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Spatio-Temporal Nitrogen Fertilizer Response in Maize: Field Study and Modeling Approach

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ABSTRACT

Maize (*Zea mays* L.) yield and its response to nitrogen (N) are affected by the spatial variability of the interaction between weather, management, and soil properties. The objectives of this study were (i) to evaluate the response of spatial variability of maize yield by homogeneous zones (HZs) to different N fertilizer rates under rainfed conditions, (ii) to test the ability of the SALUS (System Approach to Land Use Sustainability) model to simulate the effects of N rates on maize yield under rainfed and irrigated conditions, and (iii) to estimate spatial and temporal N fertilizer response risk in maize through the use of long-term simulations. In two field experiments in Parana, Argentina (−31.8333°, −60.5167°) in 2011 (Field 1) and 2012 (Field 2), four fertilization treatments (0, 70, 140, and 210 kg ha^{-1}) were evaluated in different HZs. The SALUS model was used to evaluate spatial variability in yield, N response, and net revenue over the long-term period (1971–2012). Results showed that yield was significantly affected by N rate ($p < 0.01$) in both fields and by HZ in Field 2 ($p < 0.05$), whereas N response was only affected by N rate. Simulated yield was significantly affected by N. The model accounted for the spatial variability, showing HZ effect ($p < 0.001$) and a significant HZ × N interaction ($p < 0.0001$). The optimal economic return N rate differed between HZs in both fields. Our procedure demonstrated the ability to improve N management by the selection of appropriate N rates across the field, thereby improving N use efficiency and growers' profits and reducing the potential for negative environmental impacts.

Core Ideas

- Model-based approach accounted for spatio-temporal variability of maize N response.
- Temporal variability of grain yield, N response, and net revenue increased with N rate.
- The N rate required to reach the highest net revenue differed between homogenous zones within fields.
- Selecting N rate by homogenous zones might reduce environmental and economic risk.

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Variability in crop growth and grain yield within a single field is often due to spatial variability in soil properties, topography, and management factors (Basso et al., 2001, 2013; Dharmakeerthi et al., 2005; Mamo et al., 2003). A more complete understanding of the variability of soil processes and properties may allow farmers to recognize when and where management practices can be improved. Specifically, precision agriculture technologies are proposed as a means to manage the variability of grain yield (Al-Kaisi et al., 2016; Ma et al., 2016; Mulla and Schepers, 1997; Pierce and Nowak, 1999).

Precision agriculture holds great promise for managing yield variability regarding inputs such as nitrogen (N) fertilizer because these inputs can be matched to the requirements of each section of a field. Uniform N management in fields where soils are highly variable can lead to under- or overfertilization with respect to the actual N requirements of a crop. Underfertilization can result in poor crop growth, and overfertilization can lead to nitrate leaching and nitrous oxide emission, with negative environmental consequences. In both cases, there are negative economic impacts for farmers (Hatfield and Prueger, 2004; Mamo et al., 2003; Raun and Schepers, 2008).

One alternative to consider when yield variability within a field is clearly present is to outline the homogenous management zones (HZs). Doerge (1999) defined HZs as areas of a field that express a functionally homogeneous combination of yield-limiting factors that require a single rate of a specific crop input. Each HZ is defined as an area that shows similar yield response to fertilization and other practices that need to be reliably estimated before management decisions are made (Basso et al., 2007; Miao et al., 2006).

The delineation of HZs with maize (*Zea mays* L.) is suitable because this crop is highly sensitive to variations in soil texture, soil water holding capacity, and nutrient availability (Uhart and Andrade, 1995), which result in related variations in grain yield associated with soil properties and topography.

Evaluation of all possible interactions between soil, weather, and N management is expensive and time consuming because it involves multiple replications of field experiments repeated

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Abbreviations: DEM, digital elevation map; EC, electrical conductivity; HZ, homogeneous zone; SALUS, System Approach to Land Use Sustainability; SOM, soil organic matter.

over many seasons (Batchelor et al., 2002). Alternatively, crop growth simulation models can be used to help make decisions about N management strategies that optimize productivity, maximize profit, and minimize environmental risk (Basso et al., 2012). Basso et al. (2016a) recently reviewed the performance of different simulation models and illustrated the validity of these systems to simulate yield and crop phenology under different management strategies. Simulation models generate various scenarios by taking into account the aforementioned interactions coupled with field spatial variability and long-term historical weather data (Basso et al., 2011).

The objectives of this work were (i) to evaluate the response of spatial variability of maize yield by HZs to different N fertilizer rates under rainfed conditions, (ii) to test the ability of the SALUS (System Approach to Land Use Sustainability) model to simulate the effects of N rates on maize yield under rainfed and irrigated conditions, and (iii) to estimate spatial and temporal N fertilizer response risk in maize through the use of long-term simulations.

MATERIALS AND METHODS

Site Description

This study was completed during the 2011 and 2012 growing seasons in two fields approximately 2.5 km apart at the INTA Research Station in Parana, Argentina. The 2011 study area was a 14-ha field (Field 1; –31.8536°, –60.5268°) where the soil was classified as a fine, mixed, thermic Acuic Argiudoll (Soil Survey Staff, 2010) with an average soil depth of 104 cm. Although the soil within the study area was classified as representing one soil series, different degrees of erosion have resulted in significant soil depth variability in Ap horizon, which ranged from 12 to 20 cm. The 2012 study area encompassed a 12-ha field (Field 2; –31.8354°, –60.5446°) that included three different soils: a fine, montmorillonitic, thermic Vertic Argiudoll; a loamy fine, mixed, neutral thermic Acuic Argiudoll; and a fine, mixed, thermic Acuic Argiudoll (Soil Survey Staff, 2010), with an average soil depth of 100 cm. Both study areas have been under no-till management since 1995 and are planted with a wheat/soybean–maize rotation. The region is characterized by an average annual temperature of 18.3°C that ranges from 12.8 and 23.8°C on a monthly basis. Average annual rainfall is 1025 mm, with an average of 770 mm of precipitation during the maize growing season (September–March).

Field Experiment and Homogeneous Zones

Homogeneous zones were defined for each field based on observed levels of soil organic matter (SOM), soil electrical conductivity (EC), and a digital elevation map (DEM) (Fig. 1a–1f). Soil organic matter was determined from composited samples taken to 20 cm in depth (15–20 cores; 2 cm diameter) from an area within 2 m of each grid point of a regular 30 by 30 m grid. Samples were air-dried and ground to pass a 2-mm sieve. Soil organic C was measured by dry combustion with an autoanalyzer (TRU SPEC; Leco Corp. St. Joseph, MI) on the 0.5-mm sample fraction. Soil organic matter was calculated from C using a factor of 1.72 (Fig. 1a and 1b). Apparent EC from 0 to 30 cm was determined (Veris 3100; Geoprove Systems, Salina, KS) (Fig. 1c and 1d).

To define the HZ borders, maps of SOM, EC, and DEM were standardized to a common 5 m by 5 m grid size with GS+ Version 9.0 (Gamma Design Software, 2008) using Management zone analyst software (Fridgen et al., 2004). Briefly, management zone analyst software allows zone delimitation by a fuzzy C-means clustering technique and the selection of the optimal number of zones considering the minimum values of the fuzziness performance index and the normalized classification entropy.

