Delineation of management zones with soil apparent electrical conductivity to improve nutrient management

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Site-specific management demands the identification of subfield regions with homogeneous characteristics (management zones). However, determining subfield areas is difficult because of complex correlations and the spatial variability of soil properties and nutrient concentrations, responsible for variations in crop yields within the field. We evaluated whether apparent electrical conductivity (ECa) is a potential estimator of soil properties and nutrients, and a tool for the delimitation of homogeneous zones. Two field sites with several soil series were studied in southeastern Cordoba Province, Argentina. Soil properties and nutrient concentrations were compared with ECa using principal components (PC)-stepwise regression and ANOVA. The PC-stepwise regression showed that soil properties (pH, EC1:2.5, CEC, SOM) and nutrients (Na\(^+\), Mg\(^+2\), Mn\(^+2\), Cu\(^+2\), Ca\(^+2\), Zn\(^+2\), Fe\(^+2\)) are key loading factors to explain the ECa (R\(^2\) > 0.90). In contrast, K\(^+\), P, NO\(_3\)-N and SO\(_4\)\(^2-\) were not able to explain the ECa. The ANOVA showed that ECa measurements successfully delimited two homogeneous soil zones associated with the spatial distribution of soil properties and some nutrients (Na\(^+\), Mg\(^+2\), Mn\(^+2\), Cu\(^+2\), Ca\(^+2\), Zn\(^+2\), Fe\(^+2\)). These results suggest that field-scale ECa maps have the potential to design sampling zones to implement site-specific management strategies.

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1. Introduction

The Cordoba Province of Argentina is a vast plain with approximately 7.794 (miles ha) of cropland. This province is the largest producer of soybeans and corn in Argentina, producing 12,750 ('000 ton) and 8749 ('000 ton), respectively (SAGPyA, 2009), and is composed mainly of (I) excessively drained soils, developed on sandy materials related to higher areas of land with a use capacity (usability) limited by low moisture retention (Instituto Nacional de Tecnología Agropecuaria (INTA), 1986) and (II) moderately drained to imperfect soils, moderately saline-alkali in depth, developed on sandy-loam to loam materials, related to depressed areas of land. Its usability is restrained by the presence of salts, which limits grain production. Soils vary widely in their nutrient contents and in their ability to supply sufficient micronutrients for optimal crop production. The spatial variability of soil nutrients may be affected by soil type, land forms, vegetation, climate, and anthropogenic activities. Therefore, it is not surprising that the content, distribution, and availability of soil nutrients can vary widely among soils both within and between fields (Corwin and Lesch, 2003).

Uniform management of fields does not take into account the spatial variability; therefore, it is not the most effective management strategy (Moral et al., 2010). Precision agriculture is considered the most viable approach for achieving sustainable agriculture (Kravchenko and Bullock, 2002; Bullock et al., 2007). In particular, site-specific management (SSM) is a form of precision agriculture whereby decisions on resource application and agro-nomic practices are improved to better match soil and crop requirements as they vary in the field. SSM enables the identification of regions (management zones) within the area delimited by field boundaries. These subfield regions constitute areas of the field that have similar permanent characteristics, such as topography and nutrient levels (Kitchen et al., 2005; Moral et al., 2011).

Efficient techniques to accurately measure within-field variations in soil properties are very important for homogeneous management zones (HMZ) (Peralta et al., 2013). Traditional soil sampling is costly and labor-intensive. This traditional method is not viable from an HMZ perspective, because it needs a large number of soil samples in order to achieve a good representation of soil properties and nutrient levels. The geospatial measurement of ECa...
is an efficient ground-based sensing technology that is helping to take HMZ from concept to reality (Corwin and Lesch, 2003). \( EC_a \) can be intensively recorded in an easy and inexpensive way, and it is usually related to various physico-chemical properties across a wide range of soils (Sudduth et al., 2005), because it depends on the chemical composition of the soil solution and soil exchangeable ions, clay content, and the interaction between non-exchangeable and exchangeable ions (Rhoades et al., 1989). This methodology can improve the characterization of the spatial pattern of edaphic properties that influence the nutrient content of the soil, which in turn can be used to define SSM units (Moral et al., 2010). However, the \( EC_a \) applications in HMZ showed weak and inconsistent relationships between \( EC_a \) and soil characteristics (Corwin and Lesch, 2003; Sudduth et al., 2005). These inconsistent relationships may be generated by the potentially complex interrelationships between \( EC_a \) and soil characteristics (soil properties and nutrient levels). The delimitation of HMZ with \( EC_a \) measurement to improve nutrient management has not been adequately described for excessively drained soils and moderately drained to imperfect soils (with salts present), which are characteristic of many agriculturally important soils in Argentina and throughout the world.

