Prediction of Corn Economic Optimum Nitrogen Rate in Argentina

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Abstract.

Static (i.e. texture and soil depth) and dynamic (i.e. soil water, temperature) factors play a role in determining field or subfield economically optimal N rates (EONR). We used 50 nitrogen (N) trials from Argentina at contrasting landscape positions and soil types*, various soil-crop measurements from 2012 to 2017, and statistical techniques to address the following objectives: a) characterize corn yield and EONR variability across a multi-landscape-year study in central west Buenos Aires, Argentina, b) quantify the relative importance of the dynamic versus static factors, and c) develop predictive models to assist site-specific N management in that region. Results indicated that EONR in this region varies with a coefficient of variation of 67% (range: 0 to 260 kg N ha^{-1}). Yield levels varied less than the EONR with a coefficient of variation of 27% (range: 3.8 to 17 Mg ha^{-1}). Dynamic factors explained about 47% of the spatial and temporal variability in the EONR and static variables explained 20% of the observed variation. Multi-regression analysis considering both static and dynamic factors captured between 60 and 71% of variability in EONR and corn yield. Model performance was better for yield (MAE, mean absolute error, ~1 Mg ha^{-1}) than for EONR (MAE of 39 kg N ha^{-1}). The number of rain events greater than 20 mm accumulated from planting to flowering and from planting to harvest and the amount of residue were the most important predictors of the variability (among ~ 60 variables explored). This analysis advances our understanding on the critical factors influencing EONR and yield to support development of decision N management tools to aid precision agriculture goals and strength current N guidelines.*

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Introduction

The adoption of precision agriculture and variable rate nitrogen (VRN) in particular, has rapidly increased in the Pampa's region, Argentina. It is intuitive to believe that in fields with significant variation in soil properties (i.e. soil texture, organic matter, etc.) and crop management (i.e. crop rotation), VRN application results in an effective strategy (Melchiori, 2013; Moral et al., 2010). Ideally, the main objective of VRN is to apply the economic optimum nitrogen rate (EONR) in every part of the field with the aim of increasing N fertilizer use efficiency, maximizing profits, and reducing environmental impacts. However, finding the EONR value per year and per site remains challenging (Mamo et al., 2003; Ma et al., 2005; Kyveryga et al., 2009).

There are numerous studies reporting the effect of individual factors such as soil properties or precipitation on yield and EONR (Basso et al.,2001; Dharmakeerthi et al., 2005; Mamo et al., 2003; Tremblay et al., 2012; Albarenque et al., 2016). These factors can be broadly classified into dynamic (change fast over time such as precipitation) and static variables (change slowly over time such as soil organic matter). Today N recommendation methods are based on dynamic (i.e. soil nitrate test, Bundy et al., 1995; Shapiro et al., 2008), static factors (i.e. soil properties, Tremblay et al., 2011) or both by using computer simulation models (Banger et al., 2017) or none of these factors such as the yield goal approach (e.g. Stanford, 1973). Understanding which factors or synergic relationships contribute the most to the EONR variability is complex and still elusive (Scharf, 2015). Yet, there is no study to compare the relative importance of different factors on corn yield and EONR. A targeted research is needed in which several variables are simultaneously measured to identify the most important ones for further emphasis.

Regional studies have explored relationships between yield response to N and EONR with soil texture, soil water and organic matter (OM) variability (Gregoret et al., 2006; Peralta et al., 2013; Puntel and Pagani, 2013). However, regional N recommendations mostly rely on soil N test at or before planting without accounting for other static and/or dynamic variables that are known to effect the site-specific yield response to N. Depict potential benefits of VRN in this region, its adoption has not been yet supported by local site-specific N recommendations. The main objectives of this study were to: a) characterize corn yield and EONR variability across a multi-landscape-year study in Central West Buenos Aires, Argentina, b) quantify the relative importance of the dynamic versus static factors, and c) develop predictive models to assist site-specific N management in this region.

