored the performance of the model by measuring the agreement (correlation, R²) between the observed and predicted EONR and YEONR at each forecasting time and by weather conditions based on Figure S2.

**Statistical Evaluation of Weather Scenarios**

The impact of the weather scenarios on yield and EONR predictions was evaluated by calculating the RRMSE for each scenario and then subtracting the RRMSE value of each scenario from the RRMSE of the standard approach using the 35-years of weather data. A positive difference means that a scenario (I–V) performed worse than the 35-year standard approach and a negative difference means that selection of weather years was better than the 35-year standard approach.

**Results**

**Yield Predictions at Different Forecasting Times Using 35 Years of Historical Weather**

Yield prediction at different forecast times did not significantly change during the growing season compared with yield prediction at maturity (Figure 3.2). On average, the RRMSE decreased by 1.2% from planting to maturity. Across five N rates, two crop rotations,
and 16 years APSIM explained 77% of the observed variability of corn yield (Figure 3.2) when predictions were made early in the season (planting and V6 stage), about 79% of the variability during mid-season (V12 and R1 stages), and 81% of the variability at the end of the season (R6 stage). The simulated mean yield at the four forecasting times (with unknown weather after the corresponding growth stage) was similar to the final yield prediction at R6 simulated with known weather (Figure 3.2).

At early stages (planting to V12), APSIM was able to explain ~40% of the variability in observed YEONR and 57% of the variability at maturity (Figure 3.2). The APSIM model was better at explaining the observed variability in the YEONR during warm weather years than cold weather years across the different forecasting times (R2 ~ 0.8 vs. 0.5, respectively; Table S3). Absolute differences between observed and predicted YEONR were 1.55 and 0.63 Mg ha−1 for cold and warm weather years, respectively. Overall model performance improved (R2 = 0.6; data not shown) when looking at this relationship while excluding the 2008, 2010, 2012, and 2014 extreme weather condition years in the 16-years of experiments (Figure S2).

Between the two cropping systems, yield predictions were slightly better for SC than CC rotations across all four forecasting times (RRMSE of 12.9 vs. 14.2%, respectively; Table S1). The standard deviation of the mean yield, a measure of the uncertainty around yield predictions, did not decrease from planting to R1 (Figures S3, S4). At maturity, there is no uncertainty (standard deviation = 0) because the actual weather was known (Figures S3, S4). In agreement with yield predictions, the uncertainty around the predicted mean YEONR did not decrease from planting to R1 in a significant number of the years (Figure 3.3, Figure 3.4). However, the mean deviation (precision) of yield predictions across all years was 27% lower for R1 than at planting (Figure 3.3, Figure 3.4).
**Figure 3.2** Simulated vs. observed corn yield (Top panel), economic optimum N rate (Bottom panel, EONR), and yield at EONR (Central panel, YEONR) at different corn stages using 35-yr weather data. In the top panels data presented by N-rate while in the bottom panels data presented by cropping system: CC, continuous corn and CS, soybean-corn. The V6 and V12 are the 6th and 12th leaf stage, respectively; R1 and R6 are silking and physiological maturity stages, respectively (Abendroth et al., 2011).
Figure 3.3 Predicted and observed yield at the economic optimum N rate (YEONR) for continuous corn. The connected red dots indicate APSIM model predictions at planting time, V6 (6th leaf), V12 (12th leaf), and R1 (silking) stages using actual and historical weather data (vertical bars indicate standard deviation, n = 35). At maturity (R6), the weather is known so there is no uncertainty in yield prediction. Blue squares represent the observed YEONR. The green dashed line represents the mean YEONR for the study period at this site.
Figure 3.4 Predicted and observed yield at the economic optimum N rate (YEONR) for soybean-corn. The connected red dots indicate APSIM model predictions at planting time, V6 (6th leaf), V12 (12th leaf), and R1 (silking) stages using actual and historical weather data (vertical bars indicate standard deviation, n = 35). At maturity (R6), the weather is known so there is no uncertainty in yield prediction. Blue squares represent the observed YEONR. The green dashed line represents the mean YEONR for the study period at this site.
EONR Prediction at Different Forecasting Times Using 35 Year of Historical Weather

In contrast to yield predictions, the EONR predictions were less accurate (Figure 3.2), and at different forecasting times showed different patterns across rotations and years (Figure 3.5, Figure 3.6). In some cases, the EONR prediction was more accurate at planting or V6 than at maturity (e.g., 2004, Figure 3.5). In other cases, the EONR prediction was more accurate at maturity than early in the season, but the differences in terms of actual value were small (e.g., Figure 3.5, 2007, the difference between simulated EONR at planting and maturity was 18 kg N ha⁻¹ for CC). Overall, the mean deviation (precision) of EONR predictions across all years was 25% lower for R1 than at planting (Figure 3.5, Figure 3.6). The forecasted site-mean EONR and the standard deviation was similar to the observed values, but low for SC and high for CC (Table 3.1).

Table 3.1  Site-mean and the associated standard deviation economic optimum N rate (EONR, units: kg N ha⁻¹) for each crop rotation, forecast time, and the measured site-mean across years.

<table>
<thead>
<tr>
<th></th>
<th>Soybean-Corn</th>
<th>Corn-Corn</th>
</tr>
</thead>
<tbody>
<tr>
<td>Simulated site-mean at planting (n=560)</td>
<td>135 ± 42</td>
<td>199 ± 43</td>
</tr>
<tr>
<td>Simulated site-mean at 6th corn leaf (n=560)</td>
<td>138 ± 41</td>
<td>200 ± 43</td>
</tr>
<tr>
<td>Simulated site-mean at 12th corn leaf (n=560)</td>
<td>137 ± 39</td>
<td>193 ± 40</td>
</tr>
<tr>
<td>Simulated site-mean at corn silking (n=560)</td>
<td>135 ± 40</td>
<td>199 ± 43</td>
</tr>
<tr>
<td>Simulated site-mean at corn maturity (n= 16)</td>
<td>137 ± 43</td>
<td>225 ± 33</td>
</tr>
<tr>
<td>Measured site-mean (n= 16)</td>
<td>149 ± 48</td>
<td>188 ± 42</td>
</tr>
</tbody>
</table>
Figure 3.5 Predicted and observed economic optimum N rate (EONR) for corn-corn. The connected red dots indicate APSIM model predictions at planting time, V6 (6th leaf), V12 (12th leaf), and R1 (silking) stages using actual and historical weather data (vertical bars indicate standard deviation, n = 35). At maturity (R6), the weather is known so there is no uncertainty in yield prediction. Blue squares represent the observed EONR. The green dashed line represents the mean EONR for the study period at this site.
Figure 3.6 Predicted and observed economic optimum N rate (EONR) for soybean-corn. The connected red dots indicate APSIM model predictions at planting time, V6 (6th leaf), V12 (12th leaf), and R1 (silking) stages using actual and historical weather data (vertical bars indicate standard deviation, n = 35). At maturity (R6), the weather is known so there is no uncertainty in yield prediction. Blue squares represent the observed EONR. The green dashed line represents the mean EONR for the study period at this site.
At early forecasting times (planting, V6, and V12), the absolute average differences between observed and predicted EONR for both rotations were lower for warm than for cold weather years (37 vs. 50 kg N ha$^{-1}$, respectively; Table S3). The model better explained observed variability in the EONR in cold/dry than warm/wet seasons across forecasting times and crop rotations ($R^2 = 0.32$).

In terms of uncertainty, the standard deviation of the mean EONR prediction did not show a consistent pattern of decrease during the growing season (Figure 3.5, Figure 3.6). Overall, the EONR predictions were more accurate in CC (RRMSE = 25%) than SC (RRMSE = 45%) across forecast times (Figure 3.2).

The APSIM model predicted EONR with an average error of ±38 kg N ha$^{-1}$ in 62% of the study cases (n = 31). Prediction error was below the threshold value of ±30 kg N ha$^{-1}$ in about 50% of the cases.

**Assessing the Impact of Different Weather Scenarios**

Using 35 years of weather data as input to the model resulted in marginally lower RRMSE (on average 1.4%) values and therefore better yield predictions across forecast times compared to the use of 5, 10, or 20 years of weather data or weather data that included only years with similar weather patterns (Figure 7A). Similar results were found for the EONR prediction; that is, use of 35-year weather data performed better than all other scenarios (Figure 7B). Across all forecasting times, RRMSE was 3.5% lower when using 35-years of weather data. Among the scenarios compared against the use of 35-years, the use of 20 years of weather data had the lowest RRMSE for yield and EONR at all forecasting times (Figure 7A). The exception was the yield predictions at V12 and silking stage where the RRMSE was the lowest for scenarios with 5, 10, or 20 years of weather data (Figure 7A).
Figure 3.7 Differences in relative root mean square error (RRMSE) between weather scenarios (I–V) and standard approach (use of 35-years of weather data) for predicted corn yield (A) and economic optimum N rate (B) at four forecasted times: planting, V6 (6th leaf), V12 (12th leaf), and R1 (silking) stage. The positive values indicate that using the 35-years of weather history is better than use of other weather scenarios (I–V). Continuous corn (CC) and soybean-corn (SC). Vertical bars represents the standard deviation.

Independent of the weather scenarios, RRMSE values for EONR predictions were four times higher compared to yield predictions. The selection of a specific weather scenario tended to have a greater impact on predictions early in the season than toward the end-of-season (Figure 3.7). For example, at flowering the RRMSE was on average across weather scenarios 0.8 and 2.3% lower than RRMSE at planting for yield and EORN, respectively.

Comparison between APSIM and the 16 Year Site-Mean EONR and YEONR

We use the site-mean EONR and YEONR (see green horizontal line in Figure 3.3, Figure 3.4, Figure 3.5, Figure 3.6) to benchmark the direction and magnitude of error in annual
APSIM predictions. Across 16-years in CC and 15-years in SC (n = 31 cases), the observed EONR values were in 11, 14, and 6 cases above, below and at site-mean EONR values respectively. APSIM predictions of EONR at planting time were in 11, 16, and 4 cases, above, below and at the site-mean EONR values respectively (Figures 5, 6). In 19 of 31 (62%) cases, APSIM correctly predicted the direction of annual EONR being above, below, or at average. For those cases, the average error was 38 kg N ha\(^{-1}\) which represents 20 and 25% error base on the average N rate for CC (observed mean = 184 kg N ha\(^{-1}\)) and SC (149 kg N ha\(^{-1}\)), respectively.