This process resulted in the identification of four HZs in Field 1. In Field 1, Zone 1 (HZ1F1) was located in an upper slope position with soil erosion degree type 1 (25% loss of Ap horizon). Zone 2 (HZ2F1) was located in a medium slope position without erosion (Ap horizon thickness of 17 cm), Zone 3 (HZ3F1) was located in an upper slope position with erosion degree type 2 (50% loss of

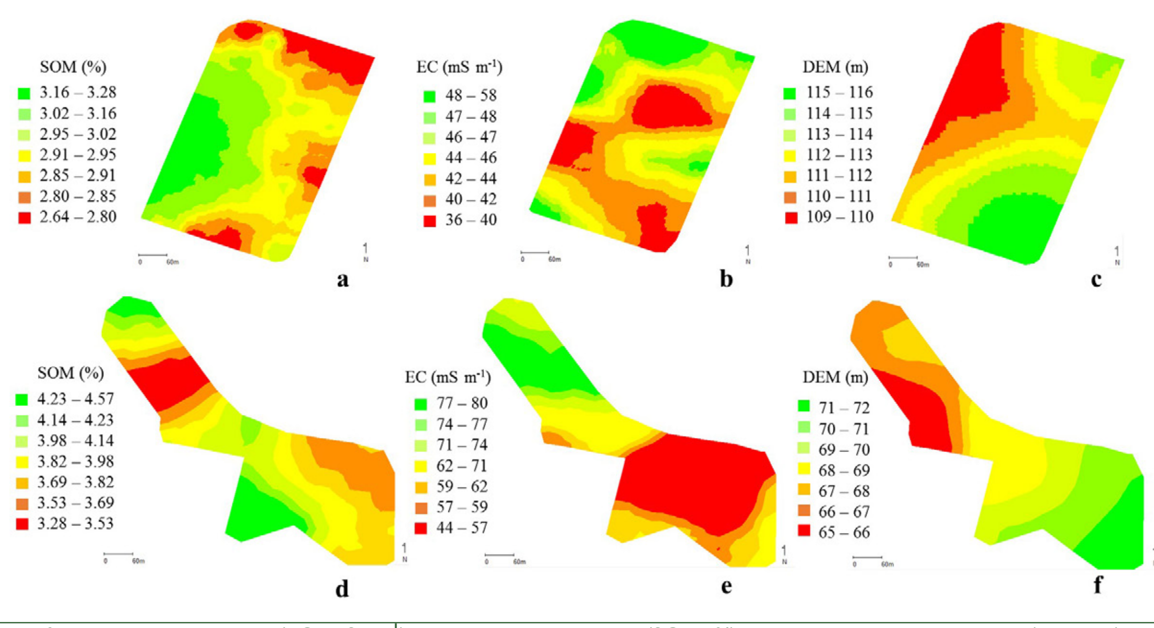

Fig. 1. Maps of electrical conductivity (EC, mS m^{-1}) and soil organic matter (SOM, %) and the digital elevation map (DEM, m) used to delineate homogeneous zones in each field. (a) Electrical conductivity, Field 1. (b) Electrical conductivity, Field 2. (c) Soil organic matter, Field 1. (d) Soil organic matter, Field 2. (e) Digital elevation map, Field 1. (f) Digital elevation map, Field 2.

Ap horizon), and Zone 4 (HZ4F1) was located in a lower slope position with depositional soils (Ap horizon thickness of 20 cm) (Fig. 2; Table 1). Similarly, three homogeneous zones were delineated in Field 2: Zone 1 (HZ1F2) was located in a high position with no detectable erosion, Zone 2 (HZ2F2) was in a medium position with no detectable erosion, and Zone 3 (HZ3F2) was located on a steep slope with erosion type 1 (Fig. 2; Table 1).

Four fertilization treatments were evaluated in each HZ of both fields on plots that were 20 m long and 10 rows wide. Fertilization treatments included three N levels ($N_{(0-60cm)}$ + fertilizer): 70 kg N ha^{-1} (N70), 140 N kg ha^{-1} (N140), and 210 N kg ha^{-1} (N210); a control without N fertilizer (N0) was included, where $N_{(0-60cm)}$ was the average soil N available as nitrate determined within each HZ before sowing. Three replications of each treatment were located within each HZ, which resulted in a total of 48 and 36 plots in Field 1 and Field 2, respectively. Each replicate within an HZ included all N treatments grouped in a block (Fig. 2), which were randomly located in the delineated HZ.

In both fields, the maize genotype was a single cross hybrid Nidera 882HCL MG. Sowing was to a depth of 0.05 m, in rows 0.53 m apart (75,000 seed ha^{-1} density), in October 2011 and September 2012. Urea (46% N) fertilizer was broadcast at sowing, as is usual in our region.

Soil and Crop Measurements

Composite soil samples were collected in each plot (five subsamples) in both fields at three depths (0–20, 20–40, and 40–60 cm) before sowing and at crop maturity. Samples were air-dried and ground to pass a 2-mm sieve to determine $N-NO_3$ with a colorimetric method (Bremner, 1965). Soil water content was measured weekly with a neutron probe (model 4300; Troxler Electronic Laboratories Inc., Research Triangle Park, NC) up to a depth of 1.6 m. Crop phenology was recorded weekly according to Ritchie and Hanway (1982). Total aboveground biomass at crop maturity was determined from 10 plants per plot that were oven dried (65°C) and weighed. Grain yield was estimated by harvesting of 10 m^2 in each plot. Nitrogen content of the biomass and grains was determined by dry combustion using an autoanalyzer LECO, model TRU SPEC (Leco Corp.). Plant samples were taken from the inner six rows of each plot, to avoid border effects. Yield response to N was calculated as the difference between grain yield for each N level and the control treatment.

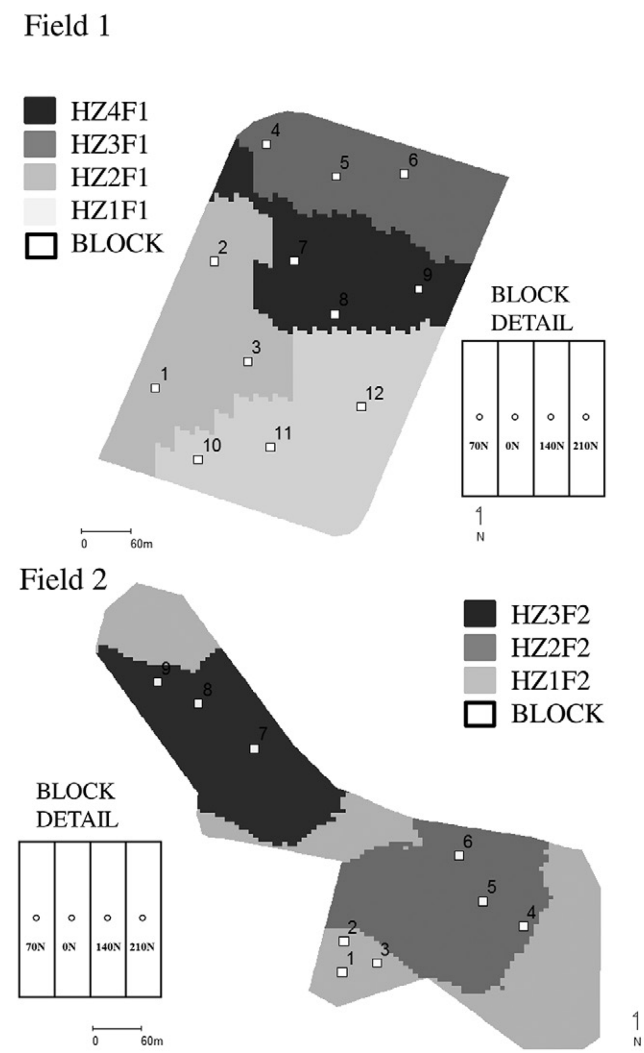

Fig. 2. Homogeneous zones (HZ) delineated in Field 1 (F1) and Field 2(F2). Open squares indicate the N fertilization plot location on in each field. At the center, there is a schematic representation of the plot distribution in each replicate, which includes the location of neutron probe access within plots. N0, no N; N70, 70 kg N ha^{-1}; N140, 140 kg N ha^{-1}; N210, 210 kg N ha^{-1}.

