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RESEARCH ARTICLE

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Use of geophysical survey as a predictor of the edaphic properties variability in soils used for livestock production

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Abstract

The spatial variability in soils used for livestock production (*i.e.* Natraquoll and Natraqualf) at farm and paddock scale is usually very high. Understanding this spatial variation within a field is the first step for site-specific crop management. For this reason, we evaluated whether apparent electrical conductivity (ECa), a widely used proximal soil sensing technology, is a potential estimator of the edaphic variability in these types of soils. ECa and elevation data were collected in a paddock of 16 ha. Elevation was negatively associated with ECa. Geo-referenced soil samples were collected and analyzed for soil organic matter (OM) content, pH, the saturation extract electrical conductivity (EC_{ext}), available phosphorous (P), and anaerobically incubated Nitrogen (Nan). Relationships between soil properties and ECa were analyzed using regression analysis, principal components analysis (PCA), and stepwise regression. Principal components (PC) and the PC-stepwise were used to determine which soil properties have an important influence on ECa. In this experiment elevation was negatively associated with ECa. The data showed that pH, OM, and EC_{ext} exhibited a high correlation with ECa (R^2=0.76; 0.70 and 0.65, respectively). Whereas P and Nan showed a lower correlation (R^2=0.54 and 0.11 respectively). The model resulting from the PC-stepwise regression analysis explained slightly more than 69% of the total variation of the measured ECa, only retaining PC1. Therefore, EC_{ext}, pH and OM were considered key latent variables because they substantially influence the relationship between the PC1 and the ECa (loading factors>0.4). Results showed that ECa is associated with the spatial distribution of some important soil properties. Thus, ECa can be used as a support tool to implement site-specific management in soils for livestock use.

Additional key words: multivariate techniques; soil properties; geographic information system; lowland soils; spatial variability.

Abbreviations used: ECa (apparent soil electrical conductivity); EC_{ext} (electrical conductivity of the saturation extract); GWR (geographically weighted regression); Nan (anaerobically incubated nitrogen); OM (soil organic matter content); P (available phosphorous); PCA (principal component analysis); PC (principal component).

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Introduction

The Argentinean pampas is a vast plain region of about 50 Mha and it is considered one of the most suitable areas for grain crop production in the world (Satorre & Slafer, 1999). However, on its southern portion (Flooting Pampas), the predominant soils of the region belong to the great group Natraquoll and Natraqualf (Soil Survey Staff, 2010). These soils exhibit a distinctive characteristic, which is the presence of a natric horizon (Btn), locally called ‘‘sodic’’ (Soil Survey Staff, 2010). Also, they have a poorly developed drainage system, normally situated in flat landscapes, with a strong textural contrast between horizons and with halomorphism and hidromorphism processes (Taboada, 2006). For these reasons these soils are used for livestock production

(Vazquez *et al.,* 2001). Furthermore, they are managed extensively and homogeneously, which in turn can reduce the system sustainability. A way to improve this type of management could be based on site specific agriculture technologies, improving soil-plant interactions knowledge and efficient production factors usage at farm and paddock level (Serrano *et al.,* 2013).

Previous research has shown that the amount of soil variability across a farm and within a field of agricultural soils (high productivity) is of key importance for determining potential benefits of adopting precision farming (King *et al.,* 2005; Bullock *et al.,* 2009). However, relatively little is known about the degree of within-field spatial variation in soils used for livestock production (Serrano *et al.,* 2013). Typically, soil sampling of the field and mapping, comprises grid-sampling and mapping approach as well as laboratory work. This is impractical at the farming scale because it is labor intensive, time consuming and expensive (King *et al.,* 2005; Peralta *et al.,* 2013). Therefore, it is desirable to find other more rapid and low cost means of obtaining information for detailed soil mapping (King *et al.,* 2005). Measurements of apparent soil electrical conductivity (ECa) can be intensively recorded in an easy and inexpensive way, being one of the most reliable techniques to characterize within-field variability of edaphic properties (Moral *et al.,* 2010; Peralta *et al.,* 2015).