The observed YEONR values were in 14, 11, and 6 cases above, below and at site-mean YEONR values respectively, across rotations and years. APSIM predictions of YEONR at planting time were in 8, 14, and 9 cases, above, below and at the site-mean YEONR values respectively (Figure 3.3, Figure 3.4). In 21 of 31 (67%) cases, APSIM correctly predicted at planting time the direction of annual YEONR being above, below, or at average.

In low or high N need years the simulated EONR deviated more from observations than in average N need years (Figure 3.5, Figure 3.6; Table 2). In 2 out of 16 years (extreme wet years; 2008 and 2010) the APSIM model greatly underestimated the EONR when > 30 kg N ha\(^{-1}\). In low fertilization need years, APSIM over predicted the N rate on average by 36 and 69 kg N ha\(^{-1}\) in CC and SC rotation, respectively (Table 3.2). Overall the distribution of the differences between APSIM predicted EONR and observed EONR was skewed to the right (~ + 30 kg N ha\(^{-1}\)) for CC and skewed to the left for SC, underestimating the observed EONR (Figure 3.8).
Table 3.2 Comparison of economic optimum nitrogen rate (EONR) estimated by APSIM to the site mean EONR and observed EONR for continuous corn and soybean-corn over three categorical EONR ranges.

<table>
<thead>
<tr>
<th>Timing</th>
<th>Categorical EONR ranges(^4)</th>
<th>APSIM-Observed annual EONR</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>Corn-Corn</td>
</tr>
<tr>
<td></td>
<td></td>
<td>--------------------------</td>
</tr>
<tr>
<td>Planting</td>
<td></td>
<td>-16</td>
</tr>
<tr>
<td>V6</td>
<td>High N need year (30 kg N ha(^{-1}) above the measured site-mean EONR)</td>
<td>-18</td>
</tr>
<tr>
<td>V12</td>
<td></td>
<td>-15</td>
</tr>
<tr>
<td>R1</td>
<td></td>
<td>-19</td>
</tr>
<tr>
<td>R6</td>
<td></td>
<td>9</td>
</tr>
<tr>
<td>Planting</td>
<td>Average year (± 30 kg N ha(^{-1}) from the measured site-mean EONR)</td>
<td>13</td>
</tr>
<tr>
<td>V6</td>
<td></td>
<td>17</td>
</tr>
<tr>
<td>V12</td>
<td></td>
<td>11</td>
</tr>
<tr>
<td>R1</td>
<td></td>
<td>17</td>
</tr>
<tr>
<td>R6</td>
<td></td>
<td>38</td>
</tr>
<tr>
<td>Planting</td>
<td>Low N need year (30 kg N ha(^{-1}) below the measured site-mean EONR)</td>
<td>40</td>
</tr>
<tr>
<td>V6</td>
<td></td>
<td>38</td>
</tr>
<tr>
<td>V12</td>
<td></td>
<td>33</td>
</tr>
<tr>
<td>R1</td>
<td></td>
<td>37</td>
</tr>
<tr>
<td>R6</td>
<td></td>
<td>65</td>
</tr>
</tbody>
</table>

Figure 3.8 Distribution of differences between simulated economic optimum N rate (EONR) at planting time, V6 (6th leaf), V12 (12th leaf), R1 (silking), and R6 (maturity) growth stages, and the site-mean EONR minus the yearly observed EONR for continuous corn (CC) and soybean corn (SC) rotation.

\(^4\) Observed categorical ranges for the EONR based on site-mean of 188 (corn-corn) and 149 kg N ha\(^{-1}\) (soybean-corn).
Discussion

We demonstrated an alternative way to utilize the power of mechanistic cropping systems models to assist N-rate decisions in real time as opposed to current ex-post use of models that are of little interest to farmers (Quiring and Legates, 2008; Thompson et al., 2015). This is the first study that concurrently forecast corn yields and their N requirements in the USA Corn Belt.

Yield Forecasts

This study showed that end-of season corn yields and YEONR can be predicted within an acceptable error (RRMSE < 17%) as early as planting time in most of the study years (Figure 3.2, Figure 3.3, Figure 3.4, and Figures S3, S4). The 16-years of data used to test our yield forecasts accounted for different weather years (wet, dry, warm, cold, Figure S1a) and management practices, which further increased our confidence that our process-based forecasting approach is robust (He et al., 2017). This means that our science-based yield forecasting approach has the potential to inform corn producers in the USA Midwest that are using the yield-goal approach to predict N-rates by “guessing” end-of-season yields (Arbuckle and Lasley, 2013; Raun et al., 2017; Morris et al., 2018). Further testing of our approach across multiple environments is needed before application. This would minimize expected errors that are often encountered when using a conventional yield approach based on yield averages across years (Raun et al., 2017).

In most cases, the simulated yield at maturity was within the standard deviation of yield prediction at planting (Figures S3, S4). The uncertainty in yield predictions did not substantially decrease from planting to silking even though that the weather uncertainty decreased (Figure S3). We believe that if we had run the forecast at 150°C-days (or 15 calendar days) after silking we would have seen a decrease in the uncertainty as two of the major determinants of corn yield (kernel number and potential kernel weight) is set (Andrade et al., 1999; Borrás and Vitantonio-
Mazzini, 2018). Previous studies have shown a decrease in the uncertainty around corn yield predictions at or about 150°C-days after silking (Thornton et al., 1997; Hansen et al., 2004; Togliatti et al., 2017). By R1 stage, about 50% of the weather is still unknown and the weather during grain fill period has substantial effects on yield. This weather uncertainty introduces yield variability in model predictions as different weather variables affects various plant and soil processes (and thus the final product that is yield) in different ways that are also phenologically time dependent (Semenov et al., 1993). For a thorough sensitivity analysis of weather effects on APSIM simulated grain yield for central Iowa, USA we refer to Togliatti et al. (2017).

In two of the years, yield predictions at maturity deviated substantially from the simulated yields at planting (2004 and 2008 in both rotations; Figure 3.3, Figure 3.4). In these years, yield predictions changed during the season as a response to extremely low temperature conditions during grain fill compared to the 35-year average temperature (Figures S2A, S5). The model responded to this weather event by increasing the length of grain fill resulting in higher yield predictions at maturity than at early stages. However, in our study the response of the model was not enough to match the observed yields; perhaps use of a newer maize version (Soufizadeh et al., 2018) of the APSIM model may capture these dynamics better. Nevertheless, this example shows that use of crop model offers both predictability and the reasons behind yield predictions (Banger et al., 2017).

EONR Forecast

The APSIM model predictions at planting time were directionally correct in 62% of the study cases. This means that our N forecasting approach is promising and has future potential to directly and/or indirectly aid N rate decisions by providing a year-to-year opportunity to adjust N rate recommendations early in the season (Figure 3.5 and 3.6). In terms of prediction accuracy, our modeling approach forecasted annual EONR values at all forecast times with an error range
of ±38 kg N ha\(^{-1}\) in about 62–69% of the simulated cases (Figure 3.5, Figure 3.6, Figure 3.8). These results emphasize the difficulty in predicting annual EONR in corn production. Given a potential threshold error range of ±30 kg N ha\(^{-1}\), this means that further improvements are needed in modeling algorithms as well as development of more precise soil and crop management inputs to the model.

To our knowledge, there is no other tool that can provide both yield and EONR forecasts as early as at planting time. The soil nitrate test and remote sensing approaches are in-season tools. Pre-season tools such as the yield-goal approach rely on yield guesses (Van Es et al., 2006; Sela et al., 2017); while the MRTN tool incorporates N response variation and accounts for price fluctuations, but does not directly adjust for year-to-year variability (Sawyer et al., 2006).

As illustrated in Figure 3.1, there are many dynamic and interactive factors involved in EONR prediction (Scharf, 2001; Mamo et al., 2003; Scharf et al., 2006; Dhital and Raun, 2016). Every year, management, environment, and genotype interactions determine the shape of the yield response to N fertilizer relationship that is used to estimate EONR. Our modeling approach accounted for the majority of the factors by simulating residue decomposition, soil organic matter dynamics, changes in soil temperature, moisture, and nitrate levels during fallow periods and accounted for management such as planting date, row spacing and date of N application. All these factors affect soil N supply and crop N demand. Low EONR predictions from the model were usually associated with high estimates of soil residual nitrate levels at planting and delays in planting. But, there are many interactions that simultaneously occur among soil-plant processes within the system that makes it difficult to simplify and generalize the reasons of yield and EONR variability (see Figure S5 and Table S2). For example, in a previous work using APSIM model, we found that spring precipitation was related to N losses and EONR (the higher
the spring precipitation the higher the EONR; Puntel et al., 2016). In contrast, a later study showed that the amount of precipitation had little influence on simulated grain yield in central Iowa because of the effect of groundwater tables (Togliatti et al., 2017).

The inter-annual prediction accuracy of the EONR forecast was lower than that of the yield forecast (Figure 3.3, Figure 3.4, Figure 3.5, Figure 3.6, Figures S3, S4). One reason is that EONR values are not a direct output of the model but a result from a regression analysis of model outputs (yields) which incorporates further uncertainty (Puntel et al., 2016). Across years, the simulated site-mean EONR value by the model was similar to the observed site-mean (Table 3.1). We believe that by running the model sequentially, annual over-and under-predictions are canceled out and the model is able to predict the site-mean values more accurately.

**Future Improvements Toward More Accurate N Rate Forecasts**

This study identified three areas for future research: (1) simulation set up, continuously vs. annual reset; (2) YEONR and EONR predictions in extreme years, and (3) weather data to drive simulations.

Our simulation protocol is characterized by a high degree of difficulty as we ran the model sequentially from 1999 to 2014 to avoid annual re-initialization of soil input parameters and to capture the carry-over effects on N dynamics (Constantin et al., 2011; Basso and Ritchie, 2015). That approach was followed because of the lack in data to update the model every year and because there was evidence from other studies that models can simulate yields and organic matter trends at different N rates in the long term (Ma et al., 2007; Puntel et al., 2016). The drawback of this approach is that simulation errors can accumulate over time and affect the next year's simulation, especially if the model fails to predict crop yield and N dynamics in one of the years (Salo et al., 2016).
We believe that yield and EONR forecasts at planting time can be further improved if additional information on soil nitrate, water, and surface residue was available to eliminate model uncertainties in simulating carry-over effects during fallow periods (Hansen et al., 2006; Carberry et al., 2009; Ines et al., 2013; Yin et al., 2017). Previous modeling work in Iowa has shown that the available soil water and N status at planting time largely affected predicted mean yields and the range of yield level probabilities (Archontoulis et al., 2016). Therefore, when the model is primarily used for accurate year-by-year yield and EONR forecasting purposes, an annual reset approach may be more appropriate than sequential (Ines et al., 2013; Iqbal et al., 2017). This information can be derived from emerging technologies such as remote sensing, and other common tools such as soil N testing (Basso et al., 2001; Jin et al., 2017; Reimer et al., 2017). Testing and possible improvements in the APSIM surface organic matter model for corn and soybean residues in future studies may improve the simulation of the carry over effects and predictions of EONR, especially in the SC rotation.

