Delineation of management zones with measurements of soil apparent electrical conductivity in the southeastern pampas

Nahuel Raúl Peralta[1,3], José Luis Costa[2,3], Mónica Balzarini[1,4], and Hernán Angelini[2]

[1]Consejo Nacional de Investigaciones Científicas y Técnicas (CONICET), Av. Rivadavia 1917, CP C1033AAJ, Buenos Aires, Argentina; [2]Estación Experimental Agropecuaria INTA, Balcarce C.C.276, (7620) Balcarce, Buenos Aires, Argentina; [3]Facultad de Ciencias Agrarias-U.N.M.D.P. Unidad Integrada Balcarce, C.C.276, (7620) Balcarce, Buenos Aires, Argentina; and [4]Facultad de Ciencias Agrarias-U.N.C. (Universidad Nacional de Córdoba), 509. (5000) Córdoba, Argentina. Received 15 March 2012, accepted 14 December 2012.

Peralta, N. R., Costa, J. L., Balzarini, M. and Angelini, H. 2013. **Delineation of management zones with measurements of soil apparent electrical conductivity in the southeastern pampas**. Can. J. Soil Sci. **93**: 205–218. Site-specific management demands the identification of subfield regions with homogeneous characteristics (management zones). However, determination of subfield areas is difficult because of complex correlations and spatial variability of soil properties responsible for variations in crop yields within the field. We evaluated whether apparent electrical conductivity (EC_a) is a potential estimator of soil properties, and a tool for the delimitation of homogeneous zones. EC_a mapping of a total of 647 ha was performed in four sites of Argentinean pampas, with two fields per site composed of several soil series. Soil properties and EC_a were analyzed using principal components (PC)–stepwise regression and ANOVA. The PC–stepwise regression showed that clay, soil organic matter (SOM), cation exchange capacity (CEC) and soil gravimetric water content (θ_g) are key loading factors, for explaining the EC_a ($R^2 \geq 0.50$). In contrast, silt, sand, extract electrical conductivity (EC_{ext}), pH values and NO_3^--N content were not able to explain the EC_a. The ANOVA showed that EC_a measurements successfully delimited three homogeneous soil zones associated with spatial distribution of clay, soil moisture, CEC, SOM content and pH. These results suggest that field-scale EC_a maps have the potential to design sampling zones to implement site-specific management strategies.

Key words: Precision agriculture, management zones, spatial variability, soil properties

Peralta, N. R., Costa, J. L., Balzarini, M. et Angelini, H. 2013. **Délimitation de zones de gestion à l' aide de la mesure de la conductivité électrique apparente du sol dans la pampa du sud-est**. Can. J. Soil Sci. **93**: 205–218. La gestion spécifique de sites exige l'identification dans la parcelle de sous-régions aux caractéristiques homogènes (zones de gestion). Cependant, la détermination de telles zones de gestion est difficile du fait de corrélations complexes et de la variabilité spatiale des propriétés du sol, responsables de variations des rendements des cultures au sein même des parcelles. Dans ce cadre, nous avons mené des expérimentations pour évaluer si la conductivité électrique apparente (EC_a) pourrait être un estimateur potentiel des propriétés du sol et donc un outil pour la délimitation de zones homogènes. L'EC_a a été mesurée et cartographiée sur un total de 647ha dans quatre sites de la pampa Argentine, avec deux zones par parcelles composées de plusieurs séries de sol. Les propriétés du sol et l'EC_a ont été objet d'une analyse en composantes principales (PC)–régression séquentielle et ANOVA. La PC–régression séquentielle a montré ue la teneur en argile, la matière organique du sol (MOS), la capacité d'échange cationique (CEC) et la teneur en eau gravimétrique du sol (θ_g) sont des facteurs clés pour expliquer l'EC_a ($R^2 \geq 0.50$). A l'inverse, le limon, le sable, la conductivité électrique extraite (EC_{ext}), les valeurs de pH et le contenu en NO_3^--N n'ont pas permis d'expliquer L'EC_a. L'ANOVA a démontré que les mesures de l'EC_a a permis de délimiter avec succès trois zones de sol homogènes associées à la distribution spatiale de l'argile, l'humidité de sol, la CEC, le contenu en MOS et le pH du sol. Ces résultats suggèrent que la mesure de l'EC_a à l'échelle de la parcelle a le potentiel de délimiter des zones d'échantillonnage pour l'implémentation de stratégies de gestion de sites spécifiques.

Mots clés: Agriculture de précision, zones de gestion, variabilité spatiale, propriétés du sol

The Argentinean pampas is a vast plain region of about 50 Mha (Alvarez et al. 1998) and it is considered one of the most suitable areas for grain crop production in the world (Satorre and Slafer 1999). On its southern portion (southeastern Pampas), the climate is sub-humid to humid, with 900 mm annual rainfall. The predominant soils of the region belong to the Mollisol order, great group Argiudolls or Paleudolls, overlying loess sediment, under a udic-thermic temperature regime (Suero et al. 1990). These soils exhibit a distinctive characteristic, which is the presence of a petrocalcic horizon, locally called ''tosca''. This layer causes a wide variability of the soil profile depth (Pazos et al. 2002).

Abbreviations: **θg**, soil gravimetric water content; **EC_{ext}**, electrical conductivity of the saturation extract; **CEC**, cation exchange capacity; **HMZ**, homogeneous management zones; **PC**, principal component; **SOM**, soil organic matter

Because of this, agricultural fields in southeastern Pampas frequently have multiple soil map units within them, despite their sometimes relatively small size, and a wide range of soil textures and properties, causing high soil spatial variability (Melchiori 2002). As a result, uniform field management is not an effective management strategy (Moral et al. 2010), because it does not take into account spatial variability. Precision agriculture is considered the most viable approach for achieving sustainable agriculture (Corwin et al. 1999). In particular, homogeneous management zones (HMZ) is a form of precision agriculture whereby decisions on resource application and agronomic practices are improved to better match soil and crop requirements as they vary in the field. Homogeneous management zones allow the identification of regions (management zones) within the area delimited by field boundaries. These subfield regions constitute areas of the field with similar characteristics, such as texture and nutrient levels (Moral et al. 2010). In order to allow the implementation of differential management practices, HMZ must have a minimum size of approximately 500 m^2. This is mainly due to the fact that it is not practical to manage smaller sections because of machinery limitations and the uncertainty of economic benefit. Otherwise, they do not represent a benefit compared to traditional uniform management (Bullock et al. 2007).

Homogeneous management zones can be delineated using electronic technologies that rapidly collect information at numerous sites in the field, allowing the characterization of field spatial variations. In this way, the measurement of apparent soil electrical conductivity (EC_a) is one of the most reliable techniques used to characterize within-field variability of edaphic properties (e.g., Corwin and Lesch 2003). The EC_a is defined as the soil capacity for conducting electric current. It involves the conductance through the soil solution, solid soil particles, and exchangeable cations that are located on that are located on clay mineral surfaces (Rhoades et al. 1989; Corwin and Lesch 2003). There are several reasons why geospatial measurements of EC_a are well-suited for characterizing spatial variability. Geospatial measurements of EC_a are reliable, quick and easy. The transportation of EC_a measurement equipment is easy and can be accomplished at a reasonable cost. Finally, and most importantly, EC_a is related to many soil physicochemical properties, such as soil water content, salinity and clay content (Kachanoski et al. 1988; Johnson et al. 2001; Kaffka et al. 2005), making it possible to establish the spatial variability in the field of these additional important soil properties. This methodology can improve the characterization of the spatial pattern of edaphic properties influencing crop yield, which in turn can be used to define site-specific management units (Moral et al. 2010). However, previous EC_a applications in HMZ have shown weak and inconsistent relationships between EC_a and soil characteristics (Corwin and Lesch 2003; Sudduth et al. 2003). These inconsistent relationships may be generated by the potentially complex interrelationships between EC_a and soil characteristics. The delimitation of HMZ with EC_a measurement has not been adequately described for soils with presence of a petrocalcic horizon, which are characteristic of many agriculturally important soils in Argentina and throughout the world.