There are two types of electrical conductivity sensors currently on the market to measure soil ECa in the field. The first type of sensor (contact method) uses electrodes, in the shape of coulters that make contact with the soil to measure the electrical conductivity. The second type of sensor (non-contact method) is based on the principle of electromagnetic induction and does not contact the soil directly (Moral *et al.,* 2010). ECa has been frequently used in the establishment of soil management zones and in the inference of several edaphic physicochemical properties and their respective spatial variation (Sudduth *et al.,* 2005; Peralta *et al.,* 2013). In agricultural soils, ECa has been used to characterize soil salinity (Rhoades *et al.,* 1989); soil texture (Sudduth *et al.,* 2003); soil depth (Peralta *et al.,* 2013); soil moisture (Hossain *et al.,* 2010); soil organic matter (OM) (Corwin & Lesch, 2005a) and cation exchange capacity (Kitchen *et al.,* 2000). However, various authors have shown inconsistent relationships between ECa and soil characteristics, probably due to the fact that ECa is influenced by complex site dependent soil properties interactions (Corwin *et al.,* 2003; Sudduth *et al.,* 2005). Some studies have shown that ECa values are related to soil properties variability in extensive livestock production systems and are also related to pasture productivity (Serrano *et al.,* 2010, 2014a,b). However, there is no information on the degree of within-field variability of the edaphic properties in Natraquoll and Natraqualf soils. Knowledge of these variations is essential if one intends to analyze the potential benefits of adopting a site specific approach to grassland and pasture field management in these soils.

The main objective of this study was to determine whether soil ECa is a potential estimator of the edaphic variability in Natraquoll and Natraqualf soils, which are characteristic of many livestock production systems around the world.

Materials and methods

Experimental site

This study was conducted at Balcarce, in the southeast of the Buenos Aires Province, Argentina (37°45′ S, 58°18′ W; mean annual rainfall: 930 mm; mean annual temperature: 13.7°C) (Figure 1). The experiment was established in a paddock of 16 ha that sustained a permanent pasture dominated by *Thinopyrum ponticum* (Podp.) Liu & Wang. The site contains various soil series: Chelforó (Typic Natraqualf), Las Armas (Typic Natraquoll) and Tandileofú series (Mollic Natraqualf) (Soil Survey Staff, 2010). These soils are characterized by a clay loam texture (0-0.30 m).

Geophysical surveys

Data collection using the Veris 3100

Soil ECa measurements were made using the Veris 3100® sensor system (Fig. 2), at a low soil moisture

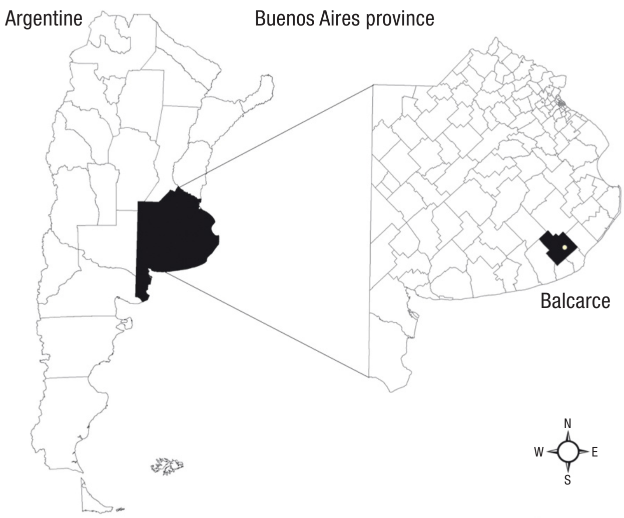


Figure 1. Location of the experiment field (indicated as a white dot) in Balcarce, Buenos Aires province, Argentine.

Figure 2. The Veris 3100 System mounted behind the truck.