There is a need for further research to improve the annual EONR predictability in extreme weather years with precipitation above or below historical average precipitations. Differences between predicted and observed EONR tended to be higher for cold weather years (temperature below the historical average), and their agreement was largely affected by the inaccurate prediction on extremely wet (i.e., 2008) and dry (i.e., 2000) weather years (Figure S2). In this study, we noticed that EONR forecast was more accurate in years that had EONR values near the long-term site average and the prediction accuracy decreased in years with extreme high or low EONR measured values (±20% from long-term site average, Table 3.2).

For the farmer, both extreme high or low EONR predictions result in economic loss, with the greatest being yield loss when under-fertilizing in high N rate requirement years.
Furthermore, when high N is predicted in low N need years the risk of N loss to the environment is greatest (Raun et al., 2017). In particular, the model failed to forecast accurate EONR values in extreme high precipitation years such as 2008 and 2010. We believe the main reason is the incorrect simulation of the carry-over effects from previous year (i.e., soil inorganic nitrogen, soil moisture, root and carbon and nitrogen inputs from previous crops) or possible underestimation of N losses from the system (He et al., 2017; Yin et al., 2017). Prediction of EONR is very complex and less accurate than yield (Figure 3.2). Perhaps an alternative way of using the model as a forecast tool may be to predict the key-components of the EONR such as yields and soil supply and plant N uptake dynamics, in which the model performs well (Archontoulis and Licht, 2017). In that way, we avoid accumulation of errors that leads to a low prediction accuracy of the EONR.

For weather uncertainty affecting yield and derived EONR forecasts (Hansen et al., 2006), our results indicated that use of the entire historical record (35 years) in the simulation process is better than selecting years based on similar weather events or using only a smaller set number of previous years (Figure 3.7). This was more evident in EONR predictions and less in yield predictions. Although the reasons are not sufficiently clear, based on other studies, we believe that simulated crop growth depends more on the distribution of weather within the season than the season average which was used to categorize the years used for the weather scenarios (Hansen and Indeje, 2004; Figure S1b).

We also found that the use of at least 10 and 20 years of weather data is associated with small error (2.5% less accuracy than the 35-year; Figure 3.7) which is an important finding given that not all sites have accurate weather records for 35 years (Hansen et al., 2004; Grassini et al., 2015). Our findings agree with Van Wart et al. (2013), who showed that 6–10 years of
weather data is needed for sites with similar rain patterns as the one used in this study. However, we also recognize there are other ways of selecting years to be used in forecasting studies and this is a topic for further investigation (Hansen et al., 2004).

**Conclusions**

This study provided evidence that use of a calibrated cropping systems model can aid yield and N rate forecasts. At planting time, model predictions were directionally correct in predicting whether the optimum N-rate for corn would be above, below or at site-mean value. The associated prediction error was within an error range of ±30 kg N ha−1 in ~60% of the years. Predictability of corn yields was more accurate than optimum N-rates at planting time. In most years, in-season yield and optimum N-rate forecasts were not better than the predictions made at the beginning of the season. Use of 35-year historical weather data was found to be more accurate than using analogous weather years based on similarity of current weather conditions. Process-based modeling forecast of corn yields and optimum N-rates is already promising and has potential for realizing further improvements in achieving even more accurate early-season predictions.

**References**


Figure S1. Cumulative annual (a) and summer (June to August, b) precipitation and mean temperature in Ames, Iowa, USA. The long-term average cumulative precipitation and temperature across years (1980-2014) are shown with the vertical and horizontal lines, respectively. These average values were used to classify years into warm, cool, dry, and wet. Years shown in red represent the years used in this study (1999–2014).
Figure S2. Example of the methodology used to assemble synthetic weather files to run the APSIM model at different forecasting times. Synthetic weather files have known weather until the time of the forecast (e.g. planting, see top panel or flowering time see bottom panel) and multiple historical weather data (35 years) until the end of a particular growing season.
Figure S3. Simulated corn yields at various corn growth stages for continuous corn at 0 and 268 kg ha\(^{-1}\) applied N rate. Simulations performed for planting time, V6 (6\(^{th}\) leaf), V12 (12\(^{th}\) leaf), and R1 (silking) stages (Abendroth et al., 2011) using actual and historical weather data (n=35; vertical bars indicate standard deviation). At R6 (maturity) stage the weather was known (n=1). The observed corn yields at harvest (Obs) are also shown (n=4 replications).
Figure S4. Simulated corn yields at various corn growth stages for soybean-corn at 0 and 268 kg ha⁻¹ applied N rate. Simulations performed for planting time, V6 (6th leaf), V12 (12th leaf), and R1 (silking) stages (Abendroth et al., 2011) using actual and historical weather data (n=35; vertical bars indicate standard error). At R6 (maturity) stage the weather was known (n=1). The observed corn yields at harvest (Obs) are also shown (n=4 replications).
Figure S5. Precipitation, maximum and minimum temperature, and radiation differences from the historical average. The lowest two panels show percent error between simulated and observed corn yield at 201 kg N ha$^{-1}$ and the economic optimum nitrogen rate (EONR) for continuous corn (CC) and soybean-corn rotation (SC).
Table S1. Root mean square error (RMSE) and relative RMSE (RRMSE) for simulated corn yields at continuous corn (CC) and soybean-corn (SC) at different forecasting times.

<table>
<thead>
<tr>
<th>Rotation</th>
<th>Timing*</th>
<th>RMSE</th>
<th>RRMSE</th>
</tr>
</thead>
<tbody>
<tr>
<td>CC</td>
<td>Planting</td>
<td>1358</td>
<td>14.7</td>
</tr>
<tr>
<td></td>
<td>V6</td>
<td>1443</td>
<td>15.6</td>
</tr>
<tr>
<td></td>
<td>V12</td>
<td>1301</td>
<td>14.1</td>
</tr>
<tr>
<td></td>
<td>R1</td>
<td>1279</td>
<td>13.9</td>
</tr>
<tr>
<td></td>
<td>R6</td>
<td>1152</td>
<td>12.4</td>
</tr>
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<td>SC</td>
<td>Planting</td>
<td>1475</td>
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<tr>
<td></td>
<td>V6</td>
<td>1463</td>
<td>12.9</td>
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<td></td>
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<tr>
<td>Combined</td>
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<tr>
<td></td>
<td>V6</td>
<td>1453</td>
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<td>R1</td>
<td>1382</td>
<td>13.5</td>
</tr>
<tr>
<td></td>
<td>R6</td>
<td>1294</td>
<td>12.6</td>
</tr>
</tbody>
</table>

*Growth stages: planting time, V6 (6th leaf), V12 (12th leaf), R1 (silking), and R6 (maturity); Abendroth et al., 2011.
Table S2. Regression coefficients \( (R^2) \) between grain yield or economic optimum nitrogen rate (EONR) error (absolute difference between simulated and observed) and weather deviations of the data presented in figure S3. The year 2013 was excluded from this analysis due to hail damage.

<table>
<thead>
<tr>
<th>Weather variable</th>
<th>CC</th>
<th>CS</th>
</tr>
</thead>
<tbody>
<tr>
<td>Yield</td>
<td>EONR</td>
<td>Yield EONR</td>
</tr>
<tr>
<td>Precipitation (pre-flowering)</td>
<td>0.0003</td>
<td>0.088</td>
</tr>
<tr>
<td>Precipitation (post-flowering)</td>
<td>0.0021</td>
<td>0.337*</td>
</tr>
<tr>
<td>Max. temperature (pre-flowering)</td>
<td>0.0025</td>
<td>0.0058</td>
</tr>
<tr>
<td>Max. temperature (post-flowering)</td>
<td>0.082</td>
<td>0.128</td>
</tr>
<tr>
<td>Min. temperature (pre-flowering)</td>
<td>0.007</td>
<td>0.0004</td>
</tr>
<tr>
<td>Min. temperature (post-flowering)</td>
<td>0.009</td>
<td>0.05</td>
</tr>
<tr>
<td>Radiation (pre-flowering)</td>
<td>0.137</td>
<td>0.0001</td>
</tr>
<tr>
<td>Radiation (post flowering)</td>
<td>0.0016</td>
<td>0.198</td>
</tr>
</tbody>
</table>

* Significant correlation at \( p < 0.05 \).

Tables S3. Correlation \( (R^2) \) and absolute difference between observed and predicted economic optimum nitrogen rate (EONR) and yield at EONR (YEONR) for four categories of weather years.

<table>
<thead>
<tr>
<th>Weather years</th>
<th>EONR-( R^2 )</th>
<th>EONR-Absolute difference</th>
<th>YEONR-( R^2 )</th>
<th>YEONR-Absolute difference</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>-</td>
<td>-----kg N ha(^{-1} )----</td>
<td>-</td>
<td>-----Mg ha(^{-1} )----</td>
</tr>
<tr>
<td>Cold and wet</td>
<td>0.02</td>
<td>49</td>
<td>0.47</td>
<td>1.40</td>
</tr>
<tr>
<td>Cold and dry</td>
<td>0.30</td>
<td>51</td>
<td>0.50</td>
<td>1.70</td>
</tr>
<tr>
<td>Warm and wet</td>
<td>0.34</td>
<td>34</td>
<td>0.87</td>
<td>0.48</td>
</tr>
<tr>
<td>Ward and dry</td>
<td>0.02</td>
<td>40</td>
<td>0.71</td>
<td>0.78</td>
</tr>
</tbody>
</table>
CHAPTER 4. DEVELOPMENT OF A NITROGEN RECOMMENDATION TOOL FOR CORN CONSIDERING STATIC AND DYNAMIC VARIABLES

Modified from a paper submitted for publication in European Journal of Agronomy, June 2018 |