Materials and Methods

Experimental sites and design

Fifty two N rate trials were conducted at contrasting landscape positions at five fields located in Nueve de Julio, Buenos Aires, Argentina across five seasons: 2012-13 (season 1), 2013-14 (season 2), 2014-15 (season 3), 2015-16 (season 4), and 2016-17 (season 5). 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 medium/low crop productivity, and Thapto-argic Hapludolls corresponding to shallower soils due to the presence of a clay pan layer at varying depth. The area is characterized by a shallow water table that responds rapidly to rain and differs from field to field because of the variable terrain (slope).

Figure 1 illustrates six of the N trials. Each N trail was a randomized complete block design with three replications. Seven N rates (0, 25, 50, 100, 150, 200, and 250 kg ha^{-1}) applied as broadcasted urea around planting. Previous crop was spring soybean or winter wheat/summer soybean. Fields were managed with no-till and the other management practices were the normally recommended for this area. Corn ears were hand harvested across two five-meter row in the center of each plot to calculate grain yield. Grain moisture was measured and final yield was expressed at 14% moisture.

Measurements and data processing

Measurements taken from each N trial included soil OM, texture, soil water content, apparent electrical conductivity (ECa), elevation, soil and water table depth, amount of residue, and hourly weather data. These measurements and subsequent calculations were classified as static and dynamic explanatory variables based on their change over time (Table 1).

Static variables

Variables that are relative constant over time were classified as static. The 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). Elevation data were 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 1).

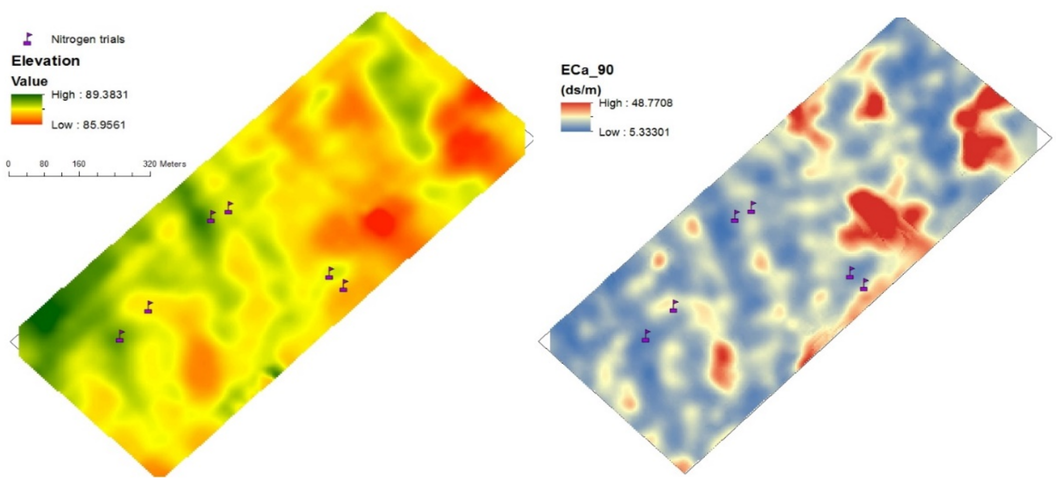

Fig 1. Example of within-field variability in elevation (meters) and apparent electrical conductivity at 90 cm depth (ECa, mS/m). Purple flags represents the position of nitrogen trials.

