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Using a nitrogen mineralization index will improve soil productivity rating by artificial neural networks

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ABSTRACT

In the Pampas, nitrogen fertilization rates are low and soil organic matter impacts crop yield. Wheat (*Triticum aestivum* L.) yield was related to total soil nitrogen (total N) and to nitrogen mineralization potential (mineralized N) to determine whether the effects of organic matter may be attributed to its capacity to act as a nitrogen source or to the improvement of the soil physical condition. Data of 386 sites from throughout the region comprised in a recent soil survey were used, in which climate and soil properties to 1 m depth were determined. Artificial neural networks were applied for total N and mineralized N estimation using climate and soil variables as inputs (R^2 = 0.59–0.70). The models allowed estimating total N and mineralizable N at county scale and related them to statistical yield information. Neural networks were also used for yield prediction. The best productivity model fitted (R^2 = 0.85) showed that wheat yield could be predicted by rainfall, the photothermal quotient, and mineralized N. The soil organic matter effect on crop yield seems to be mainly related to its nitrogen mineralization capacity. Using miner alized N as predictor would be a valuable tool for rating soil productivity.

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Introduction

The influence of organic matter on soil fertility and productivity was recognized long ago (Feller et al. 2012). The positive effects of organic matter on crop yields have been attributed to the improvement of soil physical properties and to its function as a nutrient source, especially nitrogen (Frageria 2012). Consequently, many soil productivity indexes include organic matter as a factor (De Paepe and Alvarez 2013). Disentangling the physical and nutritional effects of soil organic matter on crop yield may be a difficult task. Physical properties improve as organic matter increases (Johannes et al. 2017) and a similar phenomenon occurs with soil nitrogen mineralization capacity (Wade et al. 2016). To our knowledge, soil productivity rating using its nitrogen mineralization potential was not developed yet, and total soil organic matter level had been used as a proxy of this soil property.

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Abbreviationsmineralized N: potential nitrogen mineralization; total N: total soil nitrogen.

The impact of environmental variables on total soil nitrogen (total N) is well known. Because of the high correlation between total N and soil organic carbon (Chen et al. 2009) total N changes follow carbon changes (Schipper et al. 2010). Total N increases as rainfall increases (Dintwe et al. 2015); it is lower in coarser soils (Gami et al. 2009) and decreases under cultivation (Wang et al. 2016). The effects of the environment on the soil nitrogen mineralization potential (mineralizable N) are less known. As total N is commonly a strong control of mineralizable N (Smit and Velthof 2010) it can be reasonably assumed that the effects of climate and soil variables on mineralizable N are similar to those reported for total N. However, other factors besides total N also influence mineralizable N. Texture has a strong impact on the fraction of total N that is mineralized. As soil fine particle content increases, the mineralized fraction is reduced (Matus et al. 2008). Labile soil organic matter fractions may regulate mineralization rather than total N (Kader et al. 2010), and soil depth usually determines a strong reduction of mineralized N, greater than the total N decrease (Dodd et al. 2000). The consequence of these discrepancies between the effects of environmental variables on total N and mineralizable N leads to the need of specific predictive models for mineralizable N. As total N and mineralizable N variability may follow different trends when comparing different sites, it is possible to test whether the effect of soil organic matter on crops is produced because of its overall soil content, which may be associated with an improvement of the physical soil condition, or to changes in the capacity of the soil to act as a nitrogen source.

As indicated above, soil productivity has been evaluated by many different indexes using usually the overall organic matter content as a predictor. Because regional analysis of mineralization effects on crops yields is scarce in the bibliography, the possibility of introducing mineralization tests in the development of soil productivity index has not been investigated yet. Disentangling physical effects of organic matter on crops from nitrogen mineralization effects would allow a better understanding of its impact on yield and to guide future work aimed to develop more robust productivity indexes.

The Pampas is a vast plain in Argentina (ca. 50 Mha) and is considered one of the most important grain production regions in the world (Satorre and Slafer 1999). Wheat (*Triticum aestivum* L.) is cultivated all over the region, and its yield is affected by climate and soil variables, including soil organic matter content (De Paepe and Alvarez 2013). The reasons for this are unclear. Improvement of the soil water retention capacity (Díaz Zorita et al. 1999) or nitrogen mineralization increases (Alvarez 2009) because of greater soil organic matter content has been proposed as possible causes. Nitrogen fertilizer rates are low in the region (Alvarez et al. 2014) and crops depend largely on soil nitrogen (Alvarez et al. 2015). This makes the Pampas an interesting case for studying the dependence of wheat yield on soil mineralization potential at regional scale under a very wide range of soil conditions. The objectives were 1) to determine the main environmental controls of mineralized N in the Pampas, and 2) to estimate if total N or mineralizable N had the strongest effect on wheat yield to develop more accurate soil productivity index.

Materials and methods

Study area

The Pampas is located between 28º S and 40º S and 57º W and 68º W in Argentina. Great variability of climate and soil properties is found in the area (Alvarez et al. 2015). Temperature rises from 14 ºC in the South to 23 ºC in the North and rainfall increases from 500 mm in the West to 1200 mm in the East. The natural vegetation is grassland and, in some areas, forests are found. The relief is flat or slightly rolling with Mollisols as the predominant soils (Alvarez and Lavado 1998). Texture varies from shallow-sandy in the west to deep-clayed in the east (Alvarez and Lavado 1998) and in many places, a petrocalcic horizon may be found within the upper 1 m of the soil profile (Berhongaray et al. 2013). Agriculture was introduced in the region in 1870 approximately and expanded exponentially under a low-external-input production scheme on well-drained soils (Alvarez et al. 2016). The average nitrogen rate applied to wheat, estimated using a locally developed dataset (De Paepe and Alvarez 2013), was 28 kg N ha^{-1} in the 2000–2006 period and in the region, this crop is usually limited in nitrogen (Alvarez et al. 2015).