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Abstract

Many soil and weather variables can affect the economical optimum nitrogen (N) rate (EONR) for maize. We classified 54 potential factors as dynamic (change rapidly over time, e.g. soil water) and static (change slowly over time, e.g. soil organic matter) and explored their relative importance to EONR and yield by analyzing a dataset with 51 N trials from Argentina’s Corn Belt region. We found that dynamic factors alone explained 50% of the variability in the EONR whereas static factors explained only 20%. Best EONR predictions resulted by combining one static variable (soil depth) together with four dynamic variables (number of days with precipitation > 20 mm, surface residue amount, soil nitrate at planting and heat stress around silking) into a regression model. The resulted EONR model had a mean absolute error of 39 kg N ha⁻¹ and an adjusted $R^2$ of 0.61. Similar regression models for yield at optimum N rates and at zero N fertilization were developed and discussed. Furthermore, we found that the 51-N trial dataset had an average EONR of $113 \pm 83$ kg N ha⁻¹ and optimum yield of $12.3 \pm 2.2$ Mg ha⁻¹, which is roughly 50% higher than the current N rates and yields obtained by maize producers in the central west region of Argentina. This means that there is substantial room for yield gains in this region by improving N recommendations. The developed statistical models can assist in this direction. Lastly, our models can be easily tested and adopted in other rainfed environments.
Introduction

Maize production in Argentina has doubled over the last five years from 20 to 40 million tones (AMIS 2018). About 80% of the produced grain is exported annually, making this region a key player in the global maize market (Alexandratos and Bruinsma 2012; Andrade and Satorre 2015). The increased corn production has been mainly associated with an increase in area rather than productivity; where the average corn yield is 7.6 Mg ha\(^{-1}\), which is considerably below the potential yield of 16 Mg ha\(^{-1}\) (Andrade and Satorre 2015). Poor crop management, in particular nitrogen (N) fertilization, is the major reason for the yield gap. The average N application rate to corn in Argentina is about 61 kg N ha\(^{-1}\) (ReTAA, 2018), which is about half of the US Corn Belt average N rate (Sawyer et al. 2006). Increasing N fertilization results in increased production costs that depending on the year, site, and within-field location this investment may or may not pay off due to the multiple factors affecting the economic optimum N rate (EONR, Puntel et al., 2018).

A better understanding and predictability of the EONR variability in this region could result in higher yields and profits while reducing environmental impacts (Aparicio et. al., 2008). However, there is very little research on EONR in this region compared to other regions (Tremblay, 2004; Van Es et al., 2005; Scharf and Lory 2006; Pagani et al., 2008; Dhital and Raun 2016). Interestingly, the vast majority of published studies on EONR have focused on the effects of individual factors such as soil properties or precipitation as opposed to the compound effect of multiple factors on EONR (Albarenque et al. 2016; Basso et al. 2001, 2013; Dharmakeerthi, Kay, and Beauchamp 2005; Mamo et al. 2003).

Factors effecting EONR and yield can be broadly classified into dynamic variables (ones that change quickly within a growing season such as precipitation) and static variables (ones that
change slowly and do not vary within a growing season such as soil organic matter). Today’s N recommendation tools are based on 1) dynamic factors such as the soil N-nitrate test (Bundy and Adraski, 1995; Rozas et al. 2000; Shapiro et al., 2008), 2) static factors such as soil texture (Tremblay et al., 2011), 3) both static and dynamic factors via crop and soil modeling (Banger et al., 2017), and 4) yield expectations (Stanford et al., 1973) without considering other factors.

Regarding the static variables, some studies have reported relationships between yield or EONR and soil texture and organic matter (SOM; Gregoret et al. 2006; Peralta et al. 2013; Puntel et al., 2017). Soil texture and SOM effect water holding capacity (Gregoret et al. 2006; Sadras and Calvino 2001; Wright et al. 1990) and N cycling (Dharmakeerthi et al. 2005; Sogbedji et al. 2001), thus soil N supply and crop N uptake. However, measuring these static variables at a fine spatial resolution is expensive and labor intensive. To address this issue more accessible variables such as topography and apparent soil electrical conductivity are used (ECa; Baxter et al., 2003; Kitchen et al. 2003; Shaner et al. 2008). The ECa is correlated with soil water content (Brevik et al., 2006), compaction (Kravchenko and Bullock 2000), and salinity (Heiniger et al., 2003) and it is a very good descriptor of soil texture (King et al. 2005; Shaner et al. 2008). Topography, derived terrain parameters, and ECa have been used with varying degrees of success to determine areas with contrasting yields (Chang et al. 2004) and differential yield response to N (Jaynes et al., 2011).

Regarding the dynamic variables, several studies have indicated the importance of soil moisture, soil nitrate, rainfall and temperature on crop yields and EONR in rainfed regions (Andrade et al., 1993). For example, Hergert et al. (1995) and Kitchen et al. (2005) illustrated the importance of soil nitrate spatial and temporal dynamics on EONR. Ordóñez et al. (2015) and Rattalino Edreira and Otegui (2013) quantified heat stress effects on corn yield and EONR. Soil
temperature and moisture effects on soil N mineralization and residue decomposition and thus crop N availability and EONR are well known in literature (Andraski et al., 2000; Cabrera et al., 2005). Shallow groundwater dynamics have been found to positively effect yields in dry seasons and negatively effect yields in wet seasons (waterlogging and flooding; Ayars et al. 2006; Jaynes 2012; Nosetto et al. 2009) while also effecting environmental N losses (Elmi et al., 2000; Dinnes et al., 2002) and thus the EONR.

Understanding which factors or synergic relationships contribute the most to the EONR spatial and temporal variability is complex and still elusive (Scharf 2015). Yet, there is no study to compare the relative importance of different static and dynamics factors on EONR and corn yield. A targeted experimental research is needed in which several variables are simultaneously measured to identify the most important ones for further emphasis. To shed light on this important knowledge gap, we analyzed 51 N response trials conducted for five years in central west Buenos Aires, Argentina in which numerous static and dynamics variables were measured. Our specific objectives were to: 1) identify the range of yield and EONR variability across multiple static and dynamic factors in central west Buenos Aires, Argentina; 2) quantify the relative importance of dynamic and static factors on yield and EONR, and 3) develop and evaluate a predictive N model to aid site-specific N management.

**Materials and Methods**

**Experimental sites and design**

Fifty-three N rate trials were conducted at contrasting landscape positions on five fields located in Nueve de Julio, Buenos Aires, Argentina during five growing seasons: 2012-13 (season 1, 10 trials), 2013-14 (season 2, 10 trials), 2014-15 (season 3, 13 trials), 2015-16 (season 4, 11 trials), and 2016-17 (season 5, 9 trials). Soils were coarse-loamy, thermic Typic Hapludolls representing the most productive areas of the fields, coarse-loamy, thermic Entic Hapludolls
mostly representing sandy hills with low productivity, and Thapto-argic Hapludolls corresponding to shallower soils due to the presence of a clay pan layer at varying depths. These soils are representative of the Central-West Buenos Aires Province and other provinces in Argentina. In addition, the area is influenced by a fairly shallow water table that responds rapidly to rain, similarly to the US Corn Belt region (Fan et al., 2013). Due to severe flooding two trials were not harvested reducing the number of N trials for analysis to 51.

The N-trials were established in representative landscape positions to account for variations in elevation, ECa, soil available nitrogen, soil properties, and previous crop productivity. As an example, Figure S1 illustrates six of the N trials. Each N-trial was a small-plot randomized complete block design with three replications. Seven N rates (0, 25, 50, 100, 150, 200, and 250 kg ha\(^{-1}\)) were applied as broadcasted urea between planting and V3 stage (Abendroth et al., 2011). Plot size was 9 m long and 2.8 m wide. Phosphorus and sulfur fertilizers were applied according to soil analysis and local recommendations to ensure nutrient sufficiency. Previous crops were summer soybeans or double crop spring wheat/summer soybean. All trials had a final plant population between 65,000 and 80,000 plants ha\(^{-1}\) and row spacing was either 0.75 m or 0.52 m. Commercial corn hybrids with a relative maturity of 120 to 125 days were used. Fields were managed without tillage. Pest, diseases, and weeds were adequately controlled to ensure optimal growing conditions.

**Measurements and data processing**

Grain yields were determined by collecting ears from the center two rows of each plot (5 m length). Grain moisture was measured, and final yields were adjusted to 14% moisture. Additional measurements were taken from each N trial to explain yield response to N included: soil organic matter (SOM), texture, gravimetric water content, ECa, elevation, soil and water table depth, amount of residue from the previous crop, and hourly weather data. These
measurements and subsequent calculations were classified into static and dynamic explanatory variables, which are described below and summarized in Table 4.1.

**Static variables**

Static variables are relatively constant over time and measured once per trial (Table 4.1). ECa at 30 and 90 cm soil depth was measured on transects, approximately 20 m apart using a Veris model 3100 sensor cart system (Veris Technologies, Salina, Kansas, USA). The ECa surveys were conducted before planting or after harvest. Elevation data was obtained by a dual frequency RTK system (Trimble 5700, USA) connected to the EC Veris surveyor. Both ECa and elevation data points were interpolated using ArcGIS (ESRI, Redlands, CA, USA) and R software (R Core Team, 2018) using ordinary krigging in a regular 3-m grid (Figure S1).

Landscape characteristics were determined by primary and secondary terrain attributes (Moore et al 1991; Wilson and Gallant, 2000). We used primary attributes such as elevation, relative elevation (Rel_elev), slope, and plane curvature (pcurv) that were derived directly from digital elevation models (DEM) (Figure S1, Table 4.1). Secondary attributes such as specific catchment area (SCA) were derived from a combination of primary attributes. Digital terrain analysis was performed using the GRASS 7.0.5 (Geographic Resources Analysis Support System, grass.osgeo.org) and ArcGIS 10.5 software packages.

The r.param.scale function in GRASS was used to calculate plan curvature with a scale of 3 by 3 grid (13.9 meters). The slope and a moving-window version of relative elevation (3 x 3) (REL; Miller, 2014) were calculated in ArcGIS 10.5, using custom toolbox models (available at http://www.geographer-miller.com/relief-analysis-toolbox). Plane curvature is perpendicular to the direction of the maximum slope. A positive value indicates that the surface is sidewardly convex at that cell. A negative value indicates the surface is sidewardly concave at that cell. A
value of zero indicates the surface is linear (Figure S1). Profile curvature relates to the
convergence and divergence of water flow across a surface.

The SCA was calculated using Spatial Analyst Hydrology Tools in ArcGIS 10.5. The
SCA is defined as the area of land upslope of a width of contour, divided by the contour width,
and is a commonly used quantity in hydrology to describe complex terrain for analyzing water
flow on hill slope; it can be a surrogate for water discharge per unit flow width.