The main aims of this paper are to determine: (I) whether field-scale \( EC_a \) geospatial measurement is a potential estimator of soil properties (\( EC_{a,2.5} \), pH, SOM and CEC) and nutrient levels (P, Zn\(^{2+}\), Ca\(^{2+}\), Mg\(^{2+}\), Mn\(^{2+}\), Na\(^+\), K\(^+\), Fe\(^{2+}\), Cu\(^{2+}\), NO\(_3\)^{−}, N and SO\(_4\)^{2−}, S) and (II) whether \( EC_a \) measurement can enable the delimitation of HMZ within the field of production. If \( EC_a \) could be used to produce accurate maps of zones with the differences in the soil properties and nutrient concentrations indicated, it could be a useful tool for variable-rate seeding and for fertilizer producers.

2. Materials and methods

2.1. Experimental sites

Soil \( EC_a \) mapping was carried out in July of 2009 and soil samples were taken prior to sowing winter crops (wheat, *Triticum aestivum*). This study was conducted on two fields at La Unión, in southeastern Cordoba Province, Argentina (Fig. 1). The fields were 39 ha (F1) and 25 ha (F2) in size, cultivated under a no-tillage system since the year 2002 using a soybean–corn rotation system during the summer cropping seasons and with wheat as a cover crop during the winter season.

The soils in the two fields include a Canals series (coarse-loamy, mixed, thermic, Ertic Haplustoll), an Aromos series (coarse-loamy, mixed, thermic, Typic Calciaquoll) and Medanitos series (coarse-loamy, mixed, thermic, Typic Natralboll). The Canals series is a well-drained soil, developed on sandy materials associated with hills. The Aromos and Medanitos series are moderate to imperfect-drainage soils, moderately saline-alkali in depth, developed on sandy-loam to loam materials linked to depressed levels. The climate of this region is characterized by a thermal regime with a mean annual temperature of 17 °C and a variation of 14 °C. Average annual rainfall is 871 mm and the seasonal distribution is a monsoon type (Chida Daza and Sánchez, 2009).

2.2. Soil \( EC_a \) and elevation data collection

Soil \( EC_a \) measurements were made using the Veris 3100® (Veris 3100, Division of Geoprobe Systems, Salina, KS) (Fig. 2b). The device comprises 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 is set up to work in configuration A (0–30 cm) and B (0–90 cm) (Fig. 2a). 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 0–90 cm deep measurement, and the voltage gradient is measured between coulters 2 and 5 (Fig. 2a). Output from the Veris data logger reflects the conversion of resistance to conductivity (1/resistance = conductivity). In this paper, we are working with an \( EC_a \) measurement to 0–90 cm because it is more stable over time than the \( EC_a \) to 0–30 cm (Veris Technologies, 2001; Sudduth et al., 2003). The Veris 3100 sensor was pulled across each field behind a pick-up truck, taking simultaneous and geo-referenced \( EC_a \) measurements in real-time with a differential GPS (Trimble 132, Trimble Navigation Limited, USA) (Fig. 2), with sub-meter measurement accuracy and configured to take a satellite position once per second. On average, travel speeds through the field mapping ranged between 7 and 11 km h\(^{-1}\), corresponding to about 2–3 m spacing between measurements in the direction of travel. For ease of maneuvering, the field was traversed in the direction of crop rows in a series of parallel transects spaced at 15–30 m intervals, because a spacing greater than 30 m generates measurement errors and information loss (Farahani and Flynn, 2007). Elevation dates were collected at the same times that \( EC_a \) data, using a differential GPS (vertical accuracy of 3–5 cm).