Table 1. Average values of soil organic matter, soil electrical conductivity, and elevation in the homogeneous zones in Field 1 (2011/2012) and Field 2 (2012/2013).

Field	Zone†	$N-NO_3$	SOM‡	EC§	Elevation
		kg N ha^{-1}	%	mS m^{-1}	m
Field 1	HZ1F1	34 (9.2)¶	2.89 (0.06)	44 (2.0)	114.8 (0.67)
	HZ2F1	29 (5.3)	3.17 (0.07)	43 (3.6)	111.2 (1.00)
	HZ3F1	31 (2.0)	2.83 (0.08)	49 (3.3)	112.4 (1.08)
	HZ4F1	39 (3.1)	2.97 (0.07)	41 (2.9)	110.3 (0.83)
Field 2	HZ1F2	50 (0.4)	4.40 (0.29)	59 (3.2)	71.9 (1.78)
	HZ2F2	46 (1.1)	3.84 (0.21)	49 (3.1)	70.0 (0.77)
	HZ3F2	48 (4.7)	3.70 (0.31)	76 (3.5)	68.8 (0.41)

† F, field; HZ, homogeneous zone.
‡ Soil organic matter.
§ Electrical conductivity.
¶ Values in parentheses represent SD within each HZ.

SALUS Model Description, Calibration, and Validation

We used the SALUS model to simulate maize grain yield in the HZ within each field (Basso, 2000; Basso and Ritchie, 2015; Basso et al., 2006; Senthilkumar et al., 2009). SALUS was developed from the CERES models but includes new algorithms in several of the water balance components (runoff, drainage, soil evaporation, and transpiration), soil N, phosphorous, carbon, and tillage. SALUS simulates continuous crop, soil, water, and nutrient conditions under different management strategies over multiple years. The model uses a daily time step to calculate crop growth and can run a number of different management strategies simultaneously. Weather data required for the model include daily values of incoming solar radiation (MJ m^{-2} d^{-1}), maximum and minimum temperature (°C), and rainfall (mm). Soil data required include soil water limits such as saturation (cm^3 cm^{-3}), drain upper limit (cm^3 cm^{-3}), and lower limit (LL, cm^3 cm^{-3}), as well as soil texture (%), bulk density (g cm^{-3}), soil organic carbon (%), and N (%).

Weather data measured at the INTA Paraná Meteorological Station was used to calibrate and validate the model. Soil data (sand, silt, and clay content; bulk density; organic carbon; and total N) were obtained from a local soil survey (Van Barneveld, 1972), and soil water limits were estimated from soil texture and bulk density using the procedure of Ritchie et al. (1999), taking into account variation in site-specific soil properties.

SALUS was calibrated using data from 22 plots of contrasting HZs within the same field (i.e., HZ3F1 and HZ4F1) for all treatments (N0, N70, N140, and N210) used in the field experiments (see section Field Experiment and Homogeneous Zones). Additional plots were added in each HZ to extend the measured data range to calibrate the SALUS model. These treatments included drip irrigation with no N fertilizer (N0 + irrigation) and irrigation with N fertilizer (210 kg N ha^{-1}; N210 + irrigation). Irrigation at a rate of 30 mm weekly was used to avoid water deficit from V6 to R5.

Data from the remaining HZs (HZ1F1, HZ2F1, HZ1F2, HZ2F2, and HZ3F2) for all treatments (N0, N70, N140, and N210) of the field experiments resulted in 20 plots that were used to validate the model.

Model simulations were evaluated by a linear regression (1:1 line), plotting the simulated values on the *x* axis (Piñeiro et al., 2008). We also tested the goodness of fit by calculating the RMSE between observed and simulated data according to the following equations:

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

where S_i is simulated value, O_i is observed value, n is the total number of observations, and i is the ith observation. Additionally, we expressed RMSE in relative terms (%E) as follows:

$$\%\mathrm{E} = \frac{\mathrm{RMSE}}{\overline{x}} \times 100$$

where $\overline{x}$ is the mean of observed values over replicates.

Long-Term Simulation

Once the model was validated, long-term simulations (1971–2012) were performed to evaluate N treatments with data from the INTA weather station as inputs. We also considered soil properties for each HZ in each field. Initial conditions for soil water and N were established in the model simulations by the measured initial condition in each field and HZ. Maize was planted on 15 September. Sowing density was 7 plants m^{-2} (0.52-m row distance). Simulations were run for each field and HZ that included the same N levels evaluated in field experiments: N70, N140, and N210. A control without N fertilizer (N0) was included where N (0–60 cm) was the average soil N available as nitrate determined within each HZ before sowing (Table 1). The initial N conditions (Ni) used were determined in Field 1 and Field 2 for both seasons (2011/2012 and 2012/2013). The simulation assumed that no other nutrients and pests affect maize yield.

Net revenue ($ ha^{-1}) was calculated based on the method of Massey et al. (2008) as the product of grain yield (t ha^{-1}) and grain price ($ t^{-1}) minus production costs ($ ha^{-1}) including land, machinery costs, and variable costs, all expressed in US$. Maize and fertilizer prices for this analysis were the average value for the period from 2008 to 2013 obtained from a local database (Bolsa de Cereales de Rosario, 2016). Average prices were expressed in US$ to exclude the local inflation effect.

Data Analysis

For measured data we used an ANOVA to test the effects of HZ, N, and their interaction (HZ × N) on maize grain yield and N response in each field. We used a mixed model that included HZ and N as fixed effects and replicates as random effects. Treatments were arranged in a split-plot design, considering HZs as the whole plot and the N rate as the subplot (Fig. 2). When interactions were significant, means were calculated by N within each HZ.

For long-term simulated data, we used ANOVA to test the effects of HZ, N, and their interaction (HZ × N) on maize grain yield and N response in each field. Because the simulation model is not capable of simulating replications for a single treatment in a given HZ and year, we used the years as replicates for each treatment within a HZ. In the mixed model, replicates were considered as a random effect. Treatments were arranged in a split-plot design, considering HZ as the whole plot and the N rate as the subplot (Fig. 2). The ANOVA and means comparisons (LSD at $\alpha = 0.05$) were performed using Infostat software (Di Rienzo et al., 2016), which uses R (Ihaka and Gentleman, 1996) as a complement for mixed model analysis.

Here we propose an approach to estimate spatial and temporal N fertilizer response based on the long-term simulations of grain yield, N response, and net revenue. First, we evaluated the spatial variability of grain yield, N response, and net revenue through the significant effect of HZs on these variables. Second, the coefficient of variation among years for each N treatment within an HZ was compared to evaluate yield variation over time. Then, we built frequency histograms for each variable. An integrative analysis of the resulting information from the three steps of this approach should provide valuable information to quantify uncertainties associated with determining N rate in different HZs within a field.