Sampling and analytical methods

A soil survey was performed during 2007–2008 sampling 82 farms throughout the Pampas. The locations of the farms and the main characteristics of sampling schedule, climate, vegetation, and soil types were described previously (Berhongaray et al. 2013). Briefly, paired sites under common land uses were sampled at each farm: tree areas, areas that were never cropped under grassland vegetation, agricultural plots under seeded pastures, agricultural plots with grain crops, and hydromorphic lands released for grazing. Because not all land use treatments were found in all farms, 386 sites were sampled. At each site, the mineral soil was sampled to 1 m depth at 0.25 m intervals. When petrocalcic horizons were present, soils were sampled to their upper limit (46 sites). Pooling all sites and depths, 1456 samples were obtained with a very broad range of variability in soil properties, which have already been described (Alvarez et al. 2018). Samples were air-dried and ground through a 2 mm sieve and plant residues were discarded. Total N was determined on 1 g sample by the Kjeldahl method and ammonia was measured by steam distillation (Bremner 1996). Mineralized N was assessed after 15-day aerobic incubations of 25 g of soil in 400 mL flasks. Grounded samples were rewetted to a water content equivalent to 50% of the soil water holding capacity, and the incubation temperature was 30 ºC. Ammonium and nitrate were determined after the incubation on 20 g sample by extraction with KCl 2 N and steam distillation using Devarda alloy (Mulvaney 1996). Initial level of ammonium and nitrate N was measured on samples before incubation by similar methods and discounted. The results were estimated on areal basis for each soil layer using measured bulk density data from Berhongaray et al. (2013). Total N and mineralized N data were integrated to the profile depth (0–1 m) summing the total N stock and the mineralized N potential of the soil layers.

Databases used

When modeling total N and mineralizable N variability, data from 48 meteorological observatories from the Servicio Meteorológico Nacional for the 1933–2006 period, were used. This was the longest period available for many observatories. By normal kriging, using QGis, mean monthly temperature and rainfall of sampled sites were estimated and data were integrated for annual periods and for the 1933–2006 period. The methodology was validated against an independent dataset from 21 observatories from the Instituto Nacional de Tecnología Agropecuaria that had information available for a shorter time period, with very good performance ($R^2 > 0.93$). Estimated climate information combined with soil data obtained in the soil survey was used for modeling total N and mineralized N at the site scale (Step 1 in Figure 1) using artificial neural networks (see the following subsection). We used the longest period with full climatic information when modeling soil nitrogen pools under the assumption that soil organic matter and its components are regulated by climate in the long term.

Models fitted at site scale were used for estimating total N and mineralizable N at county scale (Step 2 in Figure 1). Soil inputs to the models at the county scale were available from a previously developed dataset (De Paepe and Alvarez 2013) from which soil texture, depth and available water storing capacity were extracted. Land use area by county was obtained from another previously developed dataset in which this information was generated by a combination of satellite image classification and national censuses (Berhongaray et al. 2013). The result of the combination of site models and county information was the generation of maps of total N and mineralizable N at county scale. The procedure was like to that used before for mapping soil organic carbon in the

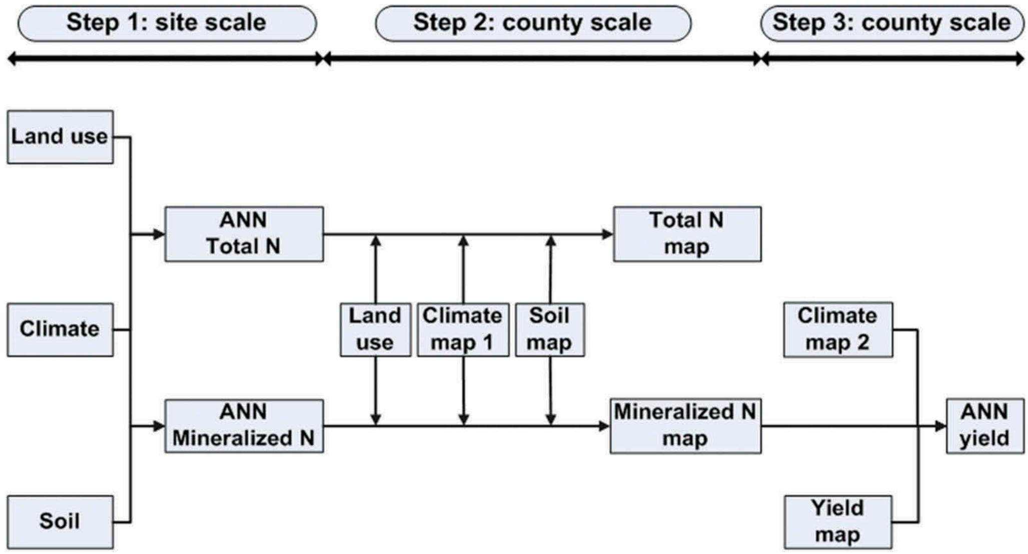

Figure 1. Flow diagram of the steps followed for the development of a model for wheat yield prediction using a nitrogen mineralization index (mineralized N) (ANN = artificial neural network).

Pampas (Berhongaray et al. 2013). Climate data used in this step (Climate map 1 in Figure 1) corresponded to the 1933–2006 period.