SOM was determined by the combustion method (Wang and Anderson, 1998) and texture
by the pipette method (Soil Survey Staff, 2014). Ten cores were taken per block from 0-20, 20-
60, 60-100 cm depth in most of the experimental sites to determine SOM and texture. For the
first two seasons, samples were collected from 0-20, 20-40, and 40-60 cm depth (Sites 1-10).
Data were combined into top (0-20 cm) and subsoil data (20-60 cm). Data below 60 cm were not
used in the analysis. Effective soil depth was measured manually with a 2-meter soil probe in
each plot. Soil depth was as shallow as 60 cm for some of the experimental sites. Using SOM,
texture data, and Saxton and Rawls (2006) pedotransfer functions, we calculated field capacity
(FC) and saturation point (SAT) for the top and subsoil layers.

**Dynamic variables**

Variables that change rapidly over time were classified as dynamic (Table 4.1).
Gravimetric soil water and N-nitrate content at 0–20 cm and 20–60 cm was measured at planting.
Soil water content was expressed as a percent of FC and SAT. N-nitrate content was expressed
as kg of N per ha by layer. The total nitrate amount across the 0–60 cm profile was used as an
explanatory variable in this analysis. Water table depth at each trial was manually measured
(from installed wells) around planting. Weather data, including hourly precipitation, radiation,
and temperature, were obtained from the closest weather station to the experimental sites
(distance less than 5 km). Precipitation was accumulated for the following periods: from harvest
of the previous crop to planting of corn (amount_H-P), from planting to silking (amount_P-S), ± 1.5 weeks around silking (critical period; amount_S), and from planting to harvest (amount_P-H). For the same time periods, we calculated and used as explanatory variables the number of rain events greater than 0 mm and greater than 20 mm per day (events_H-P, events_S, events_P-H, events_H-P_20, events_S_20, events_P-H_20). The value of 20 mm day\(^{-1}\) was arbitrarily chosen in this analysis to account for possible N leaching. The number of days with air temperature below 10 ºC during the growing season and the number of days with air temperatures above 35 ºC around maize’s critical period as well as over the entire growing season were calculated (Temp_P-H_10, Temp_P-H_35, Temp_S_35, respectively). Lastly, we calculated radiation sums around the critical period (± 1.5 weeks around silking, Radiation_S) as a proxy of crop growth rate that is known to affect kernel number.

Grain yield of the previous crop was estimated from yield monitor data at each experimental site. When yield maps were not available, yields of the previous crop at each site were estimated based on image analysis and yield records from the farmer. The amount of surface residue and its carbon (C)-to-nitrogen ratio (C:N) was directly measured in season 4 (2015-16) in each block from an area of 1 m\(^2\). A subsample of the residue was analyzed for C, N, and C:N ratio using the dry combustion method (Leco, 2008). Residue amount and quality for the other seasons were estimated from previously published grain yield and residue C:N relationships for Argentina (Melchiori et al., 2014).

**Data analysis**

The relationship between yield and N rate was described from the quadratic and quadratic-plus-plateau models using R software (R Core Team 2018). Models were deemed significant at \(p < 0.05\) and the equations with the smallest sums of squares and largest \(R^2\) were selected. The EONR and yield at the EONR (YEONR) was calculated from the N response
equations by setting the first derivative of the fitted response curve equal to a price ratio of 5.6:1
N: corn grain price (US$ kg\(^{-1}\) N: US$ kg\(^{-1}\) grain) ratio (Cerrato and Blackmer, 1990; Bullock and Bullock, 1994). Maximum yield response to N was calculated as the difference between YEONR and Yield_N0.

Relationships between explanatory variables (Table 4.1) were explored using Pearson correlation, principal component analyses, and clustering (Figure S2). We excluded highly auto-correlated variables from subsequent regression analysis (R\(^2\) > 0.5). The remaining static and dynamic variables were used to develop regression models for EONR, YEONR, and Yield_N0. The efficient branch-and-bound algorithm method within the leaps R package was used to produce a list of sub-models for consideration, and then we fit a linear model for each sub-model individually to obtain the selection criteria. The best model was selected based on adjusted R\(^2\) and k-fold (leave-one-out) cross validation error. Finally, we calculated performance indexes such as mean absolute difference (MAE) and root mean squares (RMSE, see equations in Archontoulis and Miguez, 2015).

We developed two types of regression models (Table 4.2). The first one, hereafter referred to as the full model, made use of all available information from harvesting of the previous crop to harvesting of the next crop. The second, hereafter referred to as the reduced model, made use of information from harvesting of the previous crop to planting time of the next crop.

To determine the relative importance of static and dynamic variables within the regression models we used the simple unweighted averages (\(Img\)) method (Gromping 2006). This metric decomposes R\(^2\) into absolute contributions of different factors that sum to the total R\(^2\). The advantage of this method over simpler metrics is that the \(Img\) is based on sequential R\(^2\),
while accounting for the dependence on orderings using simple unweighted averages. This analysis was performed for the full and reduced model separately.

Model validation

We used an independent set with three N trials from the 2017-2018 growing season to test the predictive capacity of both full and reduced models. The 2017–2018 season had a severely dry summer (244 mm of rain from planting to harvesting; with only 30 mm around silking time). The soils had a SOM from 2.2 to 3.5% and a sand content from 52 to 70%. The previous season’s crop was a double crop of spring wheat/summer soybean. All model inputs were calculated as described in previous sections.

Results

Spatial and temporal variability of the explanatory variables

Across seasons, the average planting to harvest precipitation was 544 mm (Figure 1). Season 1 was extremely wet (23% above average precipitation), particularly from previous crop harvest to silking (> 800 mm; Figure 4.1). Season 2 was the driest (7% below average precipitation) with 170 mm of rain before planting. During the critical period of silking, the number of precipitation events (> 0 mm) was the highest in Season 5 and the lowest in Season 2 (Figure 4.1).
Figure 4.1  Daily precipitation in Central West Buenos Aires, Argentina (top panel) and cumulative precipitation for selected periods (bottom panel). Symbols used in the top panel, P, S, and H indicate planting, silking, and harvest, respectively. In the bottom panel, numbers above the columns indicate number of precipitation events.

At planting, in dry Season 2, soils had on average 80 kg ha\(^{-1}\) of available soil N, which is 60% more compared to wet seasons 1, 4 and 5 (Figure 4.2). Soil N-nitrate varied the most during the extremely wet and dry seasons (Figure 4.2). Season 2 also had the highest within-field variation in soil water content expressed as a percent of field capacity (Figure 4.2). The depth to the water table varied from 30 to 300 cm across seasons and treatments (Figure 4.2). Season 5 had the highest number of days with temperatures below 10 °C and Season 2 had the
greatest number of days with temperatures above 35 °C (45 and 13 days, respectively; data not shown).

**Figure 4.2** Nitrate-N content from 0 to 60 cm depth, water as percent of field capacity from 20 to 60 cm soil depth (FC), soil water from 0 to 60 cm depth (SW_sum), soil organic matter at 20 cm depth (OM_20), water table depth at planting, and sand content at 20 cm depth (Sand_20).

The range of values observed for the static values are reported in **Table 4.1**. Some static variables were correlated with one another. We found that the estimated terrain parameters correlated well with soil texture, SOM, and ECa_90 (Figure S3). Soils with high slopes were characterized by low SOM and high sand content while high SCA (specific catchment area) was associated with areas of low sand content. As ECa_90 increased, soil OM, and SCA increased (Figure S3).
Table 4.1 Description of static and dynamic explanatory variables.

<table>
<thead>
<tr>
<th>Acronym</th>
<th>Description</th>
<th>Unit</th>
<th>Observed range</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Static variables (change slowly over time or do not change)</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>OM_20</td>
<td>Soil organic matter (0-20 cm depth)</td>
<td>%</td>
<td>2-4</td>
</tr>
<tr>
<td>P_Bray_20</td>
<td>Available Bray phosphorus (0-20 cm depth)</td>
<td>ppm</td>
<td>6-51</td>
</tr>
<tr>
<td>EC_20</td>
<td>Electrical conductivity (0-20 cm depth)</td>
<td>ds/cm</td>
<td>47-124</td>
</tr>
<tr>
<td>pH_20</td>
<td>pH (0-20 cm depth)</td>
<td>--</td>
<td>5-6</td>
</tr>
<tr>
<td>Sand_20</td>
<td>Sand content (0-20 cm depth)</td>
<td>%</td>
<td>36-84</td>
</tr>
<tr>
<td>Silt_20</td>
<td>Silt content (0-20 cm depth)</td>
<td>%</td>
<td>12-53</td>
</tr>
<tr>
<td>Clay_20</td>
<td>Clay content (0-20 cm depth)</td>
<td>%</td>
<td>3-16</td>
</tr>
<tr>
<td>ECa_30</td>
<td>Soil apparent electrical conductivity (0-30 cm depth)</td>
<td>ds/m</td>
<td>3-19</td>
</tr>
<tr>
<td>ECa_90</td>
<td>Soil apparent electrical conductivity (0-90 cm depth)</td>
<td>ds/m</td>
<td>4-28</td>
</tr>
<tr>
<td>Elev</td>
<td>Elevation as meters above the sea level</td>
<td>m</td>
<td>71-89</td>
</tr>
<tr>
<td>Rel_elv</td>
<td>Relative elevation using the middle elevation as the reference (REL, Miller et al., 2014)</td>
<td>%</td>
<td>-0.22-0.29</td>
</tr>
<tr>
<td>planc</td>
<td>Plan curvature</td>
<td>deg</td>
<td>-0.28-40</td>
</tr>
<tr>
<td>Slope</td>
<td>Slope of the field</td>
<td>%_raise</td>
<td>0-5</td>
</tr>
<tr>
<td>SCA</td>
<td>Specific catchment area</td>
<td>pixel value</td>
<td>0-486</td>
</tr>
<tr>
<td>MO (20-60)</td>
<td>Soil organic matter content (20-60 cm depth)</td>
<td>%</td>
<td>1-3</td>
</tr>
<tr>
<td>Sand (20-60)</td>
<td>Sand content (20-60 cm depth)</td>
<td>%</td>
<td>36-84</td>
</tr>
<tr>
<td>Silt (20-60)</td>
<td>Silt content (20-60 cm depth)</td>
<td>%</td>
<td>12-48</td>
</tr>
<tr>
<td>Clay (20-60)</td>
<td>Clay content (20-60 cm depth)</td>
<td>%</td>
<td>5-20</td>
</tr>
<tr>
<td>Soil_depth</td>
<td>Soil depth</td>
<td>m</td>
<td>0.6-2</td>
</tr>
<tr>
<td><strong>Dynamic variables (change fast over time)</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Residue_amount</td>
<td>Amount of residue from previous crop at planting</td>
<td>kg/ha</td>
<td>3636-10909</td>
</tr>
<tr>
<td>Residue_CN</td>
<td>Quality of residue as Carbon to N ratio</td>
<td>-</td>
<td>30-75</td>
</tr>
<tr>
<td>Previous Yield</td>
<td>Yield of the previous crop</td>
<td>kg/ha</td>
<td>2000-6000</td>
</tr>
<tr>
<td>N_20</td>
<td>Nitrate content (0-20 cm depth)</td>
<td>kg/ha</td>
<td>12-52</td>
</tr>
<tr>
<td>N (0-60)</td>
<td>Nitrate content (0-60 cm depth)</td>
<td>kg/ha</td>
<td>28-116</td>
</tr>
<tr>
<td>Water table</td>
<td>Water table depth</td>
<td>cm</td>
<td>30-450</td>
</tr>
<tr>
<td>SW_20</td>
<td>Soil water content (0-20 cm depth)</td>
<td>mm</td>
<td>21-72</td>
</tr>
<tr>
<td>SW (20-60)</td>
<td>Soil water content (20-60 cm depth)</td>
<td>mm</td>
<td>30-177</td>
</tr>
<tr>
<td>FC_20</td>
<td>Soil water relative to field capacity (0-20 cm depth)</td>
<td>%</td>
<td>43-237</td>
</tr>
<tr>
<td>FC (20-60)</td>
<td>Soil water as a % of field capacity at 20 to 60 cm</td>
<td>%</td>
<td>71-265</td>
</tr>
<tr>
<td>FC_w</td>
<td>Soil water as a % of field capacity 0 to 60 cm</td>
<td>%</td>
<td>65-253</td>
</tr>
<tr>
<td>Max_20</td>
<td>Soil water as a % of saturation point at 20 cm</td>
<td>%</td>
<td>23-82</td>
</tr>
<tr>
<td>Max (20-60)</td>
<td>Soil water as a % of saturation point at 20 to 60 cm</td>
<td>%</td>
<td>35-102</td>
</tr>
<tr>
<td>Max_w</td>
<td>Soil water as a % of saturation point at 0 to 60 cm</td>
<td>%</td>
<td>34-93</td>
</tr>
<tr>
<td>SW_sum</td>
<td>Soil water content (0-60 cm depth)</td>
<td>mm</td>
<td>57-277</td>
</tr>
<tr>
<td>Events_P-S</td>
<td>Number of rain events from planting to silking</td>
<td>days</td>
<td>9-28</td>
</tr>
</tbody>
</table>
### Table 4.1 Continued