The objectives of this study are to assess: (1) whether field-scale EC_a geospatial measurement is a potential estimator of soil properties and (2) whether EC_a measurement can enable the delimitation of HMZ within productive fields in the region. For this purpose, we analyzed the variation of the spatial dependence of EC_a in each field to determine whether the size of the areas is useful for implementing site-specific management.

MATERIALS AND METHODS

Experimental Sites

Soil EC_a mapping and soil sampling at Fernandez (F1 and F2), Claraz (C1) and Huesos (H1) were done in July of 2008. At Claraz (C2), Huesos (H2) and Quebracho (Q1 and Q2), mapping and sampling were done in July–August 2009. All soil samples were taken prior to planting winter crops [wheat (*Triticum aestivum*) and barley (*Hordeum vulgare*)].

Four sites were chosen, with two fields per site in the southeastern Pampas, Buenos Aires province, Argentina (Fig. 1). The four sites are composed of various soil series (Table 1), Huesos of the Mar del Plata series (fine, mixed, thermic, Typic Argiudoll); Fernandez of the Azul series (fine, illitic, thermic Typic Argiudoll); Claraz of the Tandil (fine, illitic, thermic Typic Argiudoll) and Azul series; and Quebracho of the Balcarce (fine, mixed, thermic Petrocalcic Paleudoll) and Mar del Plata series [Instituto Nacional de Tecnología Agropecuaria (INTA) 1970–1989]. These series cover an extensive area of approximately 5 490 912 ha.

The Quaternary loess sediments that cover the Pampean region are the most widely distributed continental sedimentary deposits of the southern Hemisphere. The source areas of these aeolian sediments are located to the west and southwest of the Andean and extra-Andean Patagonia region (Teruggi 1957). This contributes to a mineral association derived from neutral to basic volcanic pyroclastic materials. The sediments were transported by wind northward through modified saltation and long- and short-term suspension during several sedimentary pulses (Pye 1987), then deposited in the Pampean region over the undulating paleotopography of the tosca (local term, equivalent to calcrete) layer (2Ckm horizon, petrocalcic horizon, calcrete), generating wide variability in soil depth (Blanco et al. 2007). For example, at Huesos the petrocalcic horizon is found below 150 cm depth, so the soil samples were able to be collected from the profile to 90-cm depth, whereas in some zones of the other sites, the petrocalcic horizon was shallower

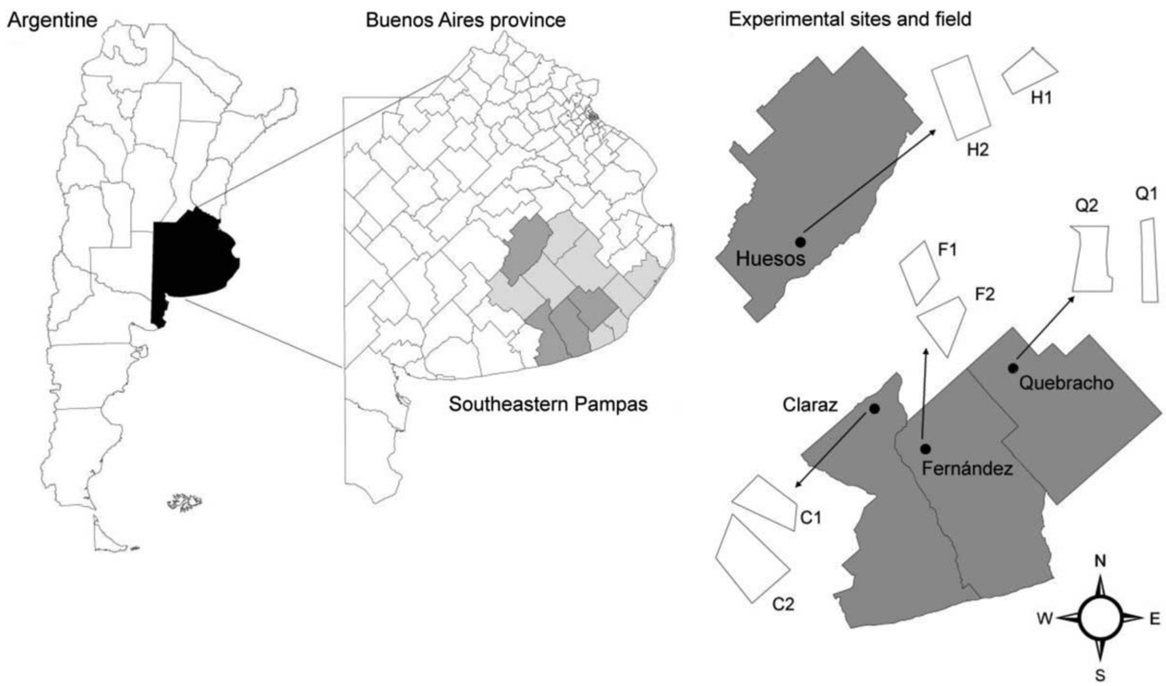

Fig. 1. The eight fields situated on the four experimental sites (●) located in southeastern Pampas, Buenos Aires province, Argentina.

than 90 cm, which limited the depth of data collection (Table 1).

Clay mineral composition of the Pampean loessic sequences are uniform, composed mainly of illitic and montmorillonitic,. On the other hand, the texture varies from silty clay loam to loam (Imbellone et al. 1993).

Electrical Conductivity Mapping

Soil EC_a measurements were made using the Veris 3100® (Veris 3100, Division of Geoprobe Systems, Salina, KS). The device consists of six disc-shaped metal electrodes, which penetrate approximately 6 cm into the soil (Fig. 2). One pair of electrodes emits an electrical current into the soil, while the other two pairs detect decreases in the emitted current due to its transmission through soil (resistance). The measurement depth is based upon the spacing of the coulter-electrodes. The center pair, situated closest to the emitting (reference) coulter-electrodes, integrates resistance between depths of 0 and 30 cm, while the outside pair integrates between 0 and 90 cm. Output from the Veris Data Logger reflects the conversion of resistance to conductivity (1/resistance = conductivity). In this paper we work with EC_a measurement to 0–90 cm because it is more stable over time than the EC_a to 0–30 cm (Sudduth et al. 2003). The Veris 3100 Sensor was pulled across each field behind a pick-up truck, while measuring simultaneous and georeferenced EC_a measurement in real-time with a

Table 1. Experimental sites and soil classifications (INTA 1970, 1989)

Site	Field	Sample number 0–90 cm	Soil type		Horizons		Series composition (%)
			Soil series	Soil classification	Topsoil	Subsoil	
Huesos	H1	36	Mar del Plata	Typic Argiudoll	Loam	Loam-clay	100
	H2	31	Mar del Plata	Typic Argiudoll	Loam	Loam-clay	100
Fernandez	F1	29	Azul	Petrocalcic Paleudoll	Clay-loam	Clayey	100
	F2	21	Azul	Petrocalcic Paleudoll	Clay-loam	Clayey	100
Claraz	C1	33	Tandil	Typic Argiudoll	Clay-loam	Clayey	60
			Azul	Petrocalcic Paleudoll	Clay-loam	Clayey	40
	C2	25	Tandil	Typic Argiudoll	Clay-loam	Clayey	70
			Azul	Petrocalcic Paleudoll	Clay-loam	Clayey	30
Quebracho	Q1	35	Balcarce	Petrocalcic Paleudoll	Clay-loam	Clayey	60
			Mar del Plata	Typic Argiudoll	Loam	Loam-clay	40
	Q2	26	Balcarce	Petrocalcic Paleudoll	Clay-loam	Clayey	60
			Mar del Plata	Typic Argiudoll	Loam	Loam-clay	40

Fig. 2. Veris 3100 coulter-based apparent soil electrical conductivity sensor.

differential GPS (Trimble R3, Trimble Navigation Limited, USA) (Fig. 2), with a sub-meter measurement accuracy and configured to take 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 manoeuvring, the field was traversed in the direction of crop rows in series of parallel transects spaced at 15- to 30-m intervals, because a spacing greater than 30 m generates measurement errors and information loss (Farahani et al. 2007).