For wheat yield modeling (Step 3 in Figure 1), climate estimations were generated by similar methods described previously, corresponding to the 2000–2006 period. This was performed for 131 counties of the five Pampean provinces in which wheat is a common crop and agricultural area occupies more than 30% of the county surface (De Paepe and Alvarez 2013). Monthly estimates were integrated for different periods of the wheat growing cycle (fallow, vegetative phase, reproductive phase and whole growing cycle = sum of the three periods). As radiation measurements were available, the photothermal quotient was calculated as described in Alvarez (2009). Wheat yield data at the county scale were obtained from official statistics of the Ministerio of Agroindustria, as already described (De Paepe and Alvarez 2013). Annual yield data were integrated for the 2000–2006 period to obtain average values at the county scale. Previous work showed that integrating five or more years allowed attaining stable yield averages in the Pampas that are useful for soil productivity rating (De Paepe and Alvarez 2013). Climate data used at this step (Climate map 2 in Figure 1) corresponded to the 2000–-2006 period. Models suited for yield estimation were fitted using neural networks testing climate and soil data as inputs, including total N and mineralizable N estimated at the county scale. Only the best neural model (see next subsection) was retained for yield prediction. Using yield data at county scale allowed the development of a regional soil rating model. We did not use long-term yield averages in our analysis and preferred the use of yield data generated in a short time frame, only a few years before our soil survey date, because of possible changes of total N and mineralizable N in the long term. By doing this we assumed that total N and mineralizable N measured during the 2007–2008 survey adequately represented the soil condition for wheat growth in our analysis.

Artificial neural networks and regression methods

Artificial neural networks are empirical modeling techniques based on neuronal structures and processing of the brain of great potential for modeling nonlinear relationships and complex interactions (Jorgensen and Bendoricchio 2001). Neural networks have proved to be better modeling techniques than regression methods in the Pampas for predicting soil organic carbon (Berhongaray et al. 2013), in situ nitrogen mineralization (Alvarez and Steinbach 2011) and wheat yield (Alvarez 2009; De Paepe and Alvarez 2013), using both large datasets and small ones.

We fitted feed-forward neural networks for generating models capable of estimating total N, mineralized N, and wheat yield. Linear transfer functions were used from the input layer to the hidden layer and from the output layer to the network output. Meanwhile, a sigmoid function connected the hidden layer to the network output. The learning process was performed by the backpropagation algorithm for fitting weights. The scaling method for input variables, learning rate, epoch size and the method of determining the number of neurons in the hidden layer were described in detail previously (Alvarez 2009). The simplest networks with the highest R^2 were chosen using the lowest number of inputs and neurons in the hidden layer as possible. Land use treatments (discrete input) were encoded for neural network fitting (Brouwer 2004). Inputs were selected by means of the sensitivity ratio including in networks only those with a sensitivity ratio above one (Miao et al. 2006). In cases when the sensitivity ratio was slightly above one, the variable was retained in the network only if it produced an increase of the R^2 greater than 1%. Cross-validation with early stopping of weight-fitting was implemented to avoid overlearning (overfitting) (Park and Vlek 2002). Data were randomly partitioned into 50% for training, 25% for testing (early stop of weights fitting) and 25% for an independent validation of the models. As the validation set was not used for networks development this dataset allowed a true validation. The software used was Statistica Neural Networks (version 2011, Stat Soft.). Inputs tested for total N estimation at the site scale were land use, mean annual rainfall and temperature of the site, depth of the soil layer, sand content, pH, conductivity and carbonate-C content. The same inputs were tested for mineralized N prediction including also measured total N content. For fitting neural networks for wheat yield estimation at the county scale, rainfall and temperature during the different crop growing periods, the photothermal quotient, soil depth, sand content, soil available water storing capacity, total N, and mineralizable N were tested as inputs.

Relationships between variables were assessed by regression and correlation analysis, with significance determined by the F test ($p < 0.05$). Multiple regression was also tested as a modeling method for total N and mineralizable N prediction for comparison with neural networks. Predictors were the same inputs tested in networks and the partition of data into training + test and validation sets were also the same. Forward stepwise regression adjustments were used to obtain the simplest model with the highest R^2. Terms were maintained in the final model only when they were significant at $p < 0.05$. Autocolinearity of independent variables was checked by the VIF value deleting from models variables with values over 5 (Neter et al. 1990). Land use was tested in models as a categorical variable. Slopes and ordinates of regressions between observed and estimated values were tested against 1 and 0, respectively, using IRENE (Fila et al. 2003). The determination coefficients of training + test sets vs. validation set were contrasted ($p< 0.05$) by the Z transformation of the Fisher's test (Kleinbaum and Kupper 1979) to determine the generalization ability of the fitted models. The root-mean-square error (RMSE) (Kobayashi and Salam 2000) was also calculated to evaluate model performance.

Results

Variability of total N and mineralizable N was very broad among sites and depths (Table 1). These changes were also accompanied by great variability of the sample textural condition. Temperature showed less variability than rainfall. Generally, the relationships between climate and soil variables, although significant, were weak (Table 1). The only strong relationship was observed between total N and mineralizable N; the greater the total N content, the more nitrogen was mineralized by samples. Total N accounted for ca. 50% of mineralized N variability ($R^2 = 0.52$). The slope of the

Table 1. Main climate and soil variables measured in the sampled sites and Pearson's correlation coefficients between the variables. Climate data correspond to sampled sites (n = 386) and soil data is a pool of all sites and depths (n = 1456). When correlating climate with soil variables the value of rainfall or temperature of the site were used for the four values (four sampling depths) of soil properties of that site.

	Mean (SD)	Rainfall	Temperature	Sand	Total N
Rainfall (mm)	874 (120)				
Temperature (ºC)	16.1 (1.33)	**0.48**			
Sand (Mg ha^{-1})	1500 (686)	**−0.42**	**−0.20**		
Total N (Mg ha^{-1})	3.03 (2.07)	**0.12**	**−0.08**	**−0.30**	
Mineralized N (kg ha^{-1})	68.6 (69.2)	**0.09**	**−0.09**	**−0.19**	**0.72**

In bold significant coefficients at $p < 0.05$.

regression line between total N and mineralized N was 23. An average of 23 kg N was mineralized during incubations by each ton of total N in the soil.