content. The Veris 3100 device has six disc-shaped metal electrodes (coulter), which penetrate approximately 6 cm into the soil. One pair of electrodes passes electrical current into the soil, while the other two pairs measure the voltage drop. The measurement depth is based on the distance between the emitting and receiving coulter-electrodes. The system can be set up to work in configuration A (0-0.30 m) or B (0-0.90 m). Configuration A comprises the inside coulters (2, 3, 4, 5) and voltage is measured between the innermost ones (3 and 4). In configuration B, the four outside coulters (1, 2, 5, 6) include the 0-0.90 m deep measurement, and the voltage gradient is measured between coulters 2 and 5. Output from the Veris data logger reflects the conversion of resistance to conductivity (1/Resistivity = Conductivity). In this work, the ECa was measured at 0-0.30 m because 80% of the pasture roots are found at this depth (Doll & Deregibus, 1986). The Veris 3100 sensor was pulled across each field behind a pick-up truck (Fig. 2), taking simultaneous and geo-referenced ECa measurements in real-time with a differential GPS with sub-meter measurement accuracy and configured to take a satellite position once per second. The differential GPS was installed over the Veris 3100. On average, travel speeds through the field mapping ranged between 7 and 11 km/h, corresponding to about 2–3 m spacing between measurements in the direction of travel. For ease of maneuvering, the field was traversed in a series of parallel transects spaced from 15 to 30 m intervals, because a spacing greater than 30 m generates measurement errors and information loss (Farahani & Flynn, 2007). Elevation data were collected at the same time as the ECa data, using a differential GPS (vertical accuracy of 3-5 cm).

Geophysical data analysis

The structure of the ECa and elevation were quantified using geostatistics analysis, which were estimated as Isaaks & Srivastava (1989):

$$\gamma^*(h) = \frac{1}{2N(h)} \sum_{i=1}^{N(h)} \left(z\left(x_i\right) - z\left(x_i + h\right)\right)^2 \qquad [1]$$

where $y^*(h)$ is the semivariogram that expresses the variation of the semivariance with the relative distance between the measured data; $z(x_i)$ is the measured sample value at sample points x_i, in which there are data at x_i; and $x_i + h$ $N(h)$ is the total number of sample pairs within the distance interval h.

The semivariogram shows the decrease of spatial correlation between two points in space when the separation distance increases. The adjusted semivariograms were used to interpolate the ECa and elevation data using ArcGIS Geostatistical Analyst (ArcGIS v9.3.1, ESRI, Redlands, CA, USA), by means of ordinary kriging after checking geo-statistical common assumptions (Isaaks & Srivastava, 1989). A final 10 m × 10 m grid cell size was chosen because it reflects the scale of variability associated with the ECa and elevation measurements (Kitchen *et al.,* 2005; Peralta & Costa, 2013).

Geographically weighted regression (GWR) is a technique for exploratory spatial data analysis. In linear regression, it is assumed that the relationship being modeled holds globally in the study area, but in many situations this is not necessarily true. The GWR provides the means for modeling such relationships (Brunsdon *et al.,* 2002). A GWR tool (ArcGIS v9.3.1, ESRI, Redlands, CA, USA) was used to analyze the regional relation between elevation and ECa. It is possible that one set of variables provides a good model for a part of the studied area, but at the same time it may be unsatisfactory for other parts; GWR will adjust the relationship coefficients in order to reflect the regional variation (Serrano et *al.,* 2010; Terrón *et al.,* 2011).

Soil sampling

Data collection strategy

Based on geophysical surveys a grid composed by 12 points was sampled at a depth of 0-0.30 m. Each point represents the spatial variability of the plot. Each composite soil sample (three subsamples) was stored in a plastic bag and air dried in the laboratory. The following soil parameters were obtained: i) soil organic matter content (OM), using the Walkley & Black (1934) method; ii) pH, using a glass electrode at a 1:2.5 soil/water ratio suspension; iii) the electrical conductivity of the saturation extract (EC_{ext}), following the Chapman (1965) method; iv) available phosphorous (P) was determined according to the Bray & Kurtz (1945) method; and v) anaerobically incubated nitrogen (Nan), following the Echeverría *et al.* (2000) method.

Data analysis

Descriptive statistics were determined for elevation, ECa, and soil properties. Georeferenced buffers of 15 m (Peralta & Costa, 2013) were created around each soil sampling point using ArcGIS 9.3.1 (ArcGIS v9.3.1, ESRI, Redlands, CA, USA) and the ECa mean was calculated within the buffer areas. Linear regressions were computed between this ECa mean and soil properties with PROC REG (SAS Inst., 2007).