Landscape characteristics such as elevation, relative elevation (Rel_elev), slope, specific catchment area (SCA), and plan curvature (pcurv) were derived directly from digital elevation models (DEM) (Figure 1). Soil organic matter (OM) was determined by a combustion method (Wang and Anderson, 1998), and texture by the pipette method (Soil Survey Staff, 2014). Eight to 10 soil cores were taken per block from 0-20, 20-60, 60-100 cm depth in most of the experimental sites. Data was summarize into top (0-20 cm) and subsoil data (20-60 cm). Data below 60 cm was not used in the analysis. The effective soil depth was measured with a 2 meters soil probe in each plot. Soil depth was as shallow as 60 to 90 cm for some of the sites. Using soil OM, 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 substantially over time were classified as dynamic. We determined gravimetric soil water and nitrate content from soil sampled at planting at the top and in the subsoil. Soil water content was expressed at a percent of FC and SAT. Water table depth at each trial was measured around planting by measuring the water level in a shallow well with a measuring tape. Weather data, including hourly precipitation, radiation and temperature, was obtained from the closest weather station to the experimental sites (distance less than 5 km). Precipitation was accumulated for the following periods: from harvesting of the previous crop to planting of the next crop (amount_H-P), from planting to silking (amount_P-S), ± 1.5 weeks around silking (critical period for yield determination; amount_S), and from planting to harvest (amount_P-H). The number of rain events greater than 0 mm and 20 mm at the same periods were used as explanatory variables (events_H-P, events_S, events_P-H, events_H-P_20, events_S_20, events_P-H_20). 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 the season and the critical period were also computed (Temp_P-H_10, Temp_P-H_35, Temp_S_35, respectively). Radiation was accounted as the sum of radiation around the critical period (± 1.5 weeks around silking, Radiation_S).

Grain yield of the previous crop was estimated from yield monitor data at each experimental site. The amount of residue and carbon-to-nitrogen ratio (C:N) was directly measured during season 4 (2015-16) in each block in an area of 1 m^2. A subsample of the residue was taken to analyze carbon, N, and C:N ratio using dry combustion technique (Leco, 2008). Residue amount and quality for the other growing seasons were estimated from previous yields and published C:N ratios.

Data analysis

The relationship between yield and the seven N rates was fit using the quadratic and quadratic-plus-plateau 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 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).

Regression analysis was performed for EONR, YEONR, and yield at Yield_N0 (Yield at N0) using static, dynamics, and their combination. Adjusted R^2 and k-fold (leave-one-out) cross validation error were used to select the best model. Mean absolute difference (MAE) and root mean squares (RMSE) were calculated (see equations in Archontoulis and Miguez, 2015). Coefficient of variation (CV %) was used to describe variability within explanatory variables as well as for yield and EONR within and across seasons. To find the importance of static and dynamic variables within the regression model we used the simple unweighted averages (lmg) method.

Results and Discussion

Temporal and spatial variability of EONR and yields

The EONR varied from 0 to 260 kg N ha^{-1} across all sites-years with a mean of 113 ± 81 kg N ha^{-1} (Figure 2). The EONR was above the mean in 90% of the sites in season 1, 33 to 41% in season 2 to 4, and 13% in season 5 (Figure 2). During season 1, Yield_N0 was below the average across all sites-years (9.5 Mg ha^{-1}) while in season 5, Yield_N0 was above average in 87% of the cases (Figure 2). In 65% of the cases the EONR was higher than 75 kg N ha^{-1}, the regional average N application rate in Argentina (Garcia et al., 2013). Furthermore, the average YEONR in our trials was 12 Mg ha^{-1} that is about 4 Mg ha^{-1} higher than the average corn yield in this region (Andrade and Satorre, 2015). Our findings strongly suggest that there is room for improvement in N management to increase corn production.

In three out of five years the spatial variation of EONR and YEONR was higher than their temporal variation (CV > 72% and 27%, respectively, Figure 2). The variability for Yield_N0 was higher across years (27%) than it was within fields (21%). The CV for yield was 20% lower than for EONR and the CV of Yield_N0 was 8% higher than for YEONR (Figure 2).

Fig 2. Observed economic optimum nitrogen rate (EONR), yield at EONR (YEONR), and yield at nitrogen zero (yield at N0). Horizontal dashed lines represent the average across the five growing seasons. Labels represent the percent coefficient of variation (CV%) for each season.