Artificial neural networks predicted total N very well (Figure 2(a, b)). The best-fitted neural model had four neurons in the hidden layer. The model had very good generalization ability, as the R^2 of the validation data set was not different than that of the training + test sets, and the RMSE was low. Conversely, regression did not allow obtaining a good model. The R^2 of the best regression was significantly lower than that of the best neural network, and the distribution of residuals was not homogeneous (Figure 2(c, d)). The regression subestimated total N in the low and

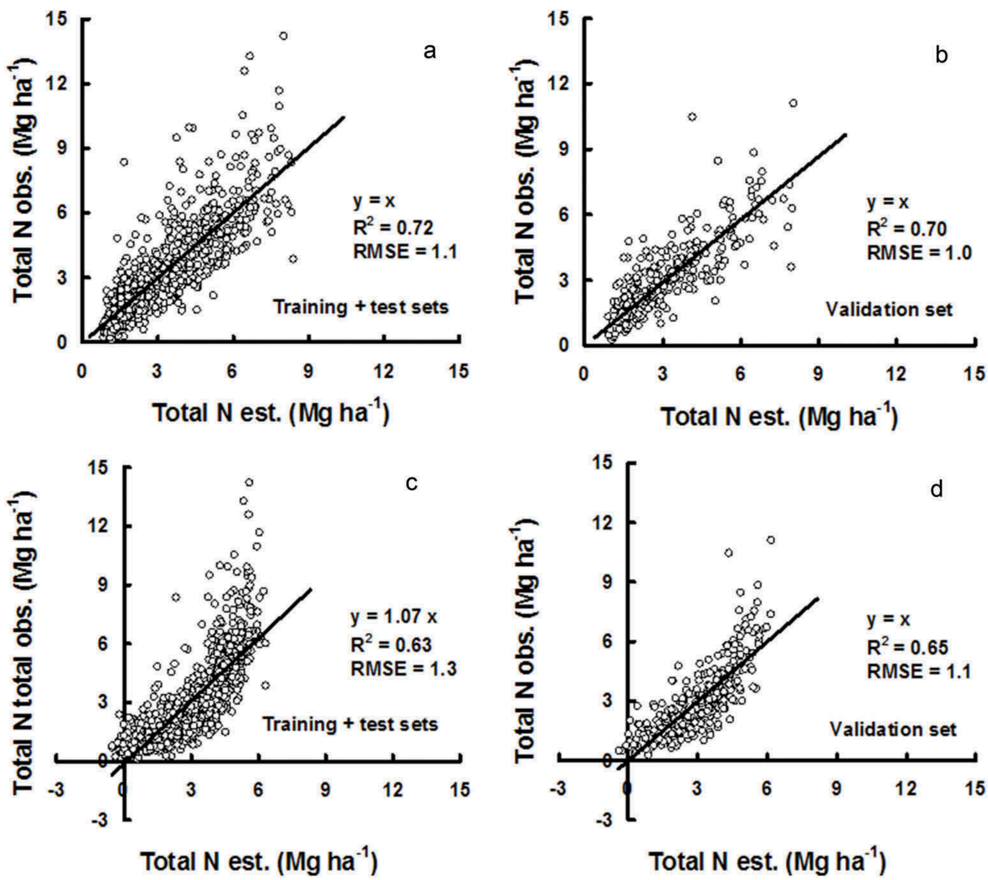

Figure 2. Relationships between observed (obs.) vs. estimated (est.) values of total N estimated by artificial neural networks (a and b) and linear regression (c and d). Estimations were performed for samples obtained in a regional soil survey of the Pampas (n = 1456) using 70% for training + test of models and 30% for an independent validation.

the high data ranges and overestimated it in the middle range. Even, some negative values were estimated by this modeling technique, the RMSE was greater, and the slope of the observed vs. estimated values of the training + test sets was different from 1.

When modeling mineralized N, a good neural network model could be fitted but with lower performance than that achieved for total N (Figure 3(a, b)). The model had six neurons in the hidden layer, and the R^2 of the regression of observed vs. estimated values was lower, although the ordinate and slope did not differ from 0 to 1, respectively, as occurred with total N. The RMSE was not small indicating the lower capability of neural models for predicting mineralized N than total N. The fitted model had also good generalization ability; the R^2 of the validation set was not different from that of the training and test sets. Regression performance for predicting mineralized N was also lower than that attained by neural networks. The R^2 was significantly lower, the RMSE doubled that of neural networks, and the distribution of residuals had the same problems that those observed with total N. Some negative values were also estimated.

Both neural models fitted for total N and mineralizable N estimation used as inputs the same variables (Figure 4). The models showed that total N and mineralizable N increased in sites with higher rainfall and decreased in those with higher temperature. They also decreased as sample texture became coarser and with depth. Land use also had significant effects. Total N and mineralizable N were greater in soils under trees and uncultivated soils than in cultivated soils or under hydromorphic conditions. The effects of soil depth and climate on mineralized N were stronger