Principal component analysis (PCA) was used to examine the relationship between soil properties and to estimate which of these exert a greater influence on ECa. Principal components (PCs) become new, independent and random variables that can be used to identify which studied soil properties influence ECa. Any PCs with an eigenvalue > 1 explains a significant soil property variance (Peralta & Costa, 2013) and therefore were used in a stepwise-regression procedure (SAS Institute, 2007) to determine if there was a significant relationship between the PCs and ECa. The stepwise-regression procedure repeatedly alters the model by adding or removing the PCs predictor until the significance level of the last one is above 0.15. When the PCs remaining in the regression model accounted for >50% of the ECa measurement variability, the eigenvectors (loading factors) were examined and the soil properties in the PCs ranked according to the amount of variability explained by the PCs. Soil properties with loading factors <0.4 were not considered key latent variables because they did not substantially influence the relationship between the PC groups and the ECa.

Results and discussion

Data exploratory analysis

The measured soil properties, elevation, and ECa are summarized on Table 1. Accordingly standard criteria suggested by Wilding *et al.* (1994) some soil properties manifested high variation coefficients, especially OM, P and EC_{ext} (43%, 72 and 61%, respectively), whereas a relative stability was registered for Nan and pH (less than 20%). High variation coefficients of soil properties normally indicate high spatial variability and consequently suggest the convenience of site-specific management (Moral *et al.,* 2010).

The ECa and elevation surfaces are shown in Figure 3. ECa showed substantial spatial variability for this particular field, ranging from 1.8 to 162.1 mS/m with a variation coefficient of 92% (Table 1). On the contrary, the elevation range is rather small (2.2 m) revealing a smooth topography with gentle slopes (Taboada, 2006) and consequently with low variation coefficients (Table 1). Elevation has a direct influence on soil forming processes and on soil water movement, and in consequence in salinity distribution within a paddock (Corwin & Lesch, 2005b). For this reason, elevation and ECa can be correlated (Tarr *et al.,* 2005; Peralta & Costa, 2013). In this case, a visual inspection indicates higher ECa values on elevation depressions despite the low elevation variability (Fig. 3), as also described by Officer *et al.* (2004) and Serrano *et al.* (2010) in agricultural and livestock aptitude soils, respectively. Therefore, elevation was negatively associated with ECa throughout the field, due to the fact that higher ECa values are observed in lower areas. These results can be explained by the fact that the soils in the depressed areas used for livestock are usually clasified as Natraqualfs soils (Batista *et al.,* 2005), which are characterized by a high solute concentration (Soil Survey Staff, 2010). However, the relationship between ECa and elevation varied spatially. The GWR analysis allowed the delineation between areas with a strong and a low relation between elevation and ECa (Fig. 4).

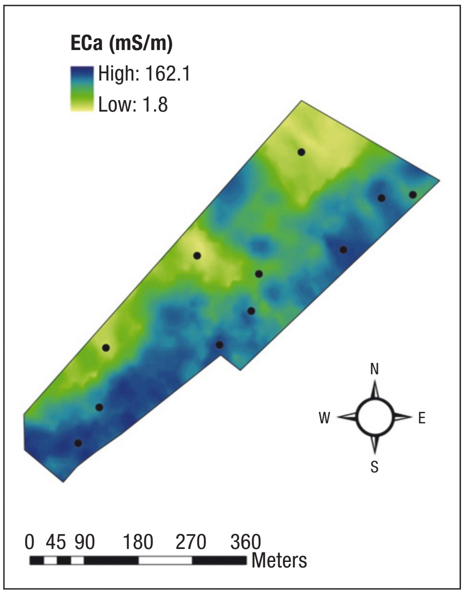
Relationships among ECa and soil properties

Regression analysis

The relationships between soil properties and ECa are shown in Table 2. The pH and EC_{ext} were posi-

Table 1. Descriptive statistics of saturation extract electrical conductivity (EC_{ext}), pH, organic matter (OM), available phosphorus (P) and anaerobically incubated nitrogen (Nan) of the 12 sampled points.