Predictive models for yield and EONR

Regression model for YEONR performed better when using static than dynamic variables (R^2 0.46 vs 0.38, respectively). In contrast, variability of EONR and Yield_N0 was better explained by dynamic rather than static variables (R^2 of 0.52 vs. 0.27, respectively). Overall, best model performance was achieved when dynamic and static variables were combined (R^2 > 0.60, Figure 3).

By accounting for factors that characterize spatial and temporal variability we were able to predict EONR and yield with an accuracy of 39 kg N ha^{-1} and ~ 1 Mg ha^{-1}, respectively (MAE, Figures 3). Model performance was better for yields than for EONR (Figure 3). Poor in-season model performance for EONR prediction was associated with extreme weather conditions in season 1 and 2 (MAE ~ 47 kg N ha^{-1}, data not shown).

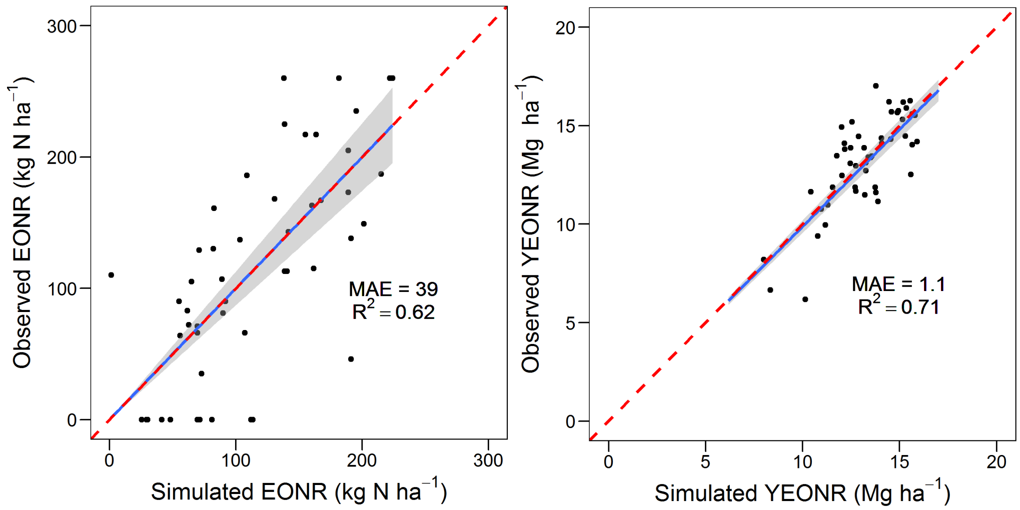

Fig 3. Predicted versus observed economic optimum N rate (EONR) and yield at EONR (YEONR). Dashed line indicates the one to one line and continuous line indicates the linear regression fitting. Mean absolute error (MAE).

Relative importance of static and dynamic variables within predictive models

According to the unweighted average analysis (LMG) of in-season and at planting regression models, dynamic variables were more important for EONR and Yield_N0 than for YEONR (Figure 3 and 4). For the in-season regression model, the number of rain events higher than 20 mm accumulated from planting to silking explained ~ 45% of the variance in EONR across sites and years. Other variables within the EONR regression models seemed to have similar explanatory power (~ 10%, Figure 4). The amount of residue and relative elevation were the most important variables within in-season YEONR model while rain events higher than 20 mm accumulated from planting to harvest and N (0-60) were the most important variables for Yield_N0 (Figure 4).

Precipitation patterns were significantly important for all predicting models (Van Es et al., 2006; Kurunc et al., 2011; Tremblay et al., 2012). Interestingly, season 4 and 5 were very productive years with yield as high as ~ 12 Mg ha^{-1} and relatively low EONR (~ 70 kg N ha^{-1}) compared to other seasons (Figure 3). This was associated with frequent low rain events and a low frequency of rain events higher than 20 mm where it is assumed that N losses will likely occur. These results were partially supported by the fact that Yield_N0 decreased when increasing precipitation, especially, from planting to silking and EONR tended to increase when decreasing Yield_N0 (data not shown; Sogbedji et al., 2001).