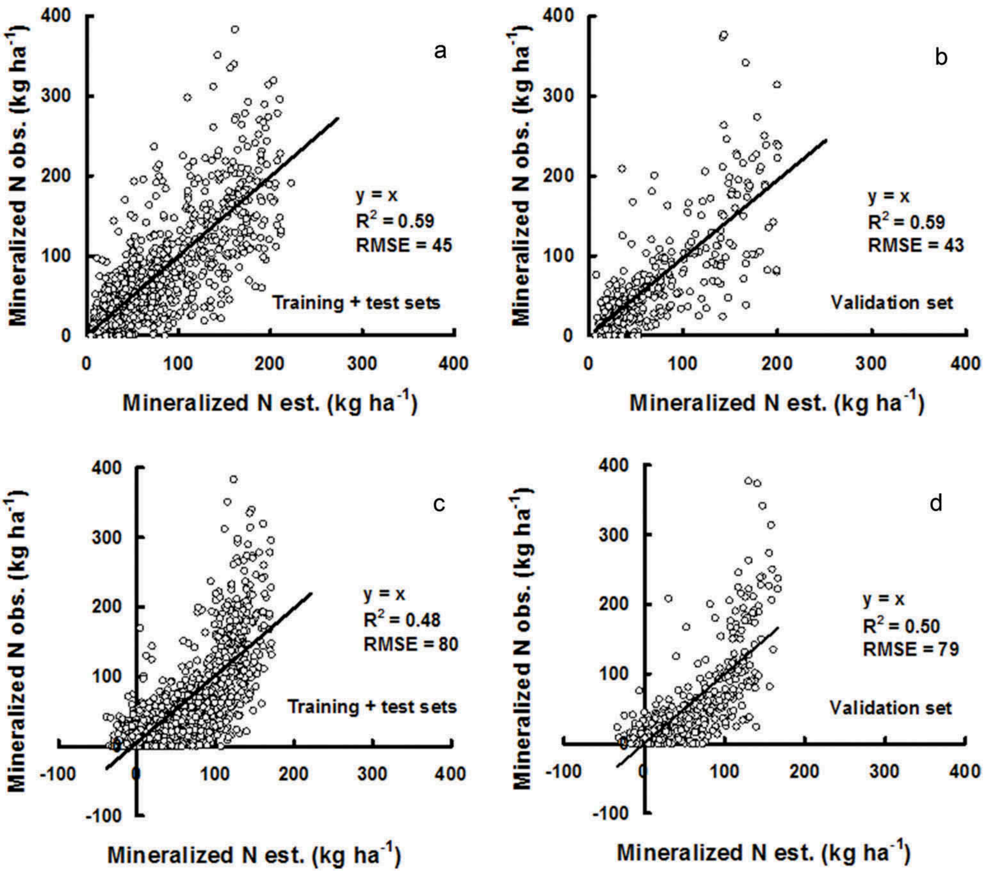

Figure 3. Relationships between observed (obs.) vs. estimated (est.) values of mineralized N estimated by artificial neural networks (A and B) and linear regression (C and D). Estimations were performed for samples obtained in a regional soil survey of the Pampas (n = 1456) using 70% for training + test of models and 30% for an independent validation.

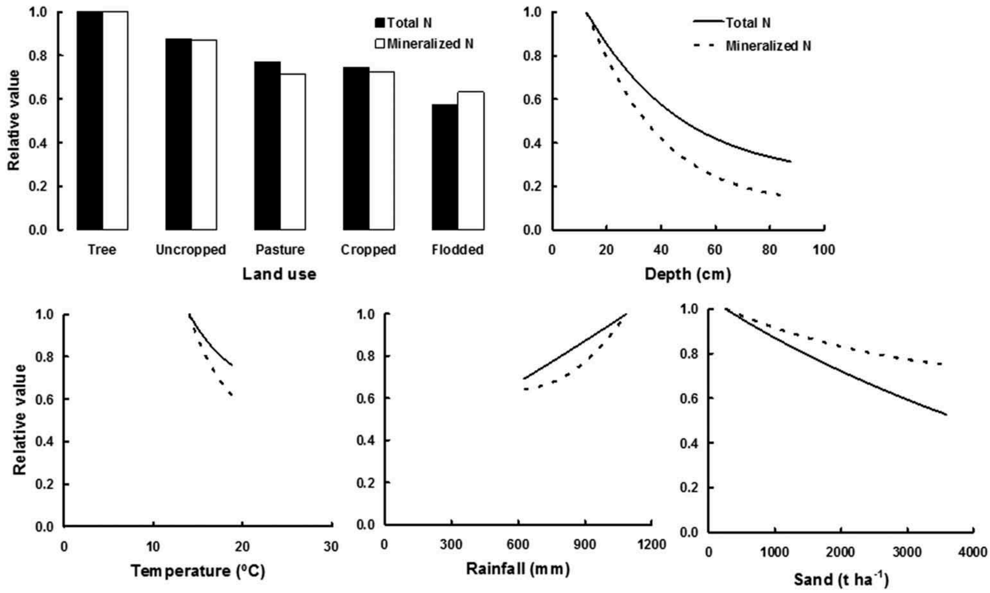

Figure 4. Modeled effects of environmental factors on total N and mineralizable N as predicted by artificial neural network models. Estimations were performed within the observed variability range of each factor keeping all other factors used as networks inputs at their average value. The maximum value predicted for each variable was taken as 1 and all other values related to that maximum.

than those on total N. Conversely, total N was more affected by soil texture than mineralized N. When total N was added as an input for mineralizable N prediction, although the effect was significant, the R^2 of the network attained a very small improvement (1%). Therefore, this variable was dropped from the model for simplicity. Regression models used as predictors the same variables used as inputs in neural networks and with similar effects but because of their lower performance these models were discarded for estimating total N and mineralizable N at county scale and neural models were preferred.

Data estimated at the county scale (Figure 5) showed less variability than at the site scale (Table 2). Relationships between climate and soil variables with yield were weak, except for mineralized N. This latter factor explained nearly 50% of wheat yield variability (Table 2). The correlation coefficient between mineralized N and total N was low, indicating that counties with high total N content did not necessarily have higher nitrogen mineralization potential, a possible consequence of the effects of the other inputs in the model.

A network model with high performance could be fitted for yield prediction (Figure 6). The network had four neurons in the hidden layer, the regression of observed vs. estimated data had an ordinate and a slope not different from 0 to 1, respectively, and its generalization ability was very good. No significant differences were detected between the R^2 of the validation set and the training + test set. The RMSE was also very low. Wheat yield was controlled by rainfall during fallow summed to the growing cycle periods, the photothermal quotient, and mineralized N. Yield increased as these variables increased, but strong interactions were detected by the neural model. Taking into account these interactions optimal combinations of variables were defined. For example, yield was very low in counties with low nitrogen mineralization potential combined with low rainfall (Figure 7). As rainfall increased, yield also increased. However, decreases in yield were modeled under excessive rainfall scenarios. These yield decreases were more pronounced in highly fertile counties and rainfall thresholds beyond which yield was negatively impacted were

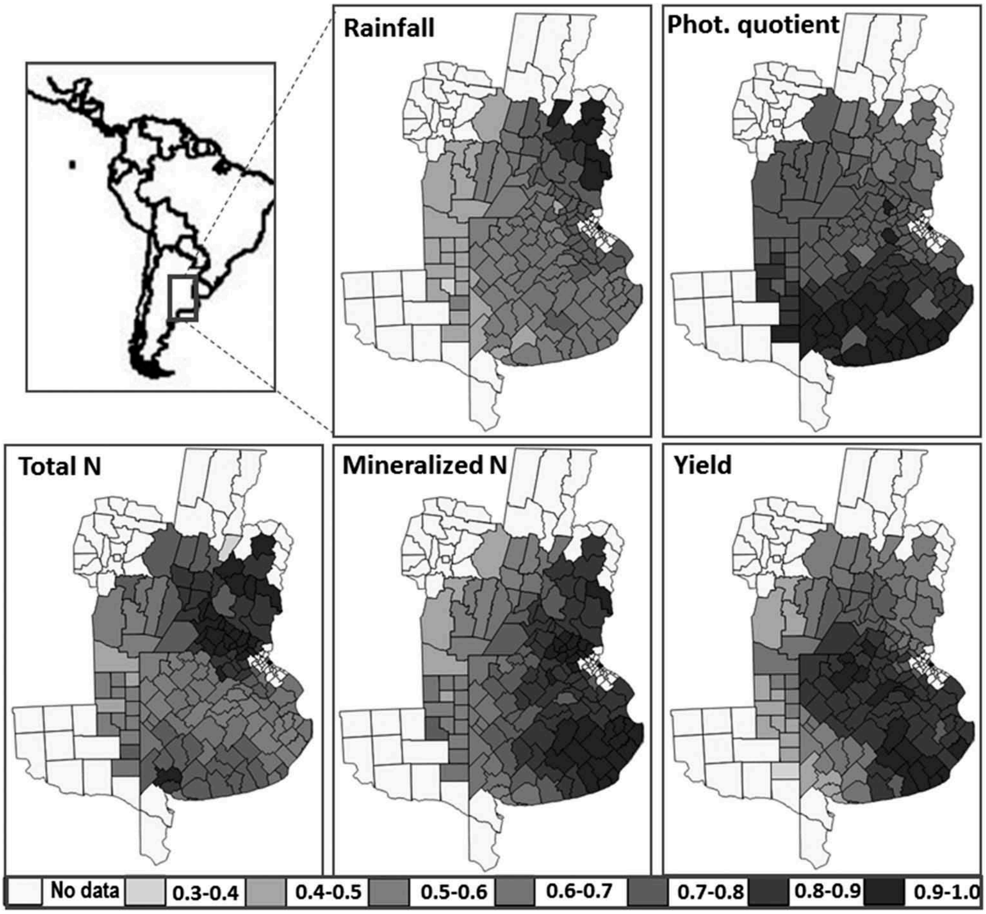

Figure 5. Maps of climate and soil variables and wheat yield at county scale. All scales were transformed to relative units for comparison assigning a value of 1 to the maximum of each variable.

Table 2. Main climate and soil variables integrated at county scale and Pearson's correlation coefficients between the variables. Data correspond to the upper 1 m of the profile (n = 131). AWSC = available water soil capacity.

	Mean (SD)	Yield	Rainfall	Phot. quot.	AWSC	Total N
Yield (kg ha^{-1})	2690 (597)					
Rainfall (mm)	552 (112)	**0.30**				
Photothermal quotient	1.31 (0.144)	**0.29**	**−0.43**			
AWSC (mm)	142 (37.2)	0.11	**0.54**	**−0.46**		
Total N (Mg ha^{-1})	11.1 (2.23)	0.06	**0.46**	**−0.24**	**0.83**	
Mineralized N (kg ha^{-1})	256 (48.2)	**0.69**	**0.64**	**0.14**	**0.37**	**0.39**

In bold significant coefficients at $p < 0.05$.

lower in the later cases. Multiple regression methods did not allow improving the fit of the simple linear regression between mineralized N and yield (R^2 = 0.48) and were not used for soil rating.

Discussion

The impacts of land use and the other environmental variables on total N were similar to those reported for organic carbon in the Pampas using the same samples (Berhongaray et al. 2013). In

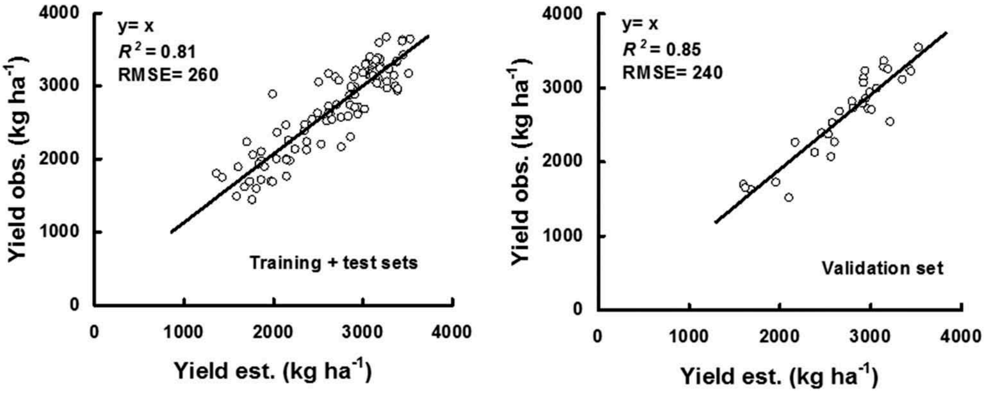

Figure 6. Relationships between observed (obs.) values of wheat yields at county scale and those estimated (est.) by artificial neural network (n = 131).

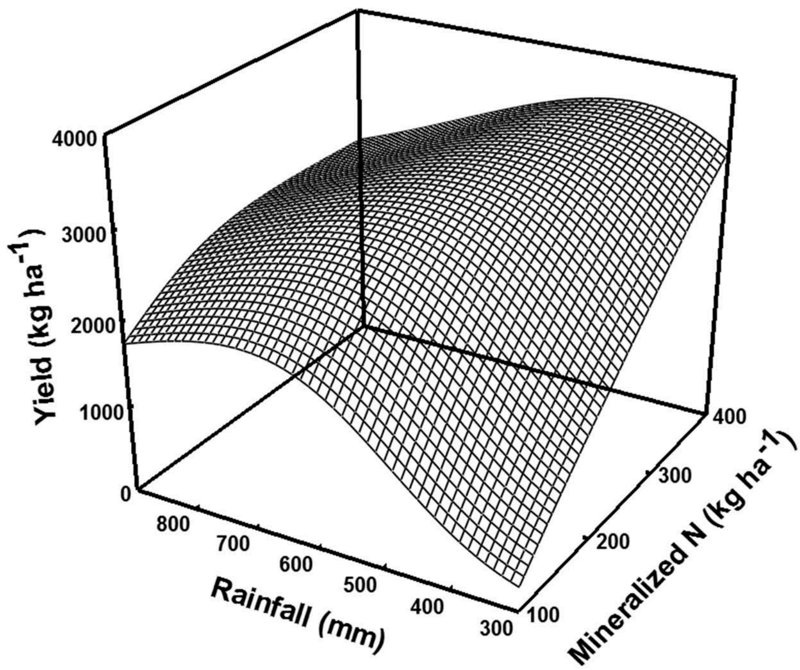

Figure 7. Wheat yield estimated by an artificial neural network as a function of the interaction between rainfall and soil mineralized N. Average photothermal quotient values were used for the estimations.

these soils, total N is mainly organic nitrogen (Alvarez et al. 2018) and may be considered as a good proxy of the organic matter content of the samples.

We used a short-term aerobic incubation to assess soil nitrogen mineralization potential. Many different methods have been developed to estimate soil nitrogen mineralization at laboratory and field scales (Ros et al. 2011). Among them, aerobic incubations have been extensively used. Kinetic analysis based on long-term incubations has been performed, in some cases, discarding the first incubation week to avoid possible handling effects on samples (Rashid et al. 2014). Nevertheless, short-term incubations (4 to 30 days) have been used as a nitrogen mineralization index in different soils (Ros et al. 2011) and were good proxies of the soil nitrogen labile pool (Dessureault-Rompré et al. 2016). The short-term aerobic and anaerobic methods give similar results in many soils (Wang et al. 2001) and in the Pampas, the former was preferred in coarse-textured soils because it can be related to different soil organic matter pools (Romano et al. 2015). By using data from Pampean soil samples (Alvarez et al. 1998), we correlated nitrogen mineralization during incubations of 14 and 84 days, under similar conditions than those used in this study. The correlation was very high (R^2 = 0.81) showing than comparison of the mineralization potential of soils may be performed using short- or long-term incubations. Additionally, the 14-day aerobic incubation test has been identified as a good predictor of field nitrogen mineralization for wheat in the Pampas. This mineralization potential index was successfully used as one of the predictors of mineralization estimated by the nitrogen budget approach under field conditions (Alvarez and Steinbach 2011; Romano et al. 2015).

We used two different climate datasets in the analysis. When modeling total N and mineralized N, the longest period (ca. 70 years) with full data was used for mean annual temperature and rainfall calculation since soil organic matter content variations are slow and regulated by environmental factors in the long term (Poeplau et al. 2011). Labile soil organic matter compounds, and probably mineralized N, are controlled by environmental factors in the same way, as their turnover times range from some years to decades (Marschner et al. 2008). Conversely, wheat yield was modeled using climate data corresponding to the time frame during which yield data were averaged. This was based on the known fact that wheat yield is determined by current conditions during the growing period as previously reported in the Pampas (De Paepe and Alvarez 2013). Nevertheless, the R^2 between mean annual rainfall and temperature of the 1933–2006 and the 2000–2006 periods were 0.90 and 0.97, respectively, showing that climate variables of both periods had very similar spatial patterns across the Pampas.

Mineralized N and total N were controlled by the same variables, with effects of the same sign but different magnitude. Among them, land use was one of the factors controlling mineralization. Soil management may alter soil nitrogen mineralization, requiring independent analysis of mineralization depending upon the management condition (Wade et al. 2016). The need to include land use as an input in the network seems to be related to differences in organic matter quality. In the non-cultivated treatments (tree soil and uncultivated control soil), the fraction of labile organic matter was possibly greater than in the other treatments, especially in the cropped soils (Poeplau and Don 2013).