<table>
<thead>
<tr>
<th>Acronym</th>
<th>Explanation</th>
<th>Unit</th>
<th>Observed range</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Dynamic variables (change fast over time) continued</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Amount_P-S</td>
<td>Cumulative rain from planting to silking</td>
<td>mm</td>
<td>202-528</td>
</tr>
<tr>
<td>Events_P-S_20</td>
<td>Number of days with rain &gt; 20 mm from planting to silking</td>
<td>days</td>
<td>2-13</td>
</tr>
<tr>
<td>Amount_P-S_20</td>
<td>Cumulative rain (only &gt; 20 mm) from planting to silking</td>
<td>mm</td>
<td>98-428</td>
</tr>
<tr>
<td>Events_S</td>
<td>Number of rain events around silking (± 1.5 weeks)</td>
<td>days</td>
<td>1-8</td>
</tr>
<tr>
<td>Amount_S</td>
<td>Cumulative rain around silking (± 1.5 weeks)</td>
<td>mm</td>
<td>25-176</td>
</tr>
<tr>
<td>Events_S_20</td>
<td>Number of days with rain &gt; 20 mm around silking</td>
<td>days</td>
<td>0-7</td>
</tr>
<tr>
<td>Amount_S_20</td>
<td>Cumulative rain (only &gt; 20 mm) around silking</td>
<td>mm</td>
<td>0-150</td>
</tr>
<tr>
<td>Events_H-P_E</td>
<td>Number of rain events from harvest to planting</td>
<td>days</td>
<td>6-25</td>
</tr>
<tr>
<td>Amount_H-P_E</td>
<td>Cumulative rain from harvest to planting</td>
<td>mm</td>
<td>140-866</td>
</tr>
<tr>
<td>Events_H-P_20</td>
<td>Number of rain events (&gt;20 mm) from harvest to planting</td>
<td>days</td>
<td>2-12</td>
</tr>
<tr>
<td>Amount_H-P_20</td>
<td>Cumulative rain events (&gt; 20 mm) from harvest to planting</td>
<td>mm</td>
<td>98-810</td>
</tr>
<tr>
<td>Events_P-H</td>
<td>Number of rain events from planting to harvest</td>
<td>days</td>
<td>11-60</td>
</tr>
<tr>
<td>Events_P-H_20</td>
<td>Number of rain events (&gt;20 mm) from planting to harvest</td>
<td>days</td>
<td>2-18</td>
</tr>
<tr>
<td>Amount_P-H</td>
<td>Cumulative rain from planting to harvest</td>
<td>mm</td>
<td>296-840</td>
</tr>
<tr>
<td>Amount_P-H_20</td>
<td>Cumulative rain (only &gt; 20 mm) from planting to harvest</td>
<td>mm</td>
<td>78-672</td>
</tr>
<tr>
<td>Temp_P-H_35</td>
<td>Number of heat days (daily temp &gt; 35 °C) around silking</td>
<td>days</td>
<td>2-13</td>
</tr>
<tr>
<td>Temp_S_35</td>
<td>Number of heat days from planting to harvest</td>
<td>days</td>
<td>1-5</td>
</tr>
<tr>
<td>Radiation_S</td>
<td>Classification of radiation around silking ***</td>
<td>-</td>
<td>1-2</td>
</tr>
<tr>
<td>Temp_P-H_10</td>
<td>Number of cold days (&lt; 10 °C) from planitng to harvest</td>
<td>days</td>
<td>23-42</td>
</tr>
</tbody>
</table>

**Temporal and spatial variability of EONR and yields**

Across the 51 N-trials, the EONR varied from 0 to 260 kg N ha\(^{-1}\) with a mean of 113 ± 81 kg N ha\(^{-1}\) (Figure 4.3). The EONR values were above the 51 trial mean in 90% of the cases in Season 1, and only 13% of the cases in Season 5 (Figure 4.3). The Yield_N0 was below the 51 trial mean value (9.5 Mg ha\(^{-1}\)) in all cases in Season 1 and above the mean value in 87% of the cases in Season 5 (Figure 4.3). The mean YEOB was 12.2 Mg ha\(^{-1}\) and its distribution across the 51 trials was skewed to the right. In 3 of the 5 seasons, the spatial variation of EONR and YEONR was higher than their temporal variation (CV of 72% versus 27%, respectively, Figure 4.3). The variability in Yield_N0 was higher across years (27%) than within fields (21%). The YEONR varied less compared to EONR and Yield_N0 (Figure 4.3).
Figure 4.3 Observed economic optimum nitrogen rate (EONR), yield at EONR (YEONR), and yield at nitrogen zero (Yield_N0, right panels) and frequency distribution (right panels). Horizontal dashed lines represent the overall mean value. The coefficient of variation (CV%) for each season is provided.

Correlations between EONR, yield and explanatory variables

Highly productive areas (fine texture) had an average EONR of 213 kg N ha\(^{-1}\), whereas the sandiest soils (sand content > 65%) during the wettest season (Season 1) also had a high EONR (~ 195 kg N ha\(^{-1}\), Figure 4.2 and 4.3). Field areas with high sand content (> 65%) and low SOM (< 2.5%) resulted in high temporal variability in yield and EONR (Figure 4.3).

We found no relationship between EONR and YEONR or Yield_N0 (Figure 4.4). However, the difference between YEONR and Yield_N0 that is the yield response to N was
highly correlated with the optimal N rate ($R_{\text{Adj.}}^2 = 0.91$; Figure 4.4). In very wet seasons the yield response to N was double that of the dry seasons. However, in the wettest season we did not find major differences in yield response to N between landscape positions (Figure 4.3). The differences in yield response to N were 3-fold higher in fine than coarse textured soils in dry and normal seasons. In general, the EONR, YEONR, and Yield_N0 tended to increase as SOM increased and sand content decreased (Figure S4). The EONR and Yield_N0 was significantly correlated with precipitation from planting to silking ($R^2$ from 0.20 to 0.57), but the magnitude of the response was associated with soil texture and SOM (data not shown).

**Figure 4.4** Economic optimum N rate (EONR) as a function of yield at EONR (YEONR), yield at N zero (Yield_N0), and the difference between YEONR and Yield_N0

**Relative importance of factors and model development**

Studying static and dynamics factors separately, we found that the variability in EONR and Yield_N0 was best explained by dynamic factors while the variability in YEONR was best described by static variables (see $R^2$ values in Figure 4.5). Prediction accuracy substantially increased when we combined dynamic and static variables ($R_{\text{Adj.}}^2 > 0.60$, Figure 4.5).

From a total of 54 static and dynamic variables examined in this study (Table 4.1), four dynamic variables (precipitation, heat stress, nitrate amount at planting, residue amount) and one static variable (soil depth) were considered in the EONR full model based on their importance.
The resulting model explained 61% of the variability in EONR with a MAE of 39 kg N ha\(^{-1}\) (Figure 4.3). The number of precipitation events (>20 mm) from planting to silking was found to be the most important variable and heat stress the least important variable in the full EONR model (see variance analysis in Figure 4.5). For YEONR and Yield_N0 predictions, we found that different variables to be important. Best single predictors for YEONR and Yield_N0 were the residue amount and the number of rain events (> 20 mm) from planting to harvest, respectively (Figure 4.5; Table 4.2).