2.3. Electrical conductivity zones and determination of sampling points

Previous research on various soils suggested that using more than three zones does not increase the available information (Peralta et al., 2013). Therefore, soil sampling was carried out by zones, based on three \( EC_a \) classes. Soil \( EC_a \) values and amplitude were classified by equal area quantiles using the Geostatistical Analyst in ArcGIS 9.3.1 (Environmental System Research Institute, Redlands, CA). Three representative geo-referenced soil-sampling points were selected within each of the three \( EC_a \) classes identified at each field (Fig. 3). Soil sample data were matched to the \( EC_a \) measurements taken using the Veris 3100 by averaging all \( EC_a \) measurements from the portion of the transect within a 20-m radius of the center-point location from which the soil cores were collected. This resulted in an average of eight to ten \( EC_a \) measurements matched to each soil sample taken.

2.4. Soil sampling and analysis

Soil samples were collected in plastic bags. Upon arrival at the laboratory, they were air-dried and analyzed for soil organic matter (SOM) by dichromate oxidation (Walkley and Black, 1934); cation exchange capacity (CEC) was measured using the neutral ammonium acetate method; pH in a 1:2.5 (soil:water) suspension and the electrical conductivity of saturation extract (\( EC_{1:2.5} \)) was measured using the electrometric method (Chapman, 1965). The NO\(_3\)^{−}, N content was determined with the calorimetric method of acid 2,4 phenoldisulfonic (Bremner, 1965). P, Zn\(^{2+}\), Ca\(^{2+}\), Mg\(^{2+}\), Mn\(^{2+}\), Na\(^+\), K\(^+\), Fe\(^{2+}\), Cu\(^{2+}\), SO\(_4\)^{2−} were quantified by extracting the soil solution with Mehlich-3 extractant (Mehlich, 1984) and analyzing the elements with a PerkinElmer Plasma System (PerkinElmer, Wellesley, MA).

2.5. Spatial variability of \( EC_a \) and elevation

The spatial dependence of \( EC_a \) and the elevation were quantified using semivariograms which characterize and determine distribution patterns such as randomness, uniformity and spatial trend.
The semivariogram was estimated using the equation (Isaaks and Srivastava, 1989):

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

where \( \gamma(h) \) is the experimental semivariance value at distance interval \( h \); \( z(x_i) \) 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 semivariograms adjusted for each field were used to interpolate the ECa and elevation by means of ordinary kriging after checking geo-statistical common assumptions (Isaaks and Srivastava, 1989), using ArcGIS Geospatial Analyst (ArcGIS v9.3.1, Environmental System Research Institute Inc. (ESRI), Redlands, CA, USA). A final 10 m x 10 m grid cell size was chosen because it reflects the scale of variability associated with the ECa measurements and elevation (Kitchen et al., 2003).

2.6. Statistical analysis

Principal-components analysis was used to examine the relationship between the soil properties (\( EC_{1:2.5} \), pH, MOS and CEC) and nutrient levels measured in this study (\( P, Zn^{2+}, Ca^{2+}, Mg^{2+}, Mn^{2+}, Na^+, K^+, Fe^{2+}, Cu^{2+}, NO_3^-N \) and \( SO_4^{2-} - S \)), and to determine which soil properties and nutrients were important influences on ECa.

Due to the colinearity of the independent variables, correlation analysis could not be used to directly relate multiple soil properties to ECa. Principal components analysis puts identified, correlated variables into groups. These groups (PCs) become new, independent, random variables that could then be used to identify which soil properties influenced ECa. In this study, the objectives of using the PC-stepwise regression analysis were to identify the key soil
properties and nutrients that had significant relationships with ECₐ; determine the strength of that relationship; and determine
the influence and role of each soil property and nutrient in the
relationship.

The PCs were identified from the correlation matrix using the
COMP procedure in SAS (SAS Institute, 2002). Any PCs with an
eigenvalue greater than 1 was selected because it explained a sig-
nificant amount of the variance present in the soil properties and
nutrients at each field. The PCs with eigenvalues >1 were then
used in a stepwise-regression procedure (SAS Institute, 2002) 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 predictor PCs until the only
remaining PCs are above the 0.15 significance level. The regres-
sion therefore effectively evaluates the result of the PCA. When
the PCs remaining in the regression model accounted for >50% of
the variability in the ECₐ measurement, the eigenvectors (load-
ing factors) were examined and the soil properties–nutrients in
the PCs ranked according to the amount of variability explained
by the PCs. For instance, a soil property and nutrient that was a
component of the PCs that accounted for most of the variability
in the regression model and had the highest loading factor in that
PC group was ranked first. Soil properties and nutrients with
loading factors <0.4 were not considered key latent variables
and were not included in the ranking because they did not sub-
stantially influence the relationship between the PC groups and
the nutrient concentration being examined. The ranking of the
soil properties and nutrients, strength of the loading factor, and
sign (positive or negative) of the loading factor were used to
determine the influence and role that each soil property and
nutrient had in explaining the variability in the ECₐ.