Electrical Conductivity Sampling

Soil sampling was done by zones, based on four EC_a classes. Previous research on various soils suggested the use of four classes to delimit homogeneous zones, because very little information is obtained using a larger number (Fleming et al. 2000). 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) (Fig. 3). Three representative geo-referenced soil-sampling points were selected within each EC_a classes identified at each field (Fig. 3). Each soil-sampling point consisted of three subsamples, centred within EC_a class areas to avoid transition zones (Fig. 3). For the organization, manipulation and data graphic display, geographic information systems and EC_a contour maps were used for the eight fields evaluated. The program used was ArcGIS v9.3.1 [Environmental System Research Institute Inc. (ESRI), Redlands, CA].

Soil Sampling and Analyses

Soil cores were taken to a depth of 90 cm using a 5-cm-diameter hydraulically driven soil tube (Giddings Machine Co., Windsor, CO). As soil profile is not uniform through the 0–90 cm depth, soil in each core was carefully mixed to homogenize the sample and therefore make it representative of the analyzed depth. The SOM content was only measured from the 0–30 cm stratum, because the highest content in the soils of the southeastern Pampas is found there (Barbieri et al. 2009).

Soil samples were collected in plastic bags. Upon arrival at the laboratory, they were air-dried and analyzed for soil gravimetric water content (θ_g) and particle-size distribution by gravitational sedimentation using the Robinson pipette method (Soil Conservation Service 1972), after passing the fine components through a 2-mm sieve. These fine components were also analyzed for pH, in 1:2.5 (soil:water) suspension, by the electrometric method (Chapman 1965). Electrical conductivity of the saturation extract (EC_{ext}), was measured using the electrometric method (Chapman 1965), SOM was determined by dichromate oxidation (Walkley and Black 1934), cation exchange capacity (CEC) was measured by the neutral ammonium acetate method and NO_3^--N content was determined by colorimeteric method (Bremner 1965). The soil $CaCO_3$ was analyzed at Fernandez, because it was only one that showed $CaCO_3$ in soil profile. The $CaCO_3$ content was determined using a Bernard calcimeter (Ministry of Agriculture, Fishing and Food 1986).

Spatial Variability of EC_a

Soil EC_a spatial correlation was quantified with semivariograms. These functions characterize distribution patterns such as randomness, uniformity and spatial trend. The function relates the semivariance, half the expected squared difference between paired data values $z(x_i)$ and $z(x_i+h)$, to the *lag* distance, h, by which sample points are separated. The semivariogram was estimated using the equation (Isaaks and Srivastava 1989):

$$\gamma^*(h) = \frac{1}{2N(h)} \sum_{i=1}^{N(h)} (z(x_i) - z(x_i + h))^2 \quad (1)$$

where $\gamma^*(h)$ is the experimental semivariance value at distance interval h; $z(x_i)$ are the measured sample values 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 degradation of spatial correlation between two points in space when the separation distance increases. Important parameters of the semivariogram include the *nugget, sill*, and *range*. The *nugget effect* (Co) relates to the variance between pairs of points separated by very small distances, and can be due either to sampling error, to short scale variability, or both. The *sill* (Co+C) is the level at which the semivariogram flattens out, where C is the dependent structural or spatial variance and represents the vertical scale for the structured component of the semivariogram. The higher the value of C with respect to Co, the better the estimation (Muñoz et al. 2006). If a *sill* exists, the soil EC_a variability is stationary beyond that range and the *sill* can be thought of as the spatial

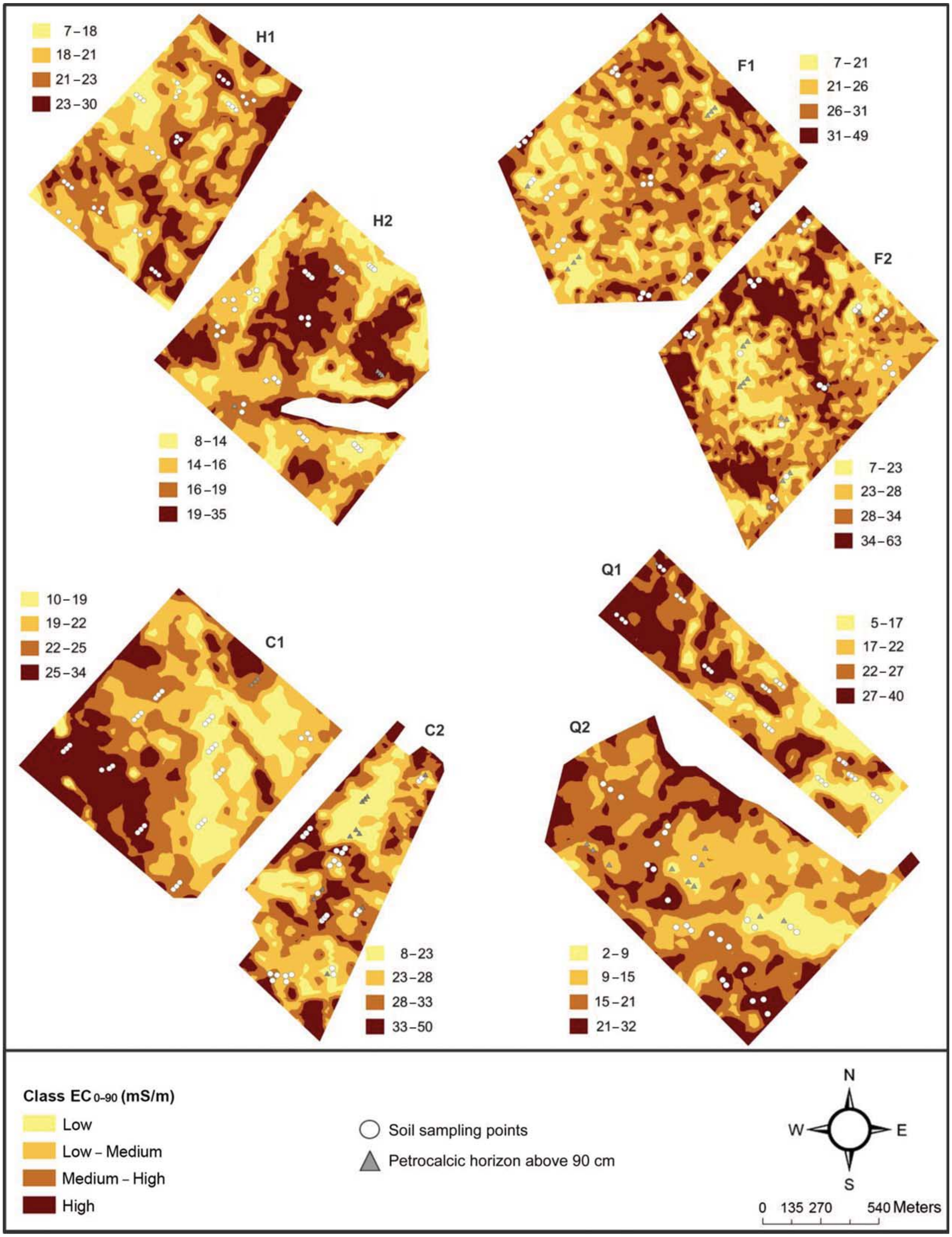

Fig. 3. Apparent electrical conductivity (EC_a) map for all fields with four electrical conductivity classes. Variations in color, from light to dark, correspond to increasing conductivity.

variance of two distantly separated points. The *range* (α) is a measure of the spatial continuity of soil EC_a and can be used as a measure of homogeneity or spatial dependency (Cohen 1994).