Conclusions

This study investigated for the first time site-specific variability of yield and EONR in Central-West Buenos Aires, and quantified the relative importance of dynamic versus static variables. Based on the observed variability of EONR (0 to 260 kg N ha^{-1}) and attainable yield at the EONR we concluded that adjusting N fertilizer rates in this region could reduce the current yield gap and adoption of variable rate N technology could be beneficial.

Statistical models were able to explain EONR, YEONR and Yield_N0 variability with an R^2 greater than 0.60. Prediction of EONR, YEONR, and Yield at N0 performed better when dynamic and static factors were included in the model because temporal and spatial variability of water and nitrogen soil dynamics were captured (MAE: 39 kg N ha^{-1}, 1.1 Mg ha^{-1}, 1.0 Mg ha^{-1}, respectively). The number of rain events greater than 20 mm accumulated from plating to silking and from planting to harvest, the amount of residue, relative elevation, and N (0-60 cm depth) were the most important variables within predictive models. Further testing and application of site-specific prediction models are needed to assist farmers in optimizing N management in Central-West Buenos Aires, Argentina.

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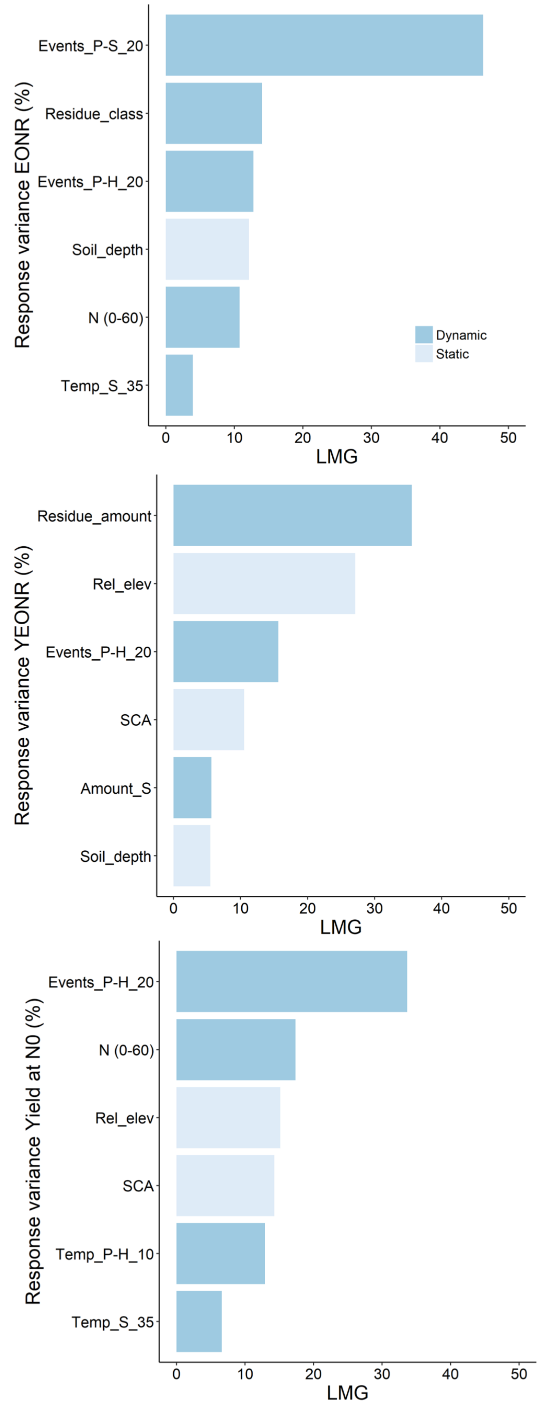

Fig 4. Relative importance (simple unweighted averages method, LMG) of static and dynamic variables as a percent of the response variance of EONR, YEONR, and Yield_N0. See Table 1 for variables description.

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