In order to determine whether the ECₐ measurements allow
delimitation of homogeneous zones within the fields, the differ-
ences in the averages of the soil properties (SOM, CEC, EC₁:2.5,
pHs) and the amount of nutrients (P, Zn²⁺, Ca²⁺, Mg²⁺, Mn²⁺, Na⁺,
K⁺, Fe²⁺, Cu²⁺, NO₃⁻/CO₃²⁻ and SO₄²⁻) were compared among the various
ECₐ classes (zones) using a mixed ANOVA model from PROC MIXED
(SAS Institute, 2002). They were compared using the LSMEANS pro-
cedure of PROC MIXED (SAS Institute 2002), with a significance le-
vel of 0.05. Descriptive statistics and simple correlations between
the soil properties–nutrients and ECₐ were calculated using the
SAS MEANS and CORR procedures (SAS Institute 2002). Significant
results with a high Pearson correlation coefficient (>0.60) indicate
situations where the CEₐ measured could be used to estimate soil

Fig. 3. Apparent electrical conductivity (ECₐ) and elevation map for the two fields with three electrical conductivity classes (zones). Variations in color, from light to dark, correspond to increasing conductivity.
and elevation are shown for F1 and F2 (Fig. 3), and —S, respectively.

+2 and Mg+2 might be caused by the greater proportion showed a positive correlation with CEC, Ca+2 (15.99 ± 3.37), and Na+ content showed higher variability among fields, while the concentration of K+, NO3–N, SO42––S, Fe2+ and Cu2+ and pH had low variability. However, P, Na+ and EC1:2.5 showed higher variability (Table 1). The higher mean of Na+ content and EC1:2.5 in F1 was probably due to the predominance of Aromos and Medanitos series, while the Canals series prevailed in F2. CVs for soil properties indicated high spatial variability and suggested the convenience of defining different management zones. High spatial variability in soil properties is the consequence of the interaction of (i) soil formation processes, (ii) meteorological processes, and (iii) anthropogenic influences. Soil formation processes are the result of complex interactions between biological, physical, and chemical mechanisms acting on a parent material over time and influenced by topography (Morales et al., 2010).

3.2. Relationships among ECa with soil properties and nutrient concentrations

Table 2 shows all PCs with an eigenvalue greater than 1, which were selected because they explained a significant amount of the variance present in the soil properties and nutrient levels at each field. In both cases, PCs had a cumulative variance of more than 80%. In both fields, the first PC (PC1) explained >60% of the total variance and was strongly influenced by all soil properties and Zn2+, Ca2+, Mg2+, Mn2+, Na+, Fe2+ and Cu2+. The second PC (PC2) and third PC (PC3) showed a more intense relationship with P, K+ and NO3–N, SO42––S, respectively.

For both fields, the PC-stepwise regression analysis only retained PCI (Table 3). EC1:2.5, pH, CEC, Ca2+, Mg2+ and Na+ contents had the highest positive loading factors and were positively related to ECa, which was associated with lower areas of the fields. In contrast, SOM, Zn2+, Mn2+, Fe2+, Cu2+ had the highest negative loading factors and were negatively related to ECa.

The correlation between elevation and ECa was significant and negative (Table 4). The higher ECa values are observed in lower areas (formed mainly by Aromos and Medanitos series) (Figs. 1 and 3), where salts, pH, Na+ and CEC levels were higher than in higher areas (formed mainly by the Canals series) (Table 5 and Fig. 4). Surface topography plays a significant role in influencing spatial ECa variation (Krafchenko and Bullock, 2002). Slope and aspect will determine the level and location of run-off and infiltration, which will influence the variation in water content and salinity. Areas where the slope is steep tend to have lower water content than areas where a depression occurs (Marques da Silva and Silva, 2008). The influence of surface topography on salinity distribution coincides with the influence of surface topography on water-flow gradients, which results in salt transport (Corwin and Lesch, 2005).