Table 2. Average daily temperature and monthly rainfall during crop growing season, Field 1 (2011/2012) and Field 2 (2012/2013). Data from the Meteorological Station at INTA Parana, Argentina (–31°50′; –60°31′). Historical records (1971–2012) are also shown.

Month	Average temperature			Rainfall		
	Field			Field		
	1	2	Historical	1	2	Historical
	°C			mm		
Sept.	–	16.7	15.2	–	47	54
Oct.	17.6	19.1	18.1	73	236	105
Nov.	22.9	22.9	20.9	130	95	110
Dec.	23.9	24.2	23.4	53	257	116
Jan.	26.4	25.0	24.8	47	34	118
Feb.	25.1	23.5	23.8	115	82	108
Total	23.2	23.0	21.0	418	750	611

Environmental Conditions during Field Experiments

Rainfall during the growing season (September–March) in Field 1 was 418 mm, 32% lower than the historical average (1971–2012). Rainfall during the 30-d period around flowering (R1) (27 Dec. 2011 ± 15 d) was 74 mm, which corresponds to 48% of potential evapotranspiration (154 mm) (Table 2). In contrast, rainfall during the growing season in Field 2 was 750 mm, which was 23% higher than the historical average. In addition, rainfall around R1 in Field 2 (257 mm) was 58% higher than potential evapotranspiration (162 mm) (Table 2). Temperatures were within the range of historical values for both growing seasons, with the exception of the period November to February in 2012, when temperatures were slightly higher than historical averages (Table 2).

RESULTS

Grain Yield and Response to N in Field Experiments

In both fields, grain yield was significantly affected by N application rate ($p = 0.0004$ in Field 1; $p < 0.0001$ in Field 2), with a significant HZ effect on grain yield only in Field 2 ($p = 0.048$). Table 3 shows that average grain yield in the most highly eroded zone of Field 1 (HZ3F1) was 39% lower than other zones in that field that exhibited less erosion (HZ1F1, HZ2F1) or that had depositional soils (HZ4F1). This contrasts with Field 2, where average grain yield was 50 and 60% higher in HZ1F2 than in HZ2F2 and HZ3F2, respectively (Table 3). Maize grain yield ranged from 3393 to 7074 kg ha^{-1} in Field 1, whereas it ranged from 4582 to 10947 kg ha^{-1} in Field 2. Treatments with higher N rates (i.e., N140 and N210) outyielded the other treatments in both fields (Table 3).

The initial soil N availability was lower in Field 1 (range, 29–39 kg N–NO_3 ha^{-1}) than in Field 2 (range, 46–50 kg N–NO_3 ha^{-1}) (Table 1). Nitrogen response was significantly affected by N rates in both fields (Table 3). Average N response was 1198 kg ha^{-1} in Field 1, in which rainfall was scarce around flowering period, in contrast with the higher average N response in Field 2 (2172 kg ha^{-1}), in which there were no water restrictions. In both fields, there were no significant differences in N response between the higher N rates (N140 and N210) or between the lowest N rate (N0 and N70).

Table 3. Measured data, average grain yield, and N response for each homogeneous zone and N application rate in Field 1 (2011/2012) and Field 2 (2012/2013). Values are averages from three replicates in each homogeneous zone within each field.

	Field 1			Field 2	
	Grain yield	N response		Grain yield	N response
	kg ha^{-1}			kg ha^{-1}	
Zone, field†					
HZ1F1	6350	960	HZ1F2	9122A‡	1672
HZ2F1	5955	1420	HZ2F2	6071B	1282
HZ3F1	3827	622	HZ3F2	5618B	1119
HZ4F1	6309	1244			
N application rate§					
N0	4853b¶	–	N0	5877b	
N70	5030b	177b	N70	5774b	–103b
N140	5914a	1061a	N140	7784a	1907a
N210	6189	1336	N210	8314a	2437a
ANOVA					
HZ	0.0757	0.4065	HZ	0.048	0.7612
N	0.0004	0.0014	N	<0.0001	0.0013
HZ × N	0.9902	0.9935	HZ × N	0.3014	0.4335

† F, field; HZ, homogeneous zone.

‡ Uppercase letters show significant differences (LSD test; α = 0.05) between homogeneous zones.

§ N0, no N; N70, 70 kg N ha^{-1}; N140, 140 kg N ha^{-1}; N210, 210 kg N ha^{-1}.

¶ Lowercase letters show differences (LSD test; α = 0.05) between N fertilization treatments.