To fit the semivariogram, spherical (Eq. 2) or exponential (Eq. 3) models were considered (Webster 1985).

$$\gamma(h) = c_0 + \begin{cases} c\left[1.5(h/a) - 0.5(h/a)^3\right], & \text{if } h \le a \\ c, & \text{if } h \ge a \end{cases} \quad (2)$$

$$\gamma(h) = c_0 + c[1 - \exp(-3h/a)], \quad (3)$$

The best model was selected according to the minimum value of Akaike's criterion (AIC). Akaike (1973) introduced the concept of information criteria as a tool for optimal model selection. The model with the smallest AIC is considered the "best" model since it minimizes the sum of squared errors.

The degree of spatial dependence of the analyzed variable (EC_a) was characterized based on the proportion of structural variance. Spatial dependence is considered strong when C/(Co+C) ratio gives values greater or equal to 0.75, moderate between 0.75 and 0.25, and weak for values less or equal to 0.25 (Cambardella et al. 1994). The variograms adjusted for each field were used to interpolate the EC_a by means of ordinary kriging after checking geostatistical common assumptions (Isaaks and Srivastava 1989).

Statistical Analysis

Principal-components analysis was used to examine the relationship among the soil properties measured in this study (clay, silt, sand, θ_g, SOM, CEC, EC_{ext}, pH and NO_3^--N) and to determine which soil properties were important influences on EC_a.

Due to the colinearity of the independent variables, correlation analysis could not be used to directly relate multiple soil properties to EC_a. 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 EC_a. In this study, the objectives of using the PC–stepwise regression analysis were to identify the key soil properties that had significant relationships with EC_a; determine the strength of that relationship; and determine the influence and role of each soil property in the relationship.

The PCs were identified from the correlation matrix using the FACTOR procedure in SAS software (SAS Institute, Inc. 2002). Any PCs with an eigenvalue greater than 1 were selected because they explained a significant amount of the variance present in the soil properties at each site. The PCs with eigenvalues >1 were then used in a stepwise regression procedure (SAS Institute, Inc. 2002) to determine if there was a significant relationship between the PCs and EC_a. 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 regression therefore effectively evaluates the result of the PCA. When PCs remaining in the regression model accounted for $>50\%$ of the variability in EC_a measurement, the eigenvectors (loading factors) were examined and the soil properties in the PCs ranked according to the amount of variability explained by the PCs. For instance, a soil property 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 with loading factors <0.4 were not considered key latent variables and were not included in the ranking because they did not substantially influence the relationship between the PC groups and the nutrient concentration being examined. The ranking of the soil properties, 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 had in explaining the variability in the EC_a.

In order to determine whether the EC_a measurements allow delimitation of homogeneous zones within the fields, the differences in the averages of the soil properties (determined as an average of the three subsamples) were compared among the EC_a classes using a mixed linear model from PROC MIXED (SAS Institute, Inc. 2002). Soil EC_a classes and locations were regarded as fixed effects, fields as random effects and sampling points within each EC_a class as random subsamples. The soil property mean comparisons were evaluated according with a significance level of 0.05, using the LSMEANS. Each EC_a class was considered as a classification factor in a randomized complete block design within each field.

RESULTS AND DISCUSSION

Structural Analysis of EC_a

The EC_a spatial variability within each field was best described with a spherical model (Table 2); the spatial dependence progressively decreased (equivalent to an increase in semivariance) with the lag distance. In the semivariogram model, EC_a showed several spatial dependence ranges (Fig. 4), attributable to the intrinsic characteristics (mainly soil-type changes) of the field. In this way, Huesos_H2 and Fernandez_F2 are composed only of one soil series (Mar del Plata and Azul series, respectively) and have a greater EC_a range because the soil properties change gradually within the field. On the other hand, the smaller range found at Quebracho_Q1 and Q2 (Fig. 4), is associated with abrupt changes in soil properties at short distances, due to different soil series (Balcarce and Mar del Plata) within each field. The range was greater than 40 m for all the fields (Fig. 4), in accordance with Bekele et al. (2005), who described that in ranges higher than 20 m it is easier to delimit management zones because the soil variables are not

Table 2. Value of Akaike's criterion of the semivariogram models for apparent electrical conductivity (EC_a) at each field

Site	Field	Model	
		Spherical	Exponencial
		AIC	AIC
Huesos	H1	4859	5284
	H2	8710	9286
Fernández	F1	6716	7370
	F2	7026	7763
Claraz	C1	1467	1687
	C2	6020	6605
Quebracho	Q1	3847	4166
	Q2	5483	6120

randomly distributed. This indicates that the fields delimited in this paper are well suited for defining HMZ.

The proportion of structural variance C/(Co+C) of EC_a was high for all fields (>0.5; Fig. 4). According to the classification proposed by Cambardella et al. (1994), the spatial dependence of EC_a within each field can be considered strong, meaning that the models were primarily explained by spatial variability and not by sampling or random error (Chang et al. 1999).

Exploratory Analysis of EC_a and Soil Properties

The results from particle size analysis indicated that soils at Huesos were mostly classified as loam soils (Tables 1 and 3). The other sites were classified as clay–loam soils (Tables 1 and 3), even though there were differences among them. Fields at Fernandez showed a higher average clay content (34.51%) than Claraz and Quebracho (32.02 and 31.81%, respectively). The whole-field mean silt content ranged from 31.29 to 37.10%, and it remained relatively constant between all fields, whereas mean whole-field clay and sand ranged from 23.36 to 34.60 and 31.37 and 44.69%, respectively. The mean whole-field EC_a ranged from 12.79 to 27.42 mS m^{-1}, with whole-field CV between 17.61 and 44.49% (Table 3). The mean EC_a in the Fernandez fields ranged from 26.34 to 27.42 mS m^{-1}, which were considerably greater than in Huesos fields, where the mean EC_a ranged from 12.79 to 14.96 mS m^{-1} (Table 3). These differences in mean EC_a between Huesos and Fernadez soils are highly associated with differences in soil particle size distribution (soil texture) between Huesos and Fernadez soils. Since the conduction of electricity in soils takes place through moisture-filled pores between soil particles, soils with high clay contents generally have more continuous water-filled pores that tend to conduct electricity easily than sandier soils (Rhoades et al. 1989). Consequently, soils at Huesos, with high sand content, and commensurately low clay content, are usually more permeable with less continuous water-filled pores and lower moisture contents, which results in lower EC_a than soils at Fernandez. Soils in Claraz and Quebracho, with soil particle size intermediate to Huesos and Fernandez (Table 3), also showed an intermediate electrical conductivity (15.81 to 19.89 mS m^{-1} and 16.99 to 21.88 mS m^{-1}, respectively).

All chemical properties, except pH, showed substantial variability, with CV varying from 9.11 to 44.89% (Table 3). The narrow pH range (6.4 to 7.1) reflected the high buffering capacities of southeastern Pampas soils, resulting from their high clay and organic matter contents (Fabrizzi 1998; Melchiori 2002). Soil NO_3^--N, CEC and SOM contents had relatively high variability among all fields, with a range from 8.12 to 14.89 mg kg^{-1}, 16.07 to 34.12 cmol kg^{-1} and 3.3 to 5.1%, respectively. A high degree of variation in the soil properties related to soil productivity indicates that uniform management within the field could be inefficient.