Three variables (EC1:1:2.5, pH and Na+) were highly correlated with ECa and presented values r > 0.67 for both fields. This high correlation is expected because it reflects the influence of salts on the ECa reading and because these properties are highly correlated (Kaffka et al., 2005). Salts and Na+ concentrations increased soil solution conductivity (Rhoades et al., 1989) and is consistent with findings in previous studies (Kaffka et al., 2005).

The ECa showed a positive correlation with CEC, Ca2+ and Mg2+ (Table 4). This indicates that changes in Ca2+ and Mg2+ to conduct electricity more easily than sandy soils (Rhoades et al., 1989).

Standard criteria suggested by Wilding et al. (1994) were used to characterize the magnitude of variability of soil properties and nutrient levels; with CV from 0% to 15%, 15% to 35%, and 35% to 100% characterizing low, medium, and high variability, respectively. Soil SOM for both fields ranged from 1.20% to 1.34% with whole field CV ranging from 23.58% to 20.57%, which showed medium variability (Table 1). Soil CEC, Ca2+, Mg2+, Zn2+ and Mn2+ contents had medium variability among fields, while the concentration of K+, NO3–N, SO42––S, Fe2+ and Cu2+ and pH had low variability. However, P, Na+ and EC1:2.5 showed higher variability (Table 1). The higher mean of Na+ content and EC1:2.5 in F1 was probably due to the predominance of Aromos and Medanitos series, while the Canals series prevailed in F2. CVs for soil properties indicated high spatial variability and suggested the convenience of defining different management zones. High spatial variability in soil properties is the consequence of the interaction of (i) soil formation processes, (ii) meteorological processes, and (iii) anthropogenic influences. Soil formation processes are the result of complex interactions between biological, physical, and chemical mechanisms acting on a parent material over time and influenced by topography (Morales et al., 2010).

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concentrations associated with changes in the CEC across the fields were influencing EC₄. Increases in the CEC contributed to the raised concentration of Ca²⁺ and Mg²⁺ in the soil solution and to increasing the electrical conductivity of soil particles, which increased the EC₄ (Shainberg et al., 1980). The CEC might be linked to clay contents, because the highest values were found in the sampling points on the Aromos series (loam). In contrast, the lowest values of CEC (and hence Ca²⁺, Mg²⁺) were associated with the Canals series (sandy loam). Heiinger et al. (2003) reported that sand was negatively affected the EC₄ and pH (CVs were >30%). The low association between EC₄ and P is probably due to the fact that equivalent conductances of common inorganic P ions in soils (e.g. H₂PO₄⁻ and HPO₄²⁻) are generally lower than ionic species (e.g. Ca²⁺ and Mg²⁺) (Motavalli et al., 2013). Furthermore, Jung et al. (2005) mentioned that the low association between EC₄ and P is attributable to the influence of fertilization form (band application) and tillage system (direct drilling, without soil removal). The available N and S levels were not related to the variability of the EC₄, this may be explained by variation and low concentrations of these anions, without influence on the electrical conductivity of the mobile soil solution. Corwin et al. (2006) found a very strong correlation between EC₄ with NO₃⁻–N and SO₄²⁻–S, contents working in fields with higher concentrations and variations.

Identification of regression models that were able to account for a large portion (50%) of the variability in soil EC₄ would indicate situations where EC₄ could be used successfully to measure soil properties and nutrient levels (Heiinger et al., 2003). As can be seen, the EC₄ was strongly linked to soil properties, mainly EC_{1:2.5} and pH (higher loading factors). It was also correlated with some exchange cations such as Zn²⁺, Ca²⁺, Mg²⁺, Mn²⁺, Na⁺, Fe²⁺ and Cu²⁺; there were no correlations with K⁺, P, NO₃⁻–N and SO₄²⁻–S, indicating that EC₄ measurements in these fields were driven primarily by salinity.