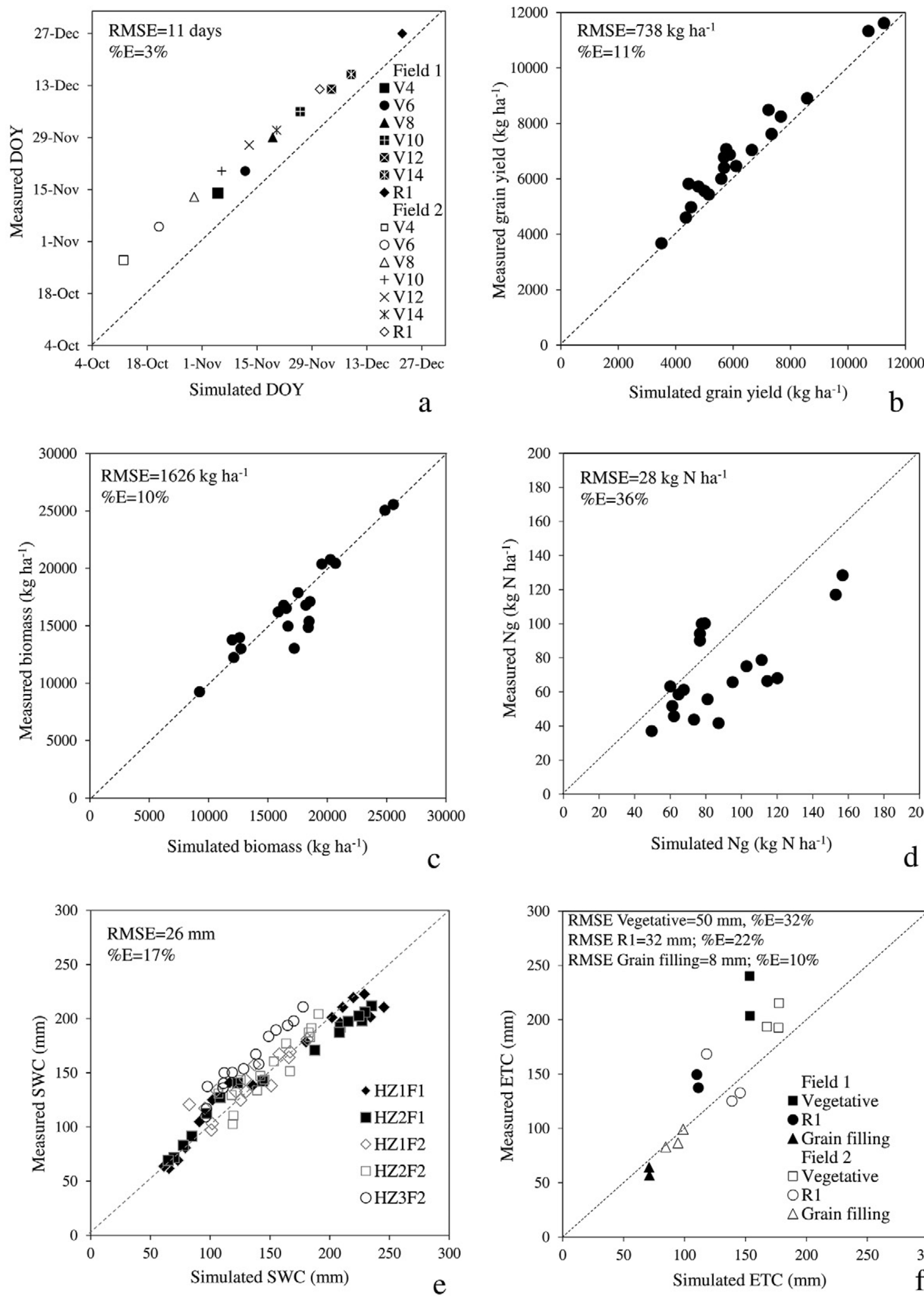

Fig. 3. SALUS model validation results. (a) Simulated and measured day of the year (DOY) at different phenological stages (V4, V6, V8, V10, V12, V14, and R1). (b) Simulated and measured maize grain yield. (c) Simulated and measured biomass. (d) Simulated and measured N in grain (Ng). (e) Simulated and measured soil water content for 0 to 160 cm (Field 1) and 0 to 100 cm (Field 2) during the crop growing season. (f) Simulated and observed accumulated crop evapotranspiration at different crop periods vegetative (around R1 and grain filling). Panels b, c, d, and f include all evaluated fertilization treatments (no N [N0], 70 kg N ha^{-1} [N70], 140 kg N ha^{-1} [N140], and 210 kg N ha^{-1} [N210]) from Homogeneous Zone 1, Field 1 (HZ1F1), HZ2F1, HZ1F2, HZ2F2 and HZ3F2. Panel e shows the accumulated soil water in the N0 treatment in five HZs selected to validate the model. Filled symbols, Field 1; empty symbols. Field 2. Dotted line represents 1:1 relationship. %E, error rate compared with measured average.

Model Validation

The SALUS model adequately simulated crop phenology, grain yield, total biomass, N accumulated in grains, soil water content, and crop evapotranspiration (Fig. 3). Crop phenology from V4 to R1 was simulated with 3% error (RMSE = 11 d; $r^2 = 0.99$). Although all growth stages were underestimated, the phenology in Field 2 was slightly better estimated than in Field 1 (Fig. 3a). Grain yield (%E = 11%; RMSE = 738 kg ha^{-1}; $r^2 = 0.98$) (Fig. 3b) and total aboveground biomass at crop maturity (%E = 10%; RMSE = 1626 kg ha^{-1}; $r^2 = 0.92$) (Fig. 3c) were better simulated than N accumulated in grains (%E = 36%; RMSE = 28 kg N ha^{-1}; $r^2 = 0.66$) (Fig. 3d). Soil water content from sowing to crop maturity (%E = 17%; RMSE = 26 mm; $r^2 = 0.86$) (Fig. 3e) and crop evapotranspiration for the whole growing season (RMSE = 34 mm; $r^2 = 0.79$) (Fig. 3f) and for the vegetative period (%E = 32%) around R1 (%E = 22%) and grain filling period (%E = 10%) were adequately simulated by the SALUS model.

Spatial and Temporal Variability of Grain Yield, N Response, and Net Revenue

Long-term grain yield simulated by the SALUS model was significantly affected by N fertilization in both fields ($p < 0.0001$) (Tables 4 and 5). Moreover, SALUS accounted for the spatial variability, as shown by the significant effect of HZ ($p < 0.0001$) (Tables 4 and 5) and significant interaction HZ × N ($p = 0.0001$) (Tables 4 and 5). In Field 1, simulated grain yield ranged from 3381 to 7948 kg ha^{-1}. The N0 treatment exceeded 3000 kg ha^{-1} in HZ3F1 and exceeded 4000 kg ha^{-1} in HZ1F1, HZ2F1, and HZ4F1 in 50% of the years (Fig. 4a, 4c, 4e, and 4g).

Simulated grain yield in Field 2 ranged from 2364 to 7267 kg ha^{-1}, and N effects differed between HZs with the highest grain yield and the lowest N effect in HZ1F2. In this field, N0 treatment showed differences between zones and exceeded 4500 kg ha^{-1} in HZ1F2, 3000 kg ha^{-1} in HZ2F2, and 2000 kg ha^{-1} in HZ3F2 in 50% of the years (Fig. 5).

Simulated response to N was significantly affected by N and HZ and showed a significant HZ × N interaction in both fields ($p = 0.0001$ in Field 1; $p < 0.0001$ in Field 2) (Tables 4 and 5). Grain yield response ranged from 32 to 91% in Field 1 and from 25 to 165% in Field 2, depending on the HZ (Tables 4 and 5). In Field 1, grain yield response to N in HZ4F1 was 9 to 31% higher than in the other HZs. In Field 2, grain yield response to N in HZ3F2 was 30% higher than in HZ1F2 and 37% higher than in HZ2F2. Nitrogen response increased linearly in less productive zones of Field 2 (HZ2F2 and HZ3F2), showing a higher response in HZ3F2.

Long-term simulation showed that grain yield variation over years, quantified by coefficient of variation of long-term results, was higher as N rate increased in both fields and for all HZs (Table 6; Fig. 6a and 6b). There was a linear relationship between average grain yield and yield variation over time within each HZ and field (Fig. 6a and 6b), reflecting that the higher yields as affected by high N rates were associated with a higher temporal variability. Additionally, in Field 1, N had a differential effect on temporal variability depending on HZ (Table 6; Fig. 6a). In fact, in the most eroded zone of Field 1 (HZ3F1), the temporal

Table 4. Simulated data, average grain yield, average N response, and net revenue for each homogeneous zone and N application rate in Field 1 (2011/12). Simulations were run for a 41-yr period (1971–2012).

Zone, field†	N application rate‡	Grain yield	N response	Net revenue
		——kg ha^{-1}——		\$ ha^{-1}
HZ1F1	N0	4131d§		218c
	N70	5550c	1419c	336b
	N140	7130b	2999b	481a
	N210	7623a	3492a	446a
HZ2F1	N0	4224d		234c
	N70	5582c	1358c	342b
	N140	6519b	2295b	380b
	N210	7566a	3343a	437a
HZ3F1	N0	3381d		94b
	N70	4691c	1310c	194a
	N140	5576b	2195b	224a
	N210	6442a	3060a	250a
HZ4F1	N0	4234d		235c
	N70	5907c	1674c	396b
	N140	7486b	3252b	540a
	N210	7948a	3715a	500a
		ANOVA		
HZ		<0.0001	<0.0001	<0.0001
N		<0.0001	<0.0001	<0.0001
HZ × N		0.0001	0.0001	0.0001

† F, field; HZ, homogeneous zone.

‡ N0, no N; N70, 70 kg N ha^{-1}; N140, 140 kg N ha^{-1}; N210, 210 kg N ha^{-1}.

§ Different letters following average values within each homogeneous zone indicate significant differences ($\alpha = 0.05$) among N rates.

Table 5. Simulated data, average grain yield, average N response, and net revenue for each homogeneous zone and N application rate in Field 2 (2012/2013). Simulations were run for a 41-yr period (1971–2012).