Relationships Among EC_a and Soil Properties

Table 4 shows that any PCs with an eigenvalue greater than 1 were selected because they explained a significant amount of the variance present in the soil properties at each field. In all cases, these PCs had a cumulative variance of >75% (Table 4). The first PC (PC1) explained in all fields >50% of the total variance and it was strongly influenced by clay, θ_g, CEC and SOM. The second PC (PC2) showed a more intense relation with EC_{ext}, NO_3^--N and pH.

For all fields, the PC–stepwise regression analysis retained the PC1 (Table 5). In PC1, clay, θ_g, CEC, SOM contents had the highest positive loading factor and, in some fields, sand contents had the highest loading factor, but negative (Table 4), indicating that clay, θ_g, CEC, and SOM were positively related to EC_a and sand negatively. Low EC_a was associated with lighter-textured areas of the field where SOM, soil moisture and CEC were lower, and high EC_a was associated with soils with finer texture and high SOM, soil moisture and CEC content. Percentage clay was positively correlated with EC_a in all fields, because the clay exhibited a significant correlation with soil moisture content (r=0.54), SOM (r=0.25), CEC (r=0.57) and EC_{ext} (r=0.38). The positive relationship of EC_a with clay percentage is consistent with findings in previous studies (Johnson et al. 2001; Sudduth et al. 2003). The correlation between EC_a and SOM for all fields, can be explained because the SOM exhibited a significant correlation with soil moisture content (r=0.49), EC_{ext} (r=0.25) and CEC (r=0.45), allowing an increase in the capacity to conduct electrical current and affecting the spatial variability at field-scale EC_a (Martinez et al. 2010). Moreover, some SOM components are responsible for the formation and stabilization of soil aggregates, generating continuous pores and macropores (Lal 2004), increasing the capacity of soil electrical conductivity.

Clay contents had the highest loading factor in all models, except at Huesos (Table 5), where the moisture content had the highest loading factor (Table 4). When clay content is low, soil moisture has a greater impact on

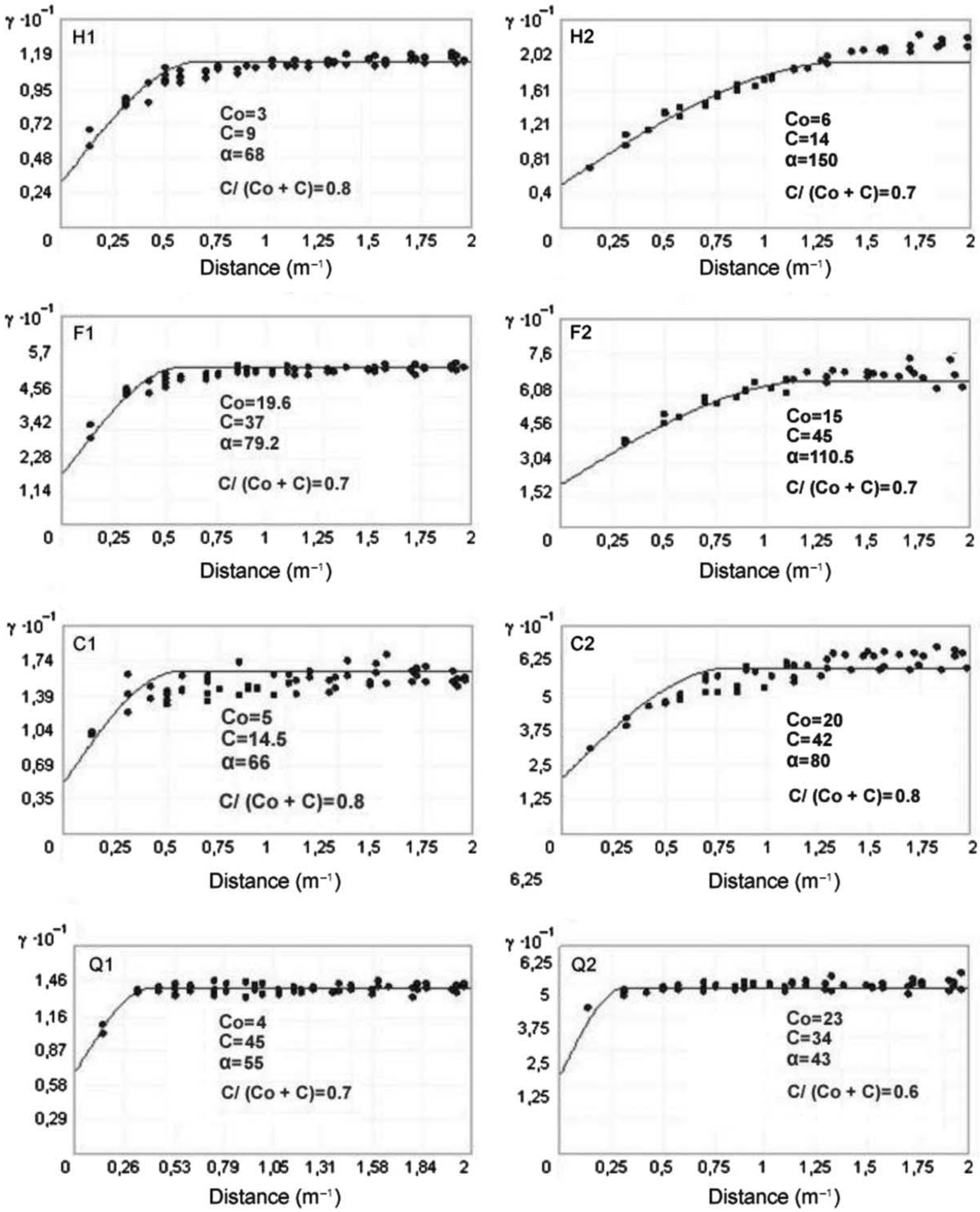

Fig. 4. Parameters of the spherical semivariogram models for apparent electrical conductivity (EC_a) at each field.

EC_a (Kachanoski et al. 1988), which may explain why soil moisture was more strongly correlated with EC_a in Huesos than in the other fields. The soils in Fernandez, Claraz and Quebracho were more clayey than in Huesos (Tables 1 and 3).

On the other hand, PC2 and PC3 showed a more intense relation with EC_{ext}, pH and NO_3^--N (Table 4). The PC2 and PC3 only were retained in the PC–regression model at F1 and F2, respectively (Table 5). In PC2, EC_{ext} and pH had the highest positive loading

Table 3. Soil physicochemical properties and apparent electrical conductivity (EC_a) at each field. Average values (mean) and coefficient of variation (CV)

	Site															
	Huesos				Fernandez				Claraz				Quebracho			
	H1		H2		F1		F2		C1		C2		Q1		Q2	
	Mean	CV (%)	Mean	CV (%)	Mean	CV (%)	Mean	CV (%)	Mean	CV (%)	Mean	CV (%)	Mean	CV (%)	Mean	CV (%)
EC_a (mS m^{-1})	14.96	21.98	12.79	25.52	26.34	22.31	27.42	25.23	15.81	44.49	19.89	17.61	16.99	35.78	21.88	26.84
Clay (%)	23.02	16.45	23.36	20.05	34.6	28.09	34.4	12.91	31.72	8.42	32.42	11.41	31.58	13.08	32.03	8.08
Silt (%)	32.29	16.96	35.03	11.17	32.3	12.68	32.62	16.83	36.91	11.84	37.1	17.13	31.09	4.22	31.51	11.8
Sand (%)	44.69	20.33	41.61	25.2	33.1	21.96	32.98	21.75	31.37	20.53	30.48	23.27	37.33	9.95	36.46	11.61
θ_g^z (g g^{-1})	0.22	11.25	0.23	11.88	0.28	10.66	0.3	9.11	0.23	24.5	0.26	10.96	0.26	12.31	0.26	12.49
SOM^z (%)	4.04	16.35	4.05	26.87	4.69	21.12	5.02	27.86	4.36	30.06	4.79	31.07	4.5	25.6	4.45	17.43
CEC^z (cmol kg^{-1})	24.27	17.45	19.28	12.75	29.75	16.36	32.61	15.19	24.25	21.12	21.89	10.57	26.48	14.31	23.3	13.82
EC_{ext}^z (dS m^{-1})	0.18	22	0.19	29.84	0.36	35.76	0.48	28.92	0.22	24.41	0.26	34.17	0.25	28.51	0.26	33.7
pH	6.42	4	6.65	6.2	7.18	7.27	7.21	3.91	6.68	4.62	6.9	9.6	7.01	5.2	6.85	4.48
NO_3^--N (mg kg^{-1})	11.79	29	9.09	35.99	12.67	28.12	9.85	44.89	12.46	32.61	7.8	35.74	7.56	36.54	7.92	28.78