3.3. Delineation of homogeneous management zones

While the PCA revealed which soil properties and nutrients explained the major total variance, and the PC-stepwise regression determined which soil properties and nutrients were more associated with EC₄, neither of these two techniques can determine significant differences among EC₄ classes. Therefore, to assess whether EC₄ can be used to determine HMZ, a mixed ANOVA model was fitted (Table 5).

The soil properties (EC_{1:2.5}, pH, CEC and SOM) had the greater significant differences among EC₄ classes in each field (Table 5), which is consistent with the results of the PCA. These soil properties were considered key latent variables (loading factors > 0.4) because they substantially influence the relationship between PC1 and the EC₄ (Table 3). The EC_{1:2.5} and pH exhibited significant differences between two EC₄ classes (Table 5). The delimitation of areas with different values of EC_{1:2.5} and pH is very important for SSM because soil salinity refers to the presence of major dissolved inorganic solutes in the soil aqueous phase. These consist of soluble and readily dissolvable salts including charged species, non-ionic solutes, and ions that combine to form ion pairs (Corwin and Lesch, 2005). Salinity limits water uptake by plants because it reduces the osmotic potential, making it more difficult for the plant to uptake water.
to extract water. Salinity may also cause specific ion toxicity or upset the nutritional balance of plants, reducing crop yields (Corwin and Lesch, 2005). Also, pH controls the nutrient availability for plants and soil microbial activity (Serrano et al., 2010). The SOM and CEC exhibited significant differences among two EC$_2$ classes, but with an inverse pattern (Table 5). Bearing in mind that CEC and SOM are relatively static over time (Shaner et al., 2008), and that they affect crop growth and development (Groenigen et al., 2000), it would be useful and necessary to classify fields into homogeneous zones. The classes of high EC$_2$ showed lower values of SOM. In a previous study published by Gambaudo et al. (2008), it was observed that in medium–low zones of EC$_2$, the SOM increased. Also, the nutrients with high loading factors (Zn$^{2+}$, Ca$^{2+}$, Mg$^{2+}$, Mn$^{2+}$, Na$^{+}$, Fe$^{2+}$, and Cu$^{2+}$) showed greater significant differences among the EC$_2$ classes in each field. The micronutrient concentrations (Zn$^{2+}$, Mn$^{2+}$, Fe$^{2+}$, and Cu$^{2+}$) exhibited significant differences among the two EC$_2$ classes. In most cases, they showed no difference between the medium–high classes, except Cu$^{2+}$ in F1 (Table 5). The high micronutrient concentrations in the low EC$_2$ class were attributed to increasing soil acidification and relatively high SOM contents (Shuman, 1991; Shi et al., 2008; Eyerabide et al., 2012). The concentrations of Ca$^{2+}$, Mg$^{2+}$ showed differences among two classes, while K$^+$ showed no significant differences among EC$_2$ classes (Table 5), possibly because of the low CV exhibited in F1 and F2 (9.96% and 14.23%, respectively) (Table 1). The Na$^{+}$ concentrations showed differences among two EC$_2$ classes (Table 5). Bosch Mayol et al. (2012), working in soils with a higher Na$^{+}$ content, found differences in three zones, concluding that the Na$^{+}$ spatial variability significantly affects EC$_2$.

However, the nutrients with low loading factors (K$^+$, P, NO$_3$–N and SO$_4^{2–}$–S), did not show significant differences among EC$_2$ classes (Table 5). The NO$_3$–N and SO$_4^{2–}$–S concentrations had low CVs, indicating that these variables showed little variation within the fields. Also, transformations in soil are controlled by soil water content, biological activity, cropping, composition and quantity of organic matter. These soil characteristics have an impact on the discordant processes of immobilization and leaching (losses) or mineralization (gains) that define NO$_3$–N and SO$_4^{2–}$–S, levels in soil (Eriksen, 1997). While P showed a high CV, it was not a variable that significantly affected the EC$_2$.