Zone, field†	N application rate‡	Grain yield	N response	Net revenue
		——kg ha^{-1}——		\$ ha^{-1}
HZ1F2	N0	4396a§	–	262a
	N70	5496b	1100a	328b
	N140	6786c	2390b	387c
	N210	7267d	2871c	424c
HZ2F2	N0	2569a	–	–41
	N70	3817b	1248a	49b
	N140	4409c	1840b	30b
	N210	5497d	2928c	94c
HZ3F2	N0	2364a	–	–75a
	N70	3801b	1437a	47b
	N140	5316c	2952b	181c
	N210	6267d	3903c	221c
		ANOVA		
HZ		<0.0001	0.0002	<0.0001
N		<0.0001	<0.0001	<0.0001
HZ × N		<0.0001	<0.0001	<0.0001

† F, field; HZ, homogeneous zone.

‡ N0, no N; N70, 70 kg N ha^{-1}; N140, 140 kg N ha^{-1}; N210, 210 kg N ha^{-1}.

§ Different letters following average values within each homogeneous zone indicate significant differences ($\alpha = 0.05$) among N rates.

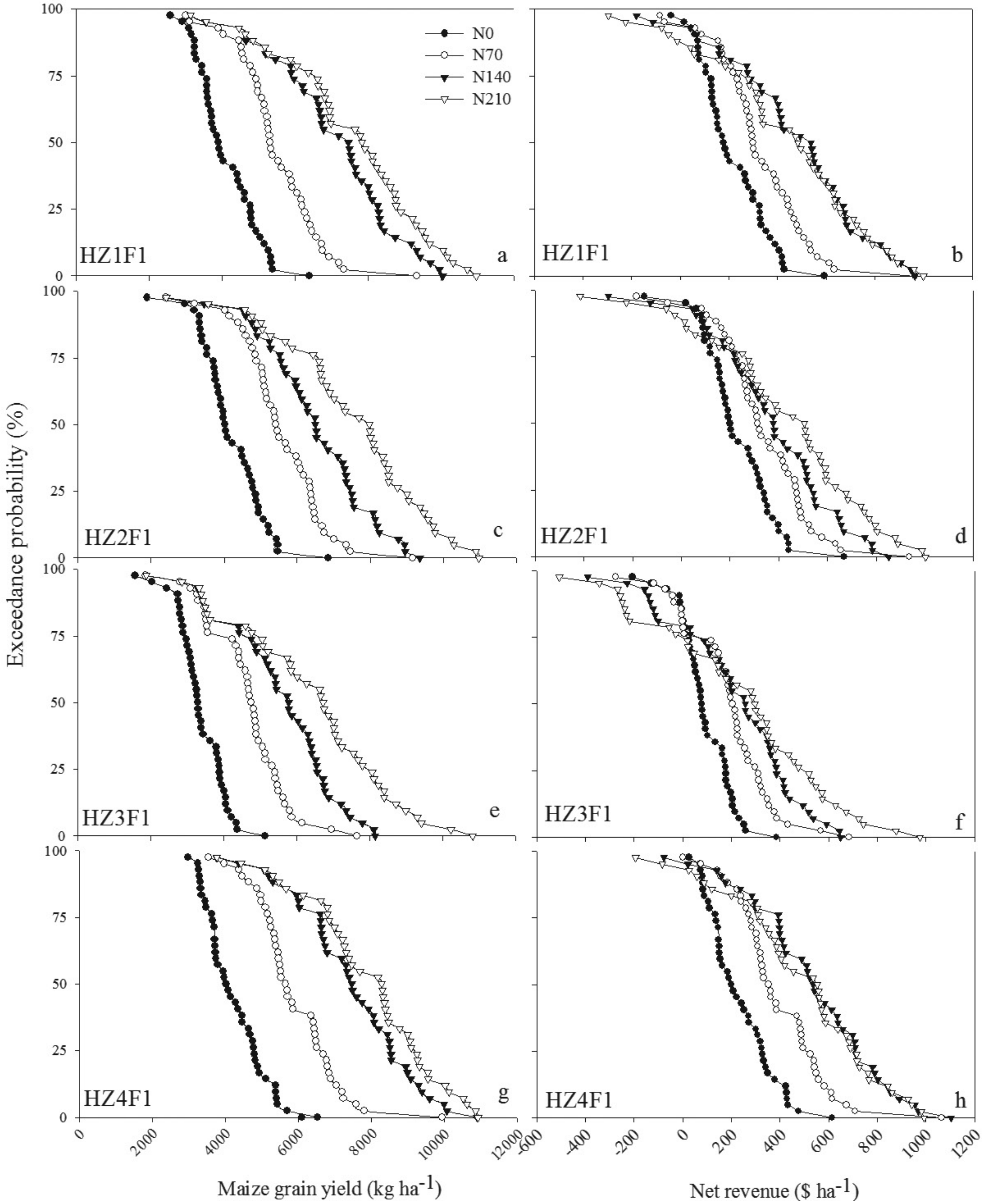

Fig. 4. Exceedance probability for maize grain yield (a, c, e, and g) and net revenue (b, d, e, and f) for the N treatments in four homogeneous zones in Field 1. Data simulated over 41 yr (1971–2012). (a and b) Homogeneous Zone 1, Field 1 (HZ1F1), (c and d) HZ2F1, (e and f) HZ3L1, and (g and h) HZ4L1. N0, no N; N70, 70 kg N ha^{-1}; N140, 140 kg N ha^{-1}; N210, 210 kg N ha^{-1}.

variability was more sensible to the changes in average grain yield (i.e., there was a higher slope of the relationship between average grain yield and the temporal variability) (Fig. 6a). In Field 2, the relationship between average grain yield and the temporal variability only was significant for the most productive HZ (HZ1F2). Similarly as for grain yield, temporal variability of N response increased with N rate (Table 6), and the increase in temporal variability of N response as affected by N rate was almost double those for grain yield.

In both fields, net revenue differed between HZ ($p < 0.0001$) and N rates ($p < 0.0001$), showing a significant HZ × N interaction ($p = 0.0001$ in Field 1; $p < 0.0001$ in Field 2) (Tables 4 and 5). The N0 treatment showed a positive revenue in Field 1 in more than 90% of the simulated years for all HZs. However, net revenue in HZ3F1 was also negative in N140 and N210 in 25% of the simulated years (Fig. 4b, 4d, 4f, and 4h). The net revenue for N0 treatments in Field 2 was positive in HZ1F2 for all simulated years. Nevertheless, there were positive net revenues only in 35% of simulated years for HZ2F2 and in 25% of the years in HZ3F2. In both fields, the N rate required to reach the highest net revenue differed between HZs (Fig. 4 and 5).

Temporal variability of net revenue in Field 1 was higher in the N0 and N210 treatments than in the other treatments (Table 6). The HZ3F1 had the highest temporal variability in the N0 treatment, in contrast with HZ4F1, which had the lowest. In Field 2, temporal variability in the N0 treatment in HZ1F2 was fourfold lower than HZ2F2 and twofold lower than HZ3F2.

DISCUSSION

Measured Grain Yield and N Response

Homogeneous zones, delineated based on EC, SOM, and altimetry, significantly differed in grain yield only in Field 2 ($p < 0.05$), whereas grain yield was significantly affected by N rate in both fields ($p < 0.01$). However, in both fields it was only possible to detect the most productive HZ from the other less productive ones rather than being able to rank all of the zones in order. This zone delimitation approach has been previously used (Gregoret et al., 2011; Kitchen et al., 2005), with varying degrees of success, to anticipate when there were significant differences in grain yield or whether those differences were negligible, as reported by Peralta and Costa (2013) and Córdoba et al. (2013). Vrindts et al. (2005) compared management zones delimitated by soil parameters against those defined by soil and crop green indices and concluded that zone outlines are more effective when important soil-limiting factors are taken into account.