$^z\theta_g$, soil moisture content; SOM, soil organic matter; CEC, cation exchange capacity; EC_{ext}, laboratory measured electrical conductivity using water saturated paste.

factor, while in PC3 only EC_{ext} (Table 4), indicating that EC_{ext} and pH were positively related to EC_a, possibly by the presence of $CaCO_3$ in some parts of the fields. The EC_{ext} of a soil with $COCa_3$ would be 0.5 dS m^{-1} (Shainberg et al. 1981). As this salt has the capacity to increase EC_{ext} and pH, it can affect the EC_a measurement (Kühn et al. 2009). On the other hand, EC_{ext} and pH showed a weak or inconsistent correlation with CE_a at Huesos, Quebracho y Claraz because both properties showed little variation (Johnson et al. 2001; Mueller et al. 2003). In similar soils of the southeastern Pampas irrigated with water containing significant amounts of soluble salts, the spatial variability of EC_{ext} is the main soil factor affecting EC_a measurement (Bosch Mayol 2009).

The PCs that were related to the NO_3^--N concentration were removed by PC–stepwise models (Table 5). This indicates that NO_3^--N levels are not related to variability in EC_a, in these fields at the time of sample collection. The available N levels were not related to variability of soil conditions, probably because anions other than inorganic N dominated the measured EC_a (Johnson et al. 2001). Zhang and Wienhold (2002) found a very strong correlation between EC_a and NO_3^--N contents working in fields with higher concentrations and variations of NO_3^--N.

Identification of regression models that were able to account for a large portion (50%) of the variability in soil EC_a would indicate situations where EC_a could be used successfully to measure soil properties (Heiniger et al. 2003). As can be seen, the relationship between EC_a and soil properties varied between fields and sites, showing strong associations with clay, SOM, CEC, soil moisture content and weak associations with EC_{ext}, pH and NO_3^--N content.

Delineation of Potential Management Zones

While the PCA revealed which soil properties explained the major total variance and the PC–stepwise regression determined which soil properties were more associated with EC_a, neither of these two techniques can determine significant differences among EC_a classes. Therefore, to assess whether EC_a can be used to determine homogeneous management zones a mixed ANOVA model was fitted. The texture, soil moisture content, CEC and EC_{ext} exhibited interaction between sites and EC_a class; for this reason the behaviour of these variables was analysed at each site (Table 7). In contrast, the SOM content, pH and NO_3^--N content did not exhibit interaction between sites and EC_a classes (Table 8), in other words, they behaved similarly for all sites. The clay, θ_g, CEC, and SOM contents had greater significant differences among EC_a classes at each site (Tables 7 and 8), which is consistent with the results of PCA. These soil properties were considered key latent variables (loading factors >0.4) because they substantially influence the relationship between the PC1 and the EC_a (Table 5). The Fernandez and Huesos sites

Table 4. Key principal components (PCs) (eigenvalues > 1.0), cumulative variance and loading factors for each soil property

					Parameter								
Site	Field	Key PCs	Eigenvalue	Cumulative σ^2	Clay	Silt	Sand	θ_g^z	SOM[z]	CEC[z]	EC_{ext}^z	pH	NO_3^--N
	H1	PC1	5.03	0.56	0.42	0.26	−0.42	0.48	0.45	0.43	0.30	0.36	0.14
Huesos		PC2	1.81	0.76	−0.38	0.53	−0.20	0.05	−0.27	0.02	−0.41	0.06	0.54
	H2	PC1	4.31	0.50	0.43	0.34	−0.41	0.51	0.46	0.43	0.17	0.21	0.29
		PC2	2.42	0.79	−0.10	−0.31	0.29	−0.36	0.00	0.13	0.42	0.52	0.46
	F1	PC1	4.52	0.52	0.54	0.27	−0.41	0.44	0.43	0.49	0.18	0.13	0.11
Fernandez		PC2	1.72	0.69	0.01	0.21	0.24	0.04	0.11	0.31	0.21	0.47	0.28
		PC3	1.33	0.84	−0.22	0.29	−0.07	−0.10	−0.27	−0.18	0.69	0.29	0.24
	F2	PC1	3.44	0.50	0.53	0.25	−0.38	0.42	0.45	0.43	0.03	−0.05	0.01
		PC2	2.34	0.68	0.04	−0.26	0.34	0.34	0.09	0.20	0.50	0.48	0.18
		PC3	1.44	0.86	−0.03	−0.27	0.22	−0.18	0.38	0.10	−0.20	−0.43	0.69
Claraz	C1	PC1	4.08	0.59	0.50	0.02	−0.23	0.42	0.42	0.42	0.39	0.38	0.14
		PC2	2.01	0.76	−0.01	0.63	−0.58	0.04	−0.25	−0.03	−0.12	0.15	−0.23
	C2	PC1	4.76	0.53	−0.48	−0.25	0.43	−0.42	−0.38	−0.46	−0.33	−0.30	−0.17
		PC2	1.48	0.69	−0.45	0.32	0.12	−0.05	0.04	−0.36	0.09	0.29	0.67
		PC3	1.27	0.83	−0.48	0.62	−0.09	0.20	0.07	0.14	−0.10	−0.45	−0.31
	Q1	PC1	4.64	0.56	0.46	0.34	−0.34	0.40	0.25	0.45	0.28	0.18	0.27
Quebracho		PC2	1.55	0.76	−0.16	−0.12	0.17	−0.21	−0.54	0.00	0.51	0.47	0.46
	Q2	PC1	3.85	0.50	0.45	−0.06	−0.18	0.42	0.41	0.42	0.33	0.36	0.23
		PC2	1.87	0.64	−0.23	0.72	−0.61	−0.01	0.05	0.02	0.13	−0.18	0.09
		PC3	1.46	0.80	−0.46	0.01	0.35	−0.30	0.21	−0.07	0.39	0.13	0.60

[z] θ_g, soil moisture content; SOM, soil organic matter; CEC, cation exchange capacity; EC_{ext}, laboratory measured electrical conductivity using water saturated paste.