Geo-referenced EC$_2$ measurements successfully delimited two homogeneous soil zones associated with spatial distribution of soil properties, such as salt concentration (EC$_{1:2.5}$), pH, CEC and SOM content. Two homogeneous soil zones were also delimited by micronutrients (Zn$^{2+}$, Mn$^{2+}$, Fe$^{2+}$ and Cu$^{2+}$) strongly associated with soil pH and SOM (Table 4); and two zones by Na$^{+}$, Ca$^{2+}$, Mg$^{2+}$, which showed high correlations with CEC. However, the K$^+$, P, NO$_3$–N and SO$_4^{2–}$–S content had few differences on average in the different EC$_2$ zones, since it would not be advisable to make management zones based on these three nutrients. Soil properties such as pH, SOM and CEC showed high correlations with nutrient levels and, as they are relatively static over time, a model that included these measurements along with EC$_2$ could be developed to predict soil nutrient content. Therefore, EC$_2$ is able to measure these soil proper-
ties directly, it has the potential to identify HMZ with differing productivity and nutrient requirements.

4. Conclusions

The results of this study indicate that for both fields, the PC-stepwise regression analysis was able to account for >50% of the variability in the ECa. Principal-component groups consisting of all soil properties (mainly EC1:2.5 and pH) and some exchange cations (Zn$^{2+}$, Ca$^{2+}$, Mg$^{2+}$, Mn$^{2+}$, Na$^{+}$, Fe$^{2+}$ and Cu$^{2+}$) were able to consistently account for the spatial variability of the ECa. In contrast, the PC-stepwise regression analysis was not able to consistently identify models that accounted for other soil nutrients (K$^{+}$, P, NO$_3$-N and SO$_4^{2-}$-S). This does not mean that ECa has no value in determining nutrient levels in the soil. Instead, this study shows that ECa could be a valuable tool when used in conjunction with multivariate statistical procedures in identifying some soil properties and nutrient content.

### Table 5

<table>
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<tr>
<th>Fields</th>
<th>EC Zones</th>
<th>EL (m)</th>
<th>SOM (%)</th>
<th>P (mg kg$^{-1}$)</th>
<th>K$^+$ (cmol kg$^{-1}$)</th>
<th>Mg$^{2+}$ (cmol kg$^{-1}$)</th>
<th>Ca$^{2+}$ (cmol kg$^{-1}$)</th>
<th>Na$^+$ (cmol kg$^{-1}$)</th>
<th>pH</th>
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<th>NO$_3$-N (mg kg$^{-1}$)</th>
<th>SO$_4^{2-}$-S (mg kg$^{-1}$)</th>
<th>Zn$^{2+}$ (mg kg$^{-1}$)</th>
<th>Mn$^{2+}$ (mg kg$^{-1}$)</th>
<th>Fe$^{2+}$ (mg kg$^{-1}$)</th>
<th>Cu$^{2+}$ (mg kg$^{-1}$)</th>
<th>EC$_{1:2.5}$ (dS m$^{-1}$)</th>
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<td>145.52</td>
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<td>F1</td>
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</table>

SOM: soil organic matter, CEC: cation exchange capacity, EC$_{1:2.5}$: laboratory-measured electrical conductivity.

a–b The same letters indicate no significant differences (P ≤ 0.05) for each site.

EL: Average elevation for each EC$_a$ zone.

![Fig. 4](image-url). Elevation vs. EC$_{1:2.5}$, Na$^{2+}$, pH and CEC in each field. The coefficient of determination ($r^2$) is given for simple linear regressions.
The $\text{K}^+$, $\text{NO}_3^-$, $\text{N}$ and $\text{SO}_4^{2-}$ content had low values and few differences in average in the different classes of EC$_r$, so it would not be advisable to create management zones based on these nutrients. However, EC$_r$ measurements successfully delimited two homogeneous soil zones associated with the spatial distribution of all soil properties and $\text{Zn}^{2+}$, $\text{Ca}^{2+}$, $\text{Mg}^{2+}$, $\text{Mn}^{2+}$, $\text{Na}^+$, $\text{Fe}^{2+}$ and $\text{Cu}^{2+}$ concentrations.

Considering that CEC, SOM content and $\text{pH}$ values are static over time and are used to determine soil fertility, these results suggest that EC$_r$ field-scale maps in areas with well-drained soil (Entic Hapludoll) and moderate to imperfect-drainage soil, moderately saline-alkali in depth (Typic Calciaclu, Typic Natralboll), can delimit two zones which are homogeneous enough to serve as meaningful zones for management and sampling purposes, without sacrificing soil spatial variability information.

In the next few years, some studies will be conducted to evaluate these subfield management zones, using yield maps to better understand the agronomic significance of this classification.

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**References**