### Table 4.2

*Full* and *reduced* regression models for the economic optimum nitrogen rate (EONR; units: kg N ha\(^{-1}\)), yield at EONR (YEONR; Mg ha\(^{-1}\)), and yield at nitrogen zero (Yield_N0; Mg ha\(^{-1}\))

<table>
<thead>
<tr>
<th>Type</th>
<th>Model</th>
</tr>
</thead>
<tbody>
<tr>
<td>Full</td>
<td>EONR= 355 – 163<em>Soil_depth + 22.4</em>Events_P-S_20 – 10.3<em>Events_P-H_20 – 1.9</em>N(0-60) + 17.1<em>Temp_S_35 + 196</em>Residue_amount</td>
</tr>
<tr>
<td></td>
<td>YEONR= 18.1 – 11.6<em>Rel_elev – 0.18</em>Events_P-H_20 – 0.008<em>SCA + 0.013</em>Amount_S – 3.8*Soil_depth</td>
</tr>
<tr>
<td></td>
<td>Yield_N0= 5.14 – 0.253<em>Events_P-H_20 + 0.047</em>N(0-60) – 13.01<em>Rel_elev – 0.008</em>SCA – 0.594<em>Temp_S_35 + 0.201</em>Temp_P-H_10</td>
</tr>
<tr>
<td>Reduced</td>
<td>EONR= 359 – 145<em>planc – 1.96</em>N(0-60) – 0.83<em>FC(20-60) + 11.1</em>Events_H-P_20 – 120<em>Soil_depth + 170</em>Residue_amount</td>
</tr>
<tr>
<td></td>
<td>YEONR= 13.8 – 11<em>Rel_elev – 0.01</em>SCA + 0.003<em>Amount_H-P + 0.016</em>SW_sum + 0.0005<em>Residue_amount – 3.7</em>Soil_depth</td>
</tr>
<tr>
<td></td>
<td>Yield_N0= 1.1 – 13.7<em>Rel_elev – 0.010</em>SCA + 0.05<em>N(0-60) + 0.006</em>Water_table + 0.010<em>FC(20-60) + 0.024</em>SW_sum</td>
</tr>
</tbody>
</table>
Figure 4.5  Diagram of regression models for the economic optimum nitrogen rate (a), yield at the EONR (b), and Yield at N0 (c) using static variables, dynamic variables, and a combination of both. Predicted versus observed values for the full models are shown. Diagonal dashed lines are 1:1. The relative importance of static and dynamic variables included in the final model as shown. All acronyms are explained in Table 4.1. Adjusted coefficient of determination ($R^2$), mean absolute error (MAE), and root mean square (RMSE) are shown.
We repeated the analysis with a reduced amount of data (from previous crop harvest to planting of the new crop) and developed three additional models that can be used for forecasting purposes at planting time. The resultant models with their key variables are listed in Table 4.2. Information on soil water and soil nitrate at planting time became highly important in the reduced EONR and Yield_N0 models (Figure 4.6 and Table 4.2). Residue amount and Rel_elev were the most important variables for the reduced YEONR model (Figure 4.6).

![Figure 4.6](image)

**Figure 4.6** Relative importance of the static and dynamic variables included in the reduced models. Left panel shows variables included in the EONR model, middle panel in the YEONR model, and right panel the Yield_N0 model.

On average, the full EONR model outperformed the reduced model’s prediction accuracy by 16% (Table 4.3). The full model predicted EONR with a higher MAE in extreme wet and dry Seasons 1 and 2 (MAE ~ 43 kg N ha\(^{-1}\)). Seasons 1 and 4 had the highest accuracy for Yield_N0 and Season 5 had the highest accuracy for EONR (MAE ~ 29 kg N ha\(^{-1}\), Table 4.3). The reduced model performed the best for EONR and Yield_N0 for the dry
Season 2 (MAE 49 kg N ha$^{-1}$) and EONR prediction error was the same as the full model in the wet Season 1 (Table 4.3).

Table 4.3  Mean absolute error for economic optimum nitrogen rate (EONR; units: kg N ha$^{-1}$), yield at EONR (YEONR; Mg ha$^{-1}$), and yield at zero nitrogen (Yield$_{N0}$; Mg ha$^{-1}$) for regression model predictions using information from previous harvest until planting (reduced model) and using information available from previous crop harvest to next harvest (full model).

<table>
<thead>
<tr>
<th>Season</th>
<th>full model</th>
<th>reduced model</th>
</tr>
</thead>
<tbody>
<tr>
<td>EONR</td>
<td>YEONR</td>
<td>Yield$_{N0}$</td>
</tr>
<tr>
<td></td>
<td></td>
<td>kg ha$^{-1}$</td>
</tr>
<tr>
<td>1</td>
<td>44</td>
<td>1.3</td>
</tr>
<tr>
<td>2</td>
<td>42</td>
<td>1.6</td>
</tr>
<tr>
<td>3</td>
<td>39</td>
<td>1.4</td>
</tr>
<tr>
<td>4</td>
<td>37</td>
<td>1.1</td>
</tr>
<tr>
<td>5</td>
<td>29</td>
<td>1.4</td>
</tr>
</tbody>
</table>

Model validation

Testing the EONR models against the 2017-18 independent dataset we found that the full model had a MAE of 58 kg N ha$^{-1}$ and the reduced model a MAE of 46 kg N ha$^{-1}$. In this validation dataset, the most accurate EONR predictions were in fields with topsoil sand content < 65 % and SOM > 2.5% (absolute difference between observed and predicted values was on average 17 kg N ha$^{-1}$). The least accurate EONR predictions were for a sandy hill site with OM < 2%. Regarding YEONR prediction, the MAE ranged from 1 to 1.9 Mg ha$^{-1}$ in most cases (Figure 4.7).
Figure 4.7 Predicted versus observed economic optimum N rate (EONR), yield at EONR (YEONR), and yield at non fertilizer (Yield_N0) for the validation data set using full model (circles) and reduced model (triangles). Diagonal dashed line shows 1:1 relationship. MAE is the mean absolute error.

**Discussion**

**Predicting corn optimum N rate**

By analyzing 51 N trials along with management, soil, terrain, crop, and weather data, we gained insight into the most important variables affecting the EONR in Argentina; a region that has become increasingly important in global corn markets because total corn production has doubled over the last five years. Our results showed that in 70% of our N trials, the EONR was higher than the regional average N application rate of 61 kg N ha$^{-1}$ currently used in Argentina (ReTAA, 2018). Furthermore, the average YEONR in our trials was 12 Mg ha$^{-1}$ that is about 4 Mg ha$^{-1}$ higher than the regional average corn yield (Andrade and Satorre, 2015; Figure 4.3). Therefore, our data strongly suggest that there is substantial room for yield increases in Argentina by improving N management. However, increasing N fertilization rate adds a significant economic risk that most producers in this region were not willing to accept because of the year-to-year variability in EONR (Puntel et al., 2017). Here we not only quantified the variability in EONR (Figure 3) – critical information that was
previously missing for this region-, but more importantly, we developed predictive models that account for weather and soil variability to aid a producer’s N decision-making for corn.

Beyond Argentina, our study provides a new approach to forecast optimum N for corn, which can be tested and adopted in other rainfed regions. Current empirical N recommendation tools either consider a single factor (e.g. soil nitrate) or use yield expectations or long-term average values (Sawyer et al., 2006) to predict EONR. Here, we developed a new empirical tool that predicts EONR using a multi-factor approach by integrating static and dynamic variables for the first time. Our tool better reflects existing knowledge on factors affecting EONR and has potential in view of increasing data availability in agriculture. While complex simulation models (that integrate multiple factors) have already proven to be well-suited to support N decisions in specific fields (Basso et al., 2011) their utilization is still low (Banger et al., 2017). This is because of challenges related to site-specific model calibration, the large number of input requirements, and social difficulties in delivering model-based results to stakeholders. Our tool uses fewer inputs than a simulation model and is easier to deploy across a broad geographic area.

Our regression models (Table 4.2) can be used as stand-alone N recommendation tools in this region, as well as in other rainfed regions based on their satisfactory predictive performance and the relatively low parameter input requirement (Figure 4.5 and Figure 4.7). Compared to other models (Liu et al. 2013; Puntel et al. 2016; Sela et al. 2017; Yang et al. 2014), the prediction error of the full EONR model is similar (MAE ~ 30–40 kg N ha⁻¹). The reduced EONR model that was designed for N forecasting at planting time, has 16% less predictive accuracy than the full model. This is not surprising given the fewer inputs that it
uses. Validation tests showed that both full and reduced models gave reasonable results (Figure 4.7).

In the future, some labor-intense input parameters currently part of our models could be further simplified (Table 4.3). For example, the amount of residue (kg/ha) can be replaced by categorical classes such as very low, low, normal, high and very high amounts. We tested this concept (data not shown) and we found that the EONR prediction accuracy remained at similar levels compared to models listed in Table 4.3. Similarly, the initial soil moisture at planting could be replaced by classes. This approach may enhance deployment of the models across environments but more work is needed to develop and test it.

During model development we faced several challenges that should be considered in future studies. We found that the relative importance of static variables selected for inclusion in the models changed based on which dynamic variables were considered. This is evident by the fact that different variables were found to be important and thus included in the full and reduced models. For example, when we removed data on soil texture and precipitation distribution, we found that ECa and terrain parameters became more important in the models (data not shown). This is because variables typically manifest themselves (Kravchenko and Bullock, 2002; Kravchenko et al., 2003). In general, our analysis agrees with Zipper et al. (2015) who indicated that static variables set the baseline on which dynamic factors control yield and optimum N rate.

Factors affecting the EONR

Our study is unique in understanding the importance of different factors influencing optimum N rate. This is because we measured several variables as opposed to a single trait measurement of grain yield that was used in the majority of previous studies (Bullock, Ruffo, Bullock, and Bollero, 2009; Colaço and Bramley, 2018). From a list of 54 factors, we
identified 14 to be the most important variables for EONR, YEONR and Yield_N0 predictions in this region (see Figure 4.5 and Figure 4.6). It is interesting to note that yield of the previous crop, currently used to develop management zones and N recommendations (Kersebaum et al., 2002), was not an important factor within the models we developed. In contrast, we found surface residue amount to explain significant portions of the YEONR and EONR variability (Figure 5 and Figure 6). Our findings suggest that future research should focus more on residue dynamics rather than on precisely estimating past crop yields to inform future N recommendations.

Further, our results suggest that variable N rate recommendations based on previous yields associated with texture and SOM could fail when weather conditions are wet or extremely wet, which agrees with other studies (Cerrato and Blackmer 1991; Vanotti and Bundy 1994). Like Kyveryga et al. (2009) and Zhu et al. (2009), we found that yield response to N during very wet seasons was double that of relatively dry seasons (Figure 4). However, in the wettest season we did not find a major difference in yield response to N between landscape positions (Figure 4.3). In dry and normal seasons, we found that yield response to N was 3-fold higher in fine than coarse textured soils, similar to Shahandeh et al. (2011).