The soil data used to identify zones do not take into account all factors that determine grain yield, such as weather variability. Thus, only those zones with contrasting soil depth (i.e., HZs with depositional or eroded soils) showed grain yield differences in a growing season with limited rainfall (Field 1). In contrast, in the second season (Field 2), rainfall was ample, and grain yield

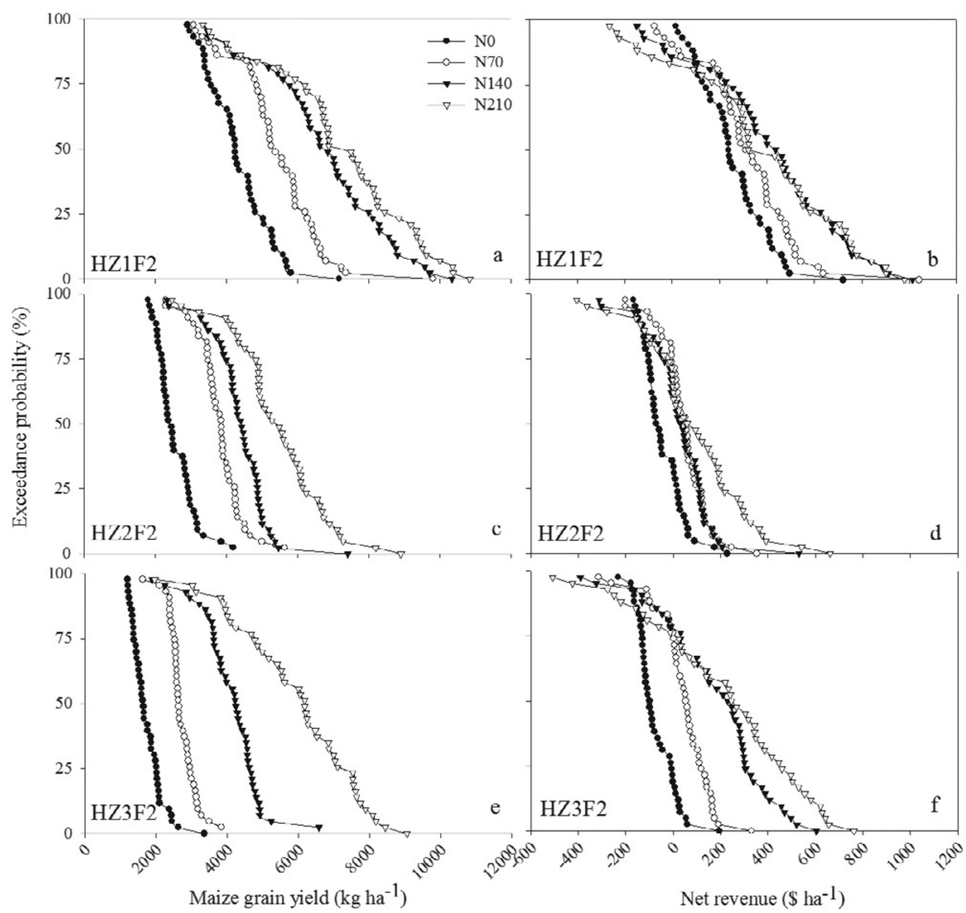

Fig. 5. Exceedance probability for maize grain yield (a, c, e, and g) and net revenue (b, d, and e) for the different N treatments in three homogeneous zones in Field 2. Data simulated over 41 yr (1971–2012). (a and b) Homogeneous Zone 1, Field 1 (HZ1F2), (c and d) HZ2F2, and (e and f) HZ3F2. N0, no N; N70, 70 kg N ha^{-1}; N140, 140 kg N ha^{-1}; N210, 210 kg N ha^{-1}.

Table 6. Grain yield, N response, and net revenue temporal variability from simulated N treatments for different homogeneous zones delineated in Field 1 (2011/2012) and Field 2 (2012/2013). Simulations were run for a 41-yr period (1971–2012).

Zone, field†	N application rate‡	Temporal variability: Grain yield	N response	Net revenue
		%		
HZ1F1	N0	20		63
	N70	21	39	57
	N140	24	44	58
	N210	25	47	72
HZ2F1	N0	21		63
	N70	21	38	58
	N140	23	42	66
	N210	26	50	75
HZ3F1	N0	20		118
	N70	23	50	94
	N140	27	52	111
	N210	33	62	141
HZ4F1	N0	19		57
	N70	20	33	49
	N140	21	38	49
	N210	22	40	58
HZ1F2	N0	21		58
	N70	23	50	64
	N140	26	50	69
	N210	28	53	86
HZ2F2	N0	21		217
	N70	17	37	212
	N140	19	39	463
	N210	24	44	235
HZ3F2	N0	21		111
	N70	18	34	250
	N140	25	41	123
	N210	30	46	141

† F, field; HZ, homogeneous zone.
‡ N0, no N; N70, 70 kg N ha^{-1}; N140, 140 kg N ha^{-1}; N210, 210 kg N ha^{-1}.

differences among zones were associated with differences in soil type (mainly texture). Although varying the N application rate allows the ability to explore a wide nutrient availability range, high yields were only reached when weather and soil conditions were nonlimiting. Gregoret et al. (2011) also determined that water and N availability influenced variable N rate in the Central Pampas region of Argentina.

As expected, in growing season 2011 where water was limiting, response to N was null or low. In contrast, N had more noticeable effects on response to N in 2012, where there were no water restrictions. This study emphasizes the relevance of the use of crop growth models to evaluate site-specific management (Batchelor et al., 2002; Sadler et al., 2000) and becomes even more important when long-term data series are used to evaluate site and weather interactions, risk, and suitability of HZs to determine N management strategies, as suggested by Basso et al. (2011).

Model Evaluation

For our objectives, the SALUS model adequately simulated crop phenology, grain yield, plant biomass, and N accumulated in grain. Soil water content and evapotranspiration were

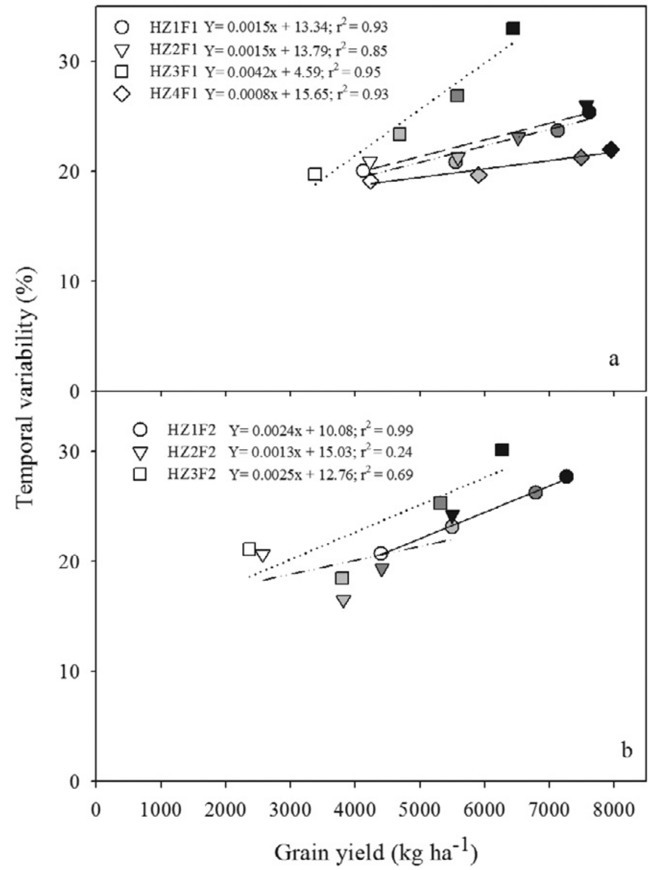

Fig. 6. Temporal variability as a function of homogeneous zone (HZ) grain yield. (a) Field 1 (F1); (b) Field 2 (F2). Symbols shows HZs. Different colors indicate N rate: no N (white), 70 kg N ha^{-1} (gray), 140 kg N ha^{-1} (dark gray), and 210 kg N ha^{-1} (black).