Table 5. Regression model resulting from the principal component (PC)–stepwise regression analysis of the relationship between apparent electrical conductivity (EC_a) and soil properties

Site	Field	Regression model	R^2	Partial R^2 PC1	Partial R^2 PC2	Partial R^2 PC3	Soil properties (loading factors >0.4) (listed in order of importence)[z]
Huesos	H1	13.78+1.66 PC1	0.61	0.61			θ_g, SOM, Clay, Sand, CEC
	H2	19.82+1.58 PC1	0.62	0.62			θ_g, SOM, Clay, CEC, Sand
Fernandez	F1	21.16+3.49 PC1+1.04 PC3	0.92	0.9		0.02	Clay, CEC, θ_g, SOM, Sand, ECext
	F2	29.57+2.19 PC1+1.3 PC2	0.72	0.58	0.14		Clay, SOM,CEC, θ_g, ECext, pH
Claraz	C1	26.37+2.16PC1	0.59	0.59			Clay, CEC, θ_g, SOM
	C2	25.67 −2.69 PC1	0.78	0.78			Clay, CEC, θ_g, Sand
Quebracho	Q1	19.91+2.73 PC1	0.81	0.81			Clay, CEC, θ_g, SOM
	Q2	16.78+2.75 PC1	0.64	0.64			Clay, CEC, θ_g, SOM

[z]θ_g, soil moisture content; SOM, soil organic matter; CEC, cation exchange capacity; EC_{ext}, laboratory measured electrical conductivity using water saturated paste.

showed significant differences in clay content in three EC_a classes (Table 7), probably because of the higher CV exhibited in the soil series from each place (20.5 and 18.2%, respectively) (Table 3). In contrast, Claraz and Quebracho showed significant differences only among two EC_a classes for lower CV (9.9 and 10.6%, respectively). The sand content also showed differences among EC_a classes for each site, especially at Huesos, where the sand content explained much of the variation of CP1. The silt content at Fernandez did not differed significantly among different EC_a classes, most likely due to a narrow range of silt content (from 31.23 to 32.20%) in the soil profile (Table 7). This is consistent with the results of PCA, where the silt content had loading factors <0.4, without substantially influencing the EC_a variation in all PC–stepwise models (Table 5). Overall, these results support previous studies that have reported that soil EC_a is influenced by the clay and sand content of the soil, which reflect the water-holding capacity of the soil (Kitchen et al. 2003).

The soil moisture content differed significantly among different EC_a classes at each site (Table 7). At Fernandez and Huesos, significant differences in moisture content were only found in two EC_a classes (Table 7), possibly because of the low CV exhibited at these two sites, 9.9 and 10.5%, respectively (Table 3). At Claraz and Quebracho the CV was higher at 17.1 and 15.4%, respectively (Table 3), with significant differences found among three EC_a classes (Table 7). The soil moisture content (dynamic soil property) affects only the magnitude of measured EC_a, not spatial patterns within a field (Sudduth et al. 2001), because it was strongly associated with stable soil properties, such as clay content and SOM (Table 6). Therefore, the areas with higher clay and SOM contents showed the highest moisture content, and areas with lower clay and SOM content showed the lowest moisture content (Veris Technologies 2001; Sudduth et al. 2003).

The CEC and SOM content showed significant differences in three EC_a classes in all sites (Tables 7 and 8). The delimitation of areas with different content of CEC and SOM are very important for site-specific management in the soils of southeastern Pampas because CEC affects crop growth and development (Groenigen et al. 2000) and SOM contributes to soil fertility and productivity through control of its physical, chemical and biological properties. Also, SOM has an important role in the water-holding capacity of the soil (Gregorich et al. 1994; Shaner et al. 2008).

Table 6. Correlations between soil properties across fields

Soil properties	Clay	Silt	Sand	θ_g	SOM	CEC	EC_{ext}	pH	NO_3^--N
	Pearson correlation coefficients (r)								
Clay	1								
Silt	NS	1							
Sand	−0.61**	0.21*	1						
θ_g^z	0.54**	0.22*	−0.38**	1					
SOM[z]	0.25*	0.21*	NS	0.49**	1				
CEC[z]	0.57**	NS	−0.39**	0.67**	0.45**	1			
EC_{ext}^z	0.38**	NS	NS	0.39**	0.25*	0.24*	1		
pH	0.28*	0.20*	NS	0.32**	0.27*	0.40**	0.53**	1	
NO_3^-	NS	NS	−0.22*	0.16*	0.32*	0.33*	0.27*	NS	1

[z]θ_g, soil moisture content; SOM, soil organic matter; CEC, cation exchange capacity; EC_{ext}, laboratory measured of electrical conductivity using water saturated paste.
*, ** Significant at the $\alpha = 0.05$ and 0.01 error level, respectively; NS, not significant.

Table 7. Soil properties means within four classes means of apparent electrical conductivity (EC_a) at each field

Site	EC_a class	Clay (%)	Silt (%)	Sand (%)	θ_g^z (g g^{-1})	CEC^z (cmol kg^{-1})	EC_{ext}^z (dS m^{-1})
Huesos	Low	21.69*c*	29.82*c*	48.49*a*	0.20*b*	18.02*c*	0.21*b*
	Medium-low	25.78*b*	33.83*b*c	40.90*b*	0.22*a*	21.67*b*	0.21*b*
	Medium-high	24.89*b*	36.77*b*	38.33*bc*	0.23*a*	22.08*b*	0.22*b*
	High	29.62*a*	37.41*a*	32.76*c*	0.24*a*	26.33*a*	0.33*a*
Fernandez	Low	29.60*c*	31.23*a*	39.99*a*	0.24*b*	21.93*c*	0.17*c*
	Medium-low	33.22*b*	32.39*a*	36.00*b*	0.26*b*	29.41*b*	0.36*b*
	Medium-high	34.96*b*	32.27*a*	29.83*c*	0.29*a*	32.61*a*	0.45*a*
	High	38.27*a*	32.20*a*	30.58*c*	0.30*a*	33.92*a*	0.51*a*
Claraz	Low	30.29*b*	28.14*b*	33.03*a*	0.17*c*	16.68*c*	0.21*b*
	Medium-low	31.24*b*	28.12*b*	31.47*a*	0.25*b*	22.59*b*	0.23*b*
	Medium-high	33.93*a*	27.13*b*	31.18*a*	0.25*b*	24.23*b*	0.20*b*
	High	33.83*a*	33.73*a*	27.13*b*	0.29*a*	26.67*a*	0.28*a*
Quebracho	Low	27.26*b*	27.89*b*	40.83*a*	0.23*c*	21.67*c*	0.21*b*
	Medium-low	28.24*b*	26.01*b*	41.79*ab*	0.25*bc*	22.47*c*	0.25*b*
	Medium-high	32.48*a*	28.06*b*	39.46*b*	0.26*b*	25.05*b*	0.24*b*
	High	31.40*a*	31.93*a*	36.65*b*	0.28*a*	29.00*a*	0.32*a*

a–c The same letters indicate no significant differences ($P \leq 0.05$) for each site.
[z]θ_g, soil moisture content; CEC, cation exchange capacity; EC_{ext}, laboratory measured of electrical conductivity using water saturated paste.

The soil properties with low loading factors (EC_{ext}, NO_3^--N contents) showed less-significant differences among EC_a classes at each site. The NO_3^--N content and EC_{ext} differed significantly only in the EC_a high class for all sites (Table 8), except at Fernandez, where the EC_{ext} exhibited differences in three classes. Only at Fernandez did the EC_{ext} have loading factors > 0.4 in the PC2, which explained the variation of EC_a in the PC–stepwise model (Table 5). These soil properties were not considered key latent variables because they did not substantially influence the relationship between the PC groups and the EC_a. The small difference in average NO_3^--N content and EC_{ext} in different EC_a classes suggests that geo-referenced EC_a measurement is weakly influenced by these soil properties. The NO_3^--N content showed low significant differences among EC_a classes, possibly because nitrogen transformations in soil are controlled by soil water content, biological activity, cropping, composition and quantity of organic matter (Stevenson 1982). These soil characteristics impact on the processes of volatilization, nitrification, immobilization, and leaching (losses) or mineralization (gains) that define NO_3^--N levels in soil (Stevenson 1982). On the other hand, the pH exhibited significant differences in three EC_a classes (Table 8). The pH was not considered a key latent variable, except at Fernadez where the pH had loading factors > 0.4 in the PC2, contributing strongly to explaining the variation of EC_a in the PC–stepwise model (Table 5).

Table 8. Soil properties means within four classes means of apparent electrical conductivity (EC_a) at each field

EC_a class	SOM^z (%)	pH	NO_3^--N (mg kg^{-1})
Low	3.37*c*	6.40*c*	8.71*b*
Medium-low	3.88*b*	6.88*b*	9.10*b*
Medium-high	3.99*b*	6.84*b*	9.28*b*
High	5.02*a*	7.06*a*	12.49*a*

[z]SOM, soil organic matter.
a–c The same letters indicate no significant differences ($P \leq 0.05$).

The results of this study indicate that for all fields, the PC–stepwise regression analysis was able to account for > 50% of the variability in EC_a. Clay content was one of the key loading factors. Principal component groups consisting of clay, SOM, soil moisture and CEC were able to consistently account for spatial variability of EC_a. In contrast, other measured soil properties (EC_{ext}, pH values and NO_3^--N content) were not able to explain the EC_a. This study shows that EC_a can be a valuble tool when used in conjunction with multivariate statistical procedures in identifying soil properties.

Zones derived from EC_a showed a potential to delimit distinct within-field soil condition areas, but the significance of differences among the EC_a zones varied depending on soil properties. Geo-referenced EC_a measurements successfully delimited three homogeneous soil zones associated with spatial distribution of clay, soil moisture, CEC, SOM content and pH. On the other hand, the NO_3^--N content and the EC_{ext} had low values, and minor differences between the different EC_a classes, so it would not be advisable to delimit management zones based on these two properties in the soils of the southeastern Pampas.

Considering that clay, CEC, SOM content and pH values are relatively static over time (Shaner et al. 2008) and influence soil fertility, these results suggest that EC_a field-scale maps in areas with Typic Argiudoll and Petrocalcic Paleudoll soils can delimit three zones which are homogeneous enough to serve as meaningful zones for management and sampling purposes, without sacrificing soil spatial variability information. This study also shows that there is a high spatial dependence of EC_a in each field, creating zones that are large enough to enable implementation of differential management practices.

The first step necessary to implement precision farming in the studied fields is the identification of the three management zones. In the following years, a variable-rate application of inputs will be carried out, providing environmental and economic benefits by decreasing fertilization in the less-productive areas (low EC_a) and minimizing the application of chemical substances as a strategy to obtain more cost-effective field management, including less use of agricultural machinery. Further studies will be conducted to evaluate these subfield management zones, using yield maps to better understand the agronomic significance of this classification.

ACKNOWLEDGEMENTS

We thank the farmers, Agricultural Engineer Tomas Gowland, Agricultural Engineer Nicolas Tagle, Agricultural Engineer Hernán Moreno and Alberto Pereira Iraola, for their help in gathering the data on the fields where the study was conducted. The experiment was conducted with funding from the INTA Project, AEAI3722. The present work is part of a thesis submitted by Nahuel Peralta towards fulfilling the requirement of the Doctoral degree in Agricultural Science, for the Postgraduate Program of Balcarce Integrated Unit (INTA-UNMdP).

Akaike, H. 1973. Information theory and an extension of the maximum likelihood principle. Pages 267–281 *in* B. N. Petrov and F. Csaki, eds. Second international symposium on information theory. Academiai Kiado, Budapest, Hungary.

Alvarez, R. and Lavado, R. S. 1998. Climate, organic matter and clay content relationships in the Pampa and Chaco soils, Argentine. Geoderma **83**: 127–141.

Barbieri, P., Echeverría, H. and Sainz Rozas, H. 2009. Nitrates in soil at planting or tillering as a diagnostic of the nitrogenated nutrition in wheat in the Southeastern Pampas. Soil Sci. **27**: 41–47.

Bekele, A., Hudnall, W. H., Daigle, J. J., Prudente, J. A. and Wolcott, M. 2005. Scale dependent variability of soil electrical conductivity by indirect measures of soil properties. J. Terramechanics **42**: 339–351.

Blanco, M. and Stoops, G. 2007. Genesis of pedons with discontinuous argillic horizons in the Holocene loess mantle of the southern Pampa landscape, Argentina. J. S. Am. Earth Sci. **23**: 30–45.

Bosch Mayol, M. 2009. Relación entre la variabilidad espacial de la Conductividad Eléctrica y el contenido de sodio del suelo. Tesis de graduación. Universidad Nacional de Mar del Plata, Facultad de Ciencias Agrarias, Balcarce, Argentina.

Bremner, J. M. 1965. Inorganic forms of nitrogen. Pages 1179–1237 *in* C. A. Black, ed. Methods of soil analysis. Part 2. Agronomy Monogr. no. 9. ASA, Madison, WI.

Bullock, D. S., Kitchen, N. and Bullock, D. G. 2007. Multidisciplinary teams: A necessity for research in precision agriculture systems. Crop Sci. **47**: 1765–1769.

Cambardella, C. A., Moorman, T. B., Novak, J. M., Parkin, T. B., Karlen, R. F. and Konopka, A. E. 1994. Field scale variability in central Iowa soils. Soil Sci. Soc. Am. J. **58**: 1501–1511.

Chang, J., Clay, D. E., Carlson, C. G., Malo, D. and Clay, S. 1999. Precision farming protocols: Part 1. Grid distance and soil nutrient impact on the reproducibility of spatial variability measurements. Precis. Agric. **1**: 227–289.

Chapman, H. D. 1965. Cation-exchange capacity. Pages 891–901 *in* C. A. Black, ed. Methods of soil analysis. Part 2. Agronomy Monogr. no. 9. ASA, Madison, WI.

Cohen, W. B. 1994. GIS applications perspective: current research on remote sensing of forest structure. Pages 91–107 *in* V. A. Sample. Remote sensing and GIS in ecosystem management. Island and Press, Washington, DC.

Corwin, D. L. and Lesch, S. M. 2003. Application of soil electrical conductivity to precision agriculture: theory, principles and quidelines. Agron. J. **95**: 455–471.

Corwin, D. L., Loague, K. and Ellsworth, T. R. 1999. Assessing non-point source pollution in the vadose zone with advanced information technologies. Pages 1–20 *in* D. L. Corwin, K. Loague, and T. R. Ellsworth, eds. Assessing non-point source pollution in the Vadose Zone. Geophysical Monographs 108, AGU, Washington, DC.

Fabrizzi, K. 1998. Long-term effects of nitrogen and phosphate fertilization on the chemical properties of soil. Graduation thesis. National University of Mar del Plata, School of Agricultural Sciences, Balcarce, Argentina.

Farahani, H. J. and Flynn, R. L. 2007. Map quality and zone delineation as affected by width of parallel swaths of mobile agricultural sensors. Precis. Agric. **96**: 151–159.

Fleming, K. L., Westfall, D. G. and Brodah, M. C. 2000. Evaluating farmer developed management zone maps for variable rate fertilizer application. Precis. Agric. **2**: 201–215.

Gregorich, E. G., Carter, M. R., Angers, D. A. and Ellert, B. H. 1994. Towards a minimum data set to assess soil organic matter quality in agricultural soil. Can. J. Soil Sci. **74**: 367–385.

Groenigen, J. W., Gandah, M. and Bouma, J. 2000. Soil sampling strategies for precision agriculture research under sahelian conditions. Soil Sci. Soc. Am. J. **64**: 1674–1680.

Heiniger, R. W., McBride, R. G. and Clay, D. E. 2003. Using soil electrical conductivity to improve nutrient management. Agron. J. **95**: 508–519.

Imbellone, P. and Teruggi, M. 1993. Paleosols on loess deposits of the Argentine pampas. Quatern. Int. **17**: 49–55.

Instituto Nacional de Tecnología Agropecuaria. 1970. CIRN. Soil Institute. File - "3760–35 "Claraz"", PBA, Castelar: Soil Institute AICET. 1970. 72 p; 4 map photo; scale 1:50.000.

Instituto Nacional de Tecnología Agropecuaria. 1989. CIRN. Soil Institute. File - "3760–22 "Chillar"", PBA, Castelar: Soil Institute AICET. 