Seasons 4 and 5 had high yields (~12 Mg ha⁻¹) with low EONR (~70 kg N ha⁻¹) compared to other seasons (Figure 4.3) because of precipitation patterns. These seasons had more frequent rain events (> 0 mm) but a low frequency of extreme rain events (> 20 mm) where N losses are likely to occur (Davis et al., 2000; Rimski-Korsakov et al., 2004). The high precipitation amount increased Yield_N0, and reduced the yield response to N, therefore, decreasing the EONR (Figure 4; Sogbedji et al., 2001). In particular, we found
that the number of days with precipitation greater than 20 mm from planting to silking, and from planting to harvesting to be very good predictors of the EONR and Yield_N0 variability in the full model (Figure 4.5). Although there is a similarity between these two variables (same variable name but different time-periods), our statistical analysis revealed no significant auto-correlation. In the reduced model, precipitation events prior to planting, and soil moisture relative to field capacity at planting, were the important variables. Our results on the importance of precipitation in N recommendation tools agree with Gregoret et al. (2006). The fact that we included precipitation in our models may increase the predictive capability compared to other N tools (Berntsen et al. 2006; Kitchen et al. 2010; Thompson et al. 2015). This is something to be explored in a future study.

Water table depth was a significant factor in the reduced EONR and Yield_N0 model (Figure 4.6) but not in the other models. Presumably this is because of its relation to precipitation and landscape position (Gleeson et al., 2011). Because of the difficulty in measuring water tables, use of elevation position may be a good alternative because of the correlation between these variables (Figure 4.5 and Figure 4.7; Nosetto et al. 2009). Interestingly, relative elevation (Table 4.1) was one of the most important explanatory variables in both YEONR and Yield_N0 models. Other static factors such as SCA, pcurv, and slope are relevant in regression models, mainly because of their control on water availability (Van Ittersum et al., 2002), N dynamics, and thus yield (Kaspar et al. 2004; Kravchenko and Bullock 2000).

Neither soil N-nitrate at planting nor the YEONR were good single predictors of the EONR (Figure 4.4 and Figure 4.6), in line with literature from rainfed regions (Lory and Scharf, 2003; Sawyer et al., 2006; Vanotti and Bundy, 1994). In contrast, when soil nitrate
information was combined with other static and dynamic factors, it proved to be a very important factor in the full Yield_N0 model and in the reduced EORN model (Figure 4.5 and Figure 4.6). This means that commonly used soil N tests (Orcellet et al., 2017; Rozas, Echeverría et al., 2000), previous yield maps (Basso et al., 2016) combined with the mass-balance approach (Stanford et al., 1973), needs to be complemented with other static and dynamic variables to better predict EONR (Figure 3; Kay et al. 2006).

Finally, we found a significant relationship between the difference of YOENR and Yield_N0 and the EONR ($R^2_{adj} = 0.92$; Figure 4.4). This relationship is interesting because it offers an alternative way to estimate EONR using information on optimum and minimum yield. In a previous study (Puntel et al., 2016), we found that the APSIM crop model predicted optimum and minimum yields more accurately than EONR. This relationship may help in the way we currently calculate EONR via crop models. Furthermore, use of this relationship will decrease the number of crop model simulations required to calculate the EONR (from 5 to 30 simulations to only two; Puntel et al., 2016).

**Conclusions**

We developed empirical regression models to predict optimum yield, optimum N rate and yield under zero N fertilization of corn by considering a selection of static (e.g. soil depth and field elevation) and dynamic factors (e.g. precipitation, residue amount, initial soil nitrate and water, and heat stress around silking) that were found to be the most important among 54 factors examined. Our approach provides a new avenue to integrating and analyzing various datatypes towards development of data-driven recommendations to growers. These multifaceted datatypes are likely to become readily available in the near future through advances in technology. At the regional level, our study fills an important knowledge gap regarding optimum N rates and their year-to-year variability in Argentina. The 51 N trial
The average optimum N rate for corn was 50% higher than the current N rates used by farmers, resulting in about 4 Mg ha\(^{-1}\) greater yields than the current yields obtained on average by farmers. The developed statistical models can assist in closing this yield gap via improved N recommendations.

**References**


**Appendix**

![Figure S1](image_url)

*Figure S1*. Elevation, apparent electrical conductivity at 90 cm depth (ECa), plan curvature, and slope maps. Purple flags show an example of the location of six trials.
Figure S2. Pearson’s correlation matrices for static and dynamic variables (top panel) and clustering analysis for the combination of static and dynamic variables.
**Figure S3.** Correlation matrix between percent sand and soil organic matter at 20 cm (Sand_20 and OM_20), apparent electrical conductivity at 90 cm depth (ECa_90), and topographical derived parameters. Specific catchment area (SCA, pixel); percent of slope; relative elevation (Rel_elev, meters); plan curvature (degrees). Density plots of the variables are shown in the diagonal.
Figure S4. Correlation matrix between the economic optimum nitrogen rate (EONR), yield at EONR (YEONR), yield at nitrogen zero (Yield_N0), difference between YEONR and Yield_N0 (CropResponse), percent sand and soil organic matter at 20 cm (Sand_20 and OM_20), soil nitrate (N_0_60, kg N ha\(^{-1}\)), and apparent electrical conductivity at 90 cm depth (ECa_90). Density plots of the variables are shown in the diagonal.
CHAPTER 5. CONCLUSIONS

The overall goal of this research was to evaluate different approaches to improve current N management guidelines in corn production systems (Figure 1.1).

The process based approach implemented in Chapter 2, provided strong evidence that for a rainfed corn-based system in the USA Midwest, a combination of process-based modeling, coupled with existing N rate recommendation methods and field data, could be a good approach to fine tune optimal N rate guidance for corn. Results suggest that for long-term site mean EONR predictions and for accurate year-by-year simulation of EONR the calibrated model could be used (RRMSE = 37%). We demonstrated that the long-term yield response to N (end-of-season) data can be of a great use to calibrate process based approaches and be powerful in detecting weakness in the model (i.e., years with low prediction accuracy). Furthermore, the calibrated model was used to explore and explain factors causing inter-annual variability in EONR. For example, the model showed that in rainfed corn-based systems in Iowa, the higher the spring precipitation (April to June) the higher the EONR because simulated N loss via denitrification and leaching increased exponentially while simulated N supply via mineralization tended to decrease.

In Chapter 3, I demonstrated an alternative way to utilize the power of mechanistic cropping systems models to assist N-rate decisions in real time as opposed to current ex-post use of models that are of little interest to farmers (Quiring and Legates, 2008; Thompson et al., 2015). This is the first study that concurrently forecast corn yields and their N requirements in the USA Corn Belt. Promising results suggest that use of a calibrated cropping systems model can aid yield and N rate forecasts. At planting time, model predictions were directionally correct in predicting whether the optimum N-rate for corn
would be above, below or at site-mean value. The associated prediction error was within an error range of ±30 kg N ha\(^{-1}\) in ~60\% of the years. Results indicate that in-season yield and optimum N-rate forecasts were not better than the predictions made at planting and has potential for realizing further improvements in achieving even more accurate early-season predictions.

Chapter 4, I developed a statistical regression model using a combination of static and dynamic variables. The model was able to predict EONR with a mean absolute error of 39 kg N ha\(^{-1}\) at the end of the season (site mean = 120 kg N ha\(^{-1}\), RRMSE = 42\%). I showed that a statistical based approach could be used as a forecasting tool with 16\% less accuracy than the end-of-season model when important variables such as initial water and N availability are known. These parameters, along with soil water conductivity, have a robust relationship with soil texture (Saxton and Rawls 2006). Therefore, the uncertainty of the in-season N recommendation can be well constrained if there is better knowledge about the within-field heterogeneity of soil organic matter and soil texture, both of which are more likely to be estimated in a scalable way (Mulder et al. 2011; Castaldi et al. 2016). Based on model performance and highly accessible input requirements this approach could increase potential of farmer use at a field level scale as oppose to crop simulation models (Jin et al., 2017).

Interestingly, process and statistical based approaches predicted and forecasted yields with similar accuracy (average RMSE = 1.3 Mg ha\(^{-1}\)) while optimal N rate was better predicted by statistical models (RMSE 42 kg N ha\(^{-1}\), Table 5.1).

In Chapter 4, I also found that even when statistical based approaches cannot identify the mechanisms behind the cause and effect of yield and optimal N rates variability, the most important static and dynamic factors were identified. In line with findings from Chapter 2,
dynamic factors related with precipitation patterns, initial soil water and nitrate, highly explained the variability in the optimal N rate. Among 55 explanatory variables the number of precipitation events greater than 20 mm accumulated from planting to silking and the amount of residue were the most important variables within optimal N rate predictive model. Finally, this last study found strong evidences that by adjusting (increasing) N fertilizer rates via variable N rate technology current yield gaps in central-west region in Argentina could be reduced. Results showed optimal N rate to be on average 120 kg N ha\(^{-1}\) and yield at optimal N rate of 12.2 Mg ha\(^{-1}\), when regional fertilizer N rates and yields are 50% lower than the ones found in this work.

Increasing and maintaining high productivity levels presents a major challenge facing farmers today and will continue into the near future. More integrative, complex, and innovative approaches to N decision-making in corn systems, besides adopting new technologies, are necessary for redesigning more productive, stable, and sustainable farming systems. In this regard, my study showed that there is not a single best approach. In this dissertation I proposed alternatives to reduce the complexity by integrating existing resources (crop models, long-term data, statistics) hoping to facilitate future adoption and promote further research. For example, investigate simple ways to incorporate more data (e.g. in-season) into process based approaches or find alternatives to combine data-drive statistical and crop simulation models to maximize their individual strengths are proposed as next steps.
Table 5.1 Relative root mean square for economic optimum N rate (EONR, kg N ha⁻¹), yield at EONR (YEONR, Mg ha⁻¹), and yield (Mg ha⁻¹) when using full and reduced process- and statistical-based models.

<table>
<thead>
<tr>
<th></th>
<th>Process-based</th>
<th>Statistical-based</th>
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</thead>
<tbody>
<tr>
<td></td>
<td>Full model</td>
<td>Reduced model</td>
</tr>
<tr>
<td>EONR</td>
<td>62</td>
<td>60</td>
</tr>
<tr>
<td>YEONR</td>
<td>1.3</td>
<td>1.9</td>
</tr>
<tr>
<td>Yields*</td>
<td>1.3</td>
<td>1.5</td>
</tr>
</tbody>
</table>

*Yields for statistical-based approach refers only to simulated yields with zero nitrogen.

References