simulated with less, though acceptable, precision. Simulated crop variables had similar errors to those reported in previous studies that used SALUS (Basso et al., 2009; Bertocco et al., 2008) as well as other models, such as EPIC, CERES-Maize, and CropSyst (Ben Nouna et al., 2000; Cabelguenne et al., 1999; Díaz-Ambrona et al., 2005).

The RMSE to estimate water content in the soil profile during the crop growing season ranged between 12 (%E = 8%) and 38 mm (%E = 23%); these results were better than those reported by Batchelor et al. (2002), who obtained RMSE values between 46 and 59 mm. Similarly, Basso (2005) reported RMSE values between 22 and 68 mm in simulations on spatial variability of soil water content using SALUS-Terrae. Our simulations showed good agreement with measured soil water content in the evaluated HZ in each field (Fig. 3e) for two contrasting growing seasons and different soils. This is a key aspect to consider when simulation models are used to evaluate variable management practices as N fertilization because maize is highly sensitive to water.

Despite the fact that the dataset used for model calibration included only two sites in different years, it should be noted that the selected fields had contrasting weather conditions in each year. This provided a larger range of values in the variables included in the study. Furthermore, to expand the data range for calibration of the SALUS model, we included irrigated plots into the simulation of each HZ.

Long-Term Yield, N Response, and Net Revenue Simulations

Long-term simulations showed spatial variability in grain yield and N response in both fields, which differed with the observed response in the field experiments, probably due to the wider range of rainfall in the simulations as compared with only one season for each field. Moreover, the availability of simulated long-term data allowed us to estimate the spatiotemporal variability of yield and net revenue for each HZ and field. In early works, Blackmore (2000) and Whelan and McBratney (2000) pointed out that the comparison between spatial and temporal variability is an important requirement to the decision to change from uniform to site-specific management.

Different N responses among HZs indicate that HZ delineation in both fields was successful over a long period of time. This reinforces the idea that N rates should be adjusted differentially within a field, as has been demonstrated in previous studies (Basso et al., 2010, 2011; Gregoret et al., 2011).

Simulation results reflected the different productivity levels of HZs, indicated by the range of yield in the N0 and N210 treatments. Remarkably, low yields in less productive HZs within each field matched the measured yields, suggesting that soil parameters used in the model (infiltration rate, lower and upper limits of water content, and Ap thickness) adequately represented field limitations, which, in turn, accounted for soil–weather interactions.

Furthermore, simulation results provide us a measure of the temporal variability of grain yield and N response as reflected by the coefficient of variation. Temporal variability of grain yield tends to increase with the N rate (Fig. 6a and 6b). The effect of N on temporal variability was higher in the less productive zone of each field (HZ3F1 and HZ3F2) (Table 6). Moreover, higher temporal variability was coincident with higher average grain yield in both fields and all HZs (Fig. 6a and 6b).

Previous works reported N as one of most limiting factors to maize production (Caviglia et al., 2014; DiNápoli and Maddonni 1996). The reported water–N interaction (Kim et al., 2008; Teixeira et al., 2014) explains the increase in grain yield temporal variability. Basso et al. (2016b) recently reported that N rates suggested by the model were able to increase profit and reduce environmental impact.

High N rates led to high yields in less productive zones when climatic conditions were not limiting. In contrast, yields in years with high climatic restrictions in these zones were not proportionally increased with N rate (see open triangles above 25% of probability of exceedance in Fig. 4e, 5c, and 5e). These results rely on the highest temporal variability of fertilized treatments as compared with controls (Fig. 4 and 5).

Temporal variability has been suggested as a key factor that limits the decision by farmers to use precision agriculture practices such as variable N fertilization rates within HZs of a field (Basso et al., 2010; Blackmore et al., 2003; Whelan and McBratney, 2000). However, most of these studies consider only a few years of field data to evaluate temporal variability (Blackmore et al., 2003; Diker et al., 2004; Whelan, 1998). The study of the effect of soil–weather interactions on N response cannot be fully addressed based on data from a limited number of years (Tremblay et al., 2012). Therefore, the approach used here is an important tool that supports N management by HZs within a field by simulating long-term variability in rainfall. Similar approaches used in different environments have found that the use of models allows evaluation of optimal N rates by zones in wheat (Basso et al., 2010, 2016a) and maize (Basso et al., 2013, 2016b; Link, 2005; Link et al., 2006; Miao et al., 2006).

Evaluation of yield, N response, and net revenue over a long period of time allowed us to quantify the risk of having negative net revenues by the use of a selected N rate in each HZ. The results revealed different average net revenue among HZs. Additionally, the temporal variability could help to select the most suitable N rate for each HZ, thereby minimizing both economic and environmental risk. Our results showed a low probability to reach high grain yield or net revenue in more productive zones with the lower N rate, clearly in less than 25% of the years. These results correspond to years with ample rainfall amounts.

This information could help determine N fertilization rates according to a farmer's aversion to risk, a factor that usually limits adoption of precision agriculture techniques (Whelan and McBratney, 2000). Even more importantly, if weather forecasts change during given growing season, N rate adjustments may be made to improve N management as proposed by Basso et al. (2011). This approach might be especially useful for regions with uncertain rainfall patterns.

Our systems approach suggests that selecting the adequate N rate in each HZ is economically beneficial and that it may also have important consequences in minimizing the environmental impact of overfertilization. Nitrogen losses from agriculture to the environment are critical to surface and ground water quality (Röckstrom et al., 2009). It should be noted that use of a uniform N application rate in space and time may generate N excesses in some or all HZ and years, depending on rainfall patterns. In fact, N losses are often associated with inadequate fertilization management (Cassman et al., 2002).

Additionally, climate change scenarios in our region predict an increase in rainfall variability and storm intensity (Barros et al., 2015). Therefore, our approach could further contribute to designing N management strategies that mitigate the effect of climate change on N use efficiency by including the predicted scenarios in synthetically created weather-data series.

CONCLUSIONS

Spatial variability effects on observed grain yield were not as important as those in the simulated grain yield in the previously delineated zones. The modeling approach adopted in our study was successful in accounting for spatial variability in maize grain yield and in identifying the best rate to optimize N response and net revenue.

Temporal variability of grain yield and net revenue increased with N rate increasing the frequency of negative net revenues, which emphasizes the need to account for the impact of weather on N management decisions. Also, soil characteristics that define high- or low-productivity HZs established a strong pattern in long-term N response, appearing as a critical issue to be considered for optimizing N rate decisions.

Our systems approach demonstrated the ability to contribute to the design of N management strategies that improve N use efficiency and reduce the environmental and economic risk associated with selecting the appropriate N rate across the field.

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