	ECa (mS/m)	Elevation	Soils properties				
			EC_{ext} (mS/m)	pH	OM (%)	P (Mg/kg)	Nan (Mg/kg)
Mean	42.4	121.5	90.0	8.4	5.2	17.7	167.1
Min	1.8	120.6	20.0	6.0	2.6	4.5	120.1
Max	162.1	122.4	170.0	10.2	9.0	44.7	201.6
CV (%)	92.6	0.4	61.0	19.9	43.2	72.4	14.1



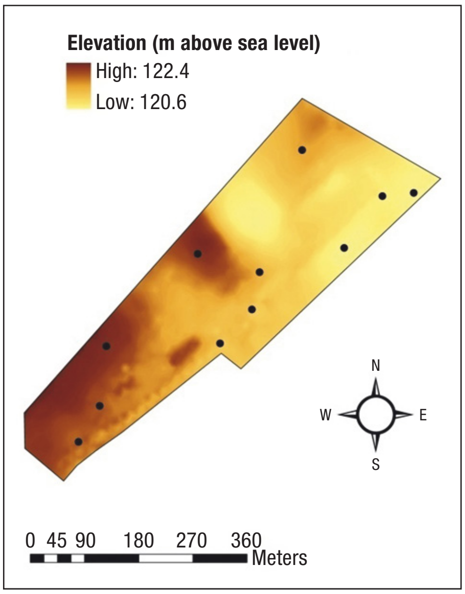


Figure 3. Maps of apparent soil electrical conductivity (ECa) to a depth of 0.30 m (left) and elevation (m above sea level) (right). Position of soil samples are indicated as black dots.

tively associated with ECa. These high correlations are expected because they reflect the influence of salts and pH on the measured ECa and because these properties are highly correlated (Corwin *et al.,* 2003; Peralta & Costa, 2013). Salts concentration and pH increased soil solution conductivity and is consistent with findings in previous studies (Rhoades *et al.,* 1989; Kaffka *et al.,* 2005). These results also agree with those reported by Peralta *et al.* (2013) in agricultural soils of the Argentinean pampas.

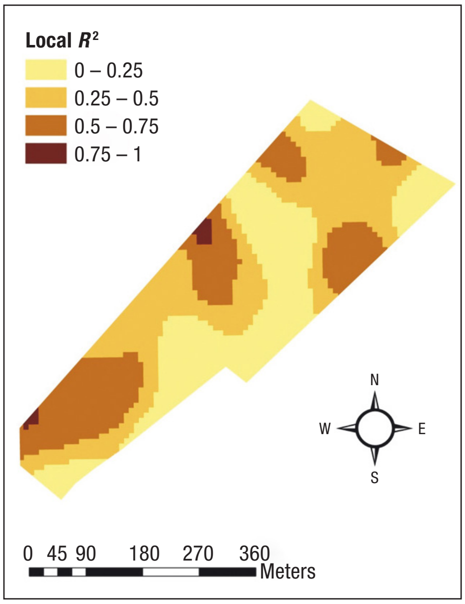


Figure 4. Map of local coefficient of determination (R^2) between apparent soil electrical conductivity (ECa) to a depth of 0.30 m and elevation (m above sea level) obtained by means of geographically weighted regression (GWR).

Our results showed that significant and negative correlation coefficients were found between ECa and OM (Table 2). This may be due to the fact that in these soils, the areas with thin superficial horizon, and in consequence with lower OM content, also have the highest solute concentrations (Batista *et al.,* 2005), which increases the measured ECa. On the contrary, in agricultural soils of the Argentinean pampas, a direct association was established between ECa and OM (Peralta *et al.,* 2013).

The P showed a weak association with ECa (Table 2). This nutrient is less positively correlated, but still significant (p<0.05). Jung *et al.* (2005) mentioned that the low association between ECa and P is attributable to the influence of the fertilization method (band application) usually used in the Argentinean pampas (Simón *et al.,* 2013). On the contrary, no association was established between ECa and Nan (Table 2). This behavior may be explained

Table 2. Models describing the relationships between ECa and saturation extract electrical conductivity (EC_{ext}), pH, organic matter (OM), available phosphorus (P) and anaerobically incubated nitrogen (Nan).

Property	Equation	R^2	*p*-value
EC_{ext}	1.33x + 26.14	0.65	0.0027
pH	0.0422x + 6.25	0.76	0.0005
OM	-0.055x + 8.009	0.70	0.0013
P	$0.009x^2 + 1.11x - 5.78$	0.54	0.04
Nan	-0.225x + 178.3	0.11	0.32

by variation and low concentrations of N. These results agree with those reported by Peralta & Costa (2013).