The network model estimated a different stratification pattern of mineralized N and total N. The former had a stronger decrease in deep soil layers than the latter. Soil organic matter age and stability increases with depth (Balesdent et al. 2018) and different studies reported that a lower fraction of total N is mineralized in deep soil layers than at surface soil (Dodd et al. 2000; Iversen et al. 2011) as observed in Pampean soils. The fitted neural model allowed a quantification of the depth effect on mineralization for different combinations of environmental factors. For example, it estimated that under trees the mineralized N profile was less stratified than in the other treatments under herbaceous vegetation and that the fraction of total N mineralized was greater in deeper soil (results not presented). This seems to be the consequence of the deeper root systems of temperate forest compared to crops and grasslands (Jackson et al. 1996) and a proportionally greater input of fresh organic matter to deep soil layers.

Site rainfall and temperature impacted sample mineralized N during incubations. Some previous studies detected similar effects of climate on nitrogen mineralization during laboratory incubations (Dessureault-Rompé et al. 2010). As in other soils (Barrett and Burke 2000), in our dataset this effect seems to be the consequence of the climate impact on total N and the high correlation between the latter factor and mineralized N. Our results of lower mineralization in sites of higher mean annual temperature are not in conflict with a previous report of the positive correlation between temperature and mineralization in the Pampas (Alvarez and Steinbach 2011). Previous studies related in season mineralization during wheat and corn cycles with the apparent nitrogen mineralization under field conditions as calculated by a mass balance approach. The higher the temperature (summer vs. winter), the greater the mineralization at the same site. But sites from different locations and climatic scenarios had mineralized N values inversely correlated with the site temperature. Using total N as input for modeling mineralized N did not improve the neural network fit for this reason. The additional information provided by this input was minimal when rainfall and temperature were included in the model. We preferred to use rainfall and temperature as predictors of mineralized N for county scale prediction of mineralization, not only because of their higher sensitivity ratio but also because the network constructed allowed an estimation of mineralized N in one step, avoiding the need for a previous estimation of total N.

In coarser soils, mineralized N predicted by the neural network decreased less than total N. Therefore, the fraction of total N mineralized increase with soil sand content. Because of the known association between soil fine particle content and soil organic matter, usually, more nitrogen is mineralized in finer soils (O´Connell et al. 2003; Bechtold and Naiman 2006). However, when the soil mineralization potential is normalized using the soil organic matter (or nitrogen) content (Bechtold and Naiman 2006), or covariation models are used for disengaging texture and organic matter effects (Dessureault-Rompé et al. 2010), less nitrogen is mineralized by unit of total nitrogen in fine soils. As more nitrogen is associated with the soil sand fraction, the higher is the nitrogen mineralization capacity (Matus et al. 2008). Our model predicts that sandy soils would have a greater capacity to act as a nitrogen source for crops that finer ones when the total N level is similar.

Because the FAO methodology used for soil rating had a poor performance for wheat in the Pampas, previous models developed in the region for wheat yield estimation used soil organic carbon as a predictor (Alvarez 2009; De Paepe and Alvarez 2013). Combined with climate data, soil available water storing capacity and harvest year they explained approximately 60% of yield variability over time and space. Our neural model, which was fitted using a 7-year average yield, can perform a very good estimation of yield over space using mineralized N and may be suitable for developing a regional soil productivity index using easily obtainable soil properties. It improves yield variability explanation to 85%.

It is unclear why soil water storing capacity was not selected by the neural model as input. This variable had proven to be a good predictor of wheat yield in the Pampas as outlined above. We believe that it may be attributed to the fact that fine and deep soils in which available water storing capacity is high had also high mineralized N and are in areas where rainfall is also high, and these two variables subrogate the effect of the available water holding capacity of the soil. Experimental data showed a positive interaction between rainfall and mineral nitrogen availability at seeding (nitrate nitrogen + fertilizer nitrogen) on wheat yield in the Pampas (Romano et al. 2015). In more humid environments, the efficiency of mineral nitrogen utilization by wheat is greater. Our results showed that as rainfall increases, the efficiency of nitrogen use from mineralization also seems greater. The negative interaction between rainfall and mineralizable N on yield predicted by the neural network may be the result of an increased attack of diseases in humid environments, which are a very serious constraint for wheat yield in the region (Alvarez 2009). This problem is worst in more fertile areas as crop biomass increases.

The methodology we developed is not user-friendly. To run the artificial neural networks specific software is required. Nevertheless, a simple meta-model can be generated in the form of a table. Productivity values can be calculated for different combinations of the network inputs for agronomist. Special attention must be focused on the scale of analysis. Our methodology works fine at county scale (the scale of the yield data) but for many purposes, the field scale would be of more interest. The validation of the technique at this latter scale must be addressed in future work under a broad range of climate and soil conditions. If this is possible, the mineralized N test combined with artificial intelligence modeling would be useful for soil rating at the production plot scale and official institutions will have available a much better tool available that currently used productivity indexes.

Conclusions

Our data indicated that the effects of soil organic matter on wheat yield in the Pampas may be attributed to its nitrogen mineralization capacity rather than to other possible influences on soils and crops. Artificial neural networks may be used successfully for modeling nitrogen mineralization at the regional scale and for developing models capable of predicting soil productivity. These models could be used as the basis for soil rating in the region. Possibly, similar methodologies to that described here can be developed for other regions, crops, and scales of analysis.

Disclosure statement

No potential conflict of interest was reported by the authors.

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