Principal component analysis and PC-stepwise regression

A significant relation was found between some soil properties (pH, OM, EC_{ext} and P) and ECa (Table 2). However, due to the co-linearity of the independent variables, mutivariate statistical methods that include PC analysis are more appropriate to evaluate the relation between soils properties and ECa (Moral *et al.,* 2010; Peralta & Costa, 2013).

Table 3 shows the three first PCs. These PCs had a cumulative variance of more than 95%. The first PC (PC1) explained 69% of the total variance and was positively influenced by pH and EC_{ext}, and negatively by OM (loading factors>0.4) (Table 3). On the other hand, the second PC (PC2) and third PC (PC3) only explained 20 and 10% of the total variance respectively. PC2 was highly related to Nan, whereas PC3· was related to P (Table 3).

PCs with an eigenvalue greater than 1 explain a significant amount of the variance present in the soil properties (Peralta & Costa, 2013). In this case only PC1 had an eigenvalue greater than 1 (Table 3). Confirming this, the PC-stepwise regression analysis only retained PC1 (Table 3). Therefore, EC_{ext}, pH and OM were considered key latent variables because they substantially influence the relationship between the PC1 and the ECa (loading factors>0.4) (Table 3). Conversely, as previously mentioned, PC2 and PC3 showed a more intense relationship with Nan and P (Table 3). Nevertheless, these PCs were not retained in the PC-regression model. Figure 5 shows the spatial distribution of PC1. The sites with lower values of PC1 correspond to sectors of the field where the ECext and the pH are low and the OM is high.

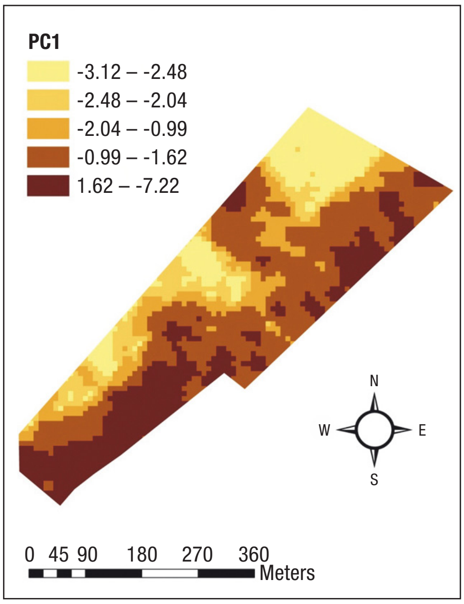


Figure 5. Map of the spatial variability from the PC1 of principal components analysis (PCA).

As conclusion, identification of regression models that were able to account for a large portion (50%) of the variability in soil ECa would indicate situations where this parameter could be used successfully to measure soil properties (Heiniger *et al.,* 2003). Our model explained slightly more than 69% of the total variation of the ECa measured. Therefore, our results provide evidence that soil ECa is useful in identifying sites with different pH, EC_{ext} and OM (loading factors>0.4) in soils used for livestock. Thus, ECa can be used as a support tool to implement site-specific management in permanent pastures.

This study shows that soil pH, OM and EC_{ext} have a reasonably strong spatial correlation with the ECa of the soil. The use of geo-electric sensors in the particular type of soil of the studied site can be promising for the nutritional management of pastures. This will enable increased economic, environmental and energy efficiency. It also allows mapping the soil at field scale with a low input of resources.

Table 3. Key principal components (PCs), eigenvalues, cumulative variance, loading factors for each soil property and regression model resulting from the principal component stepwise regression analysis.

Key PCs	Eigenvalue	Cumulative variance	Loading factors				
			EC_{ext}	pH	OM	P	Nan
PC1	3.41	0.68	**0.52**	**0.52**	**-0.52**	0.39	-0.12
PC2	1.00	0.88	0.10	-0.02	0.05	0.25	**0.96**
PC3	0.48	0.98	-0.19	-0.36	0.19	**0.87**	-0.22

The PC-stepwise regression:
Model regression: 50.15 +15.5PC1, R^2: 0.69, p-value: 0.001

Bold values indicate significant loading factors > 0.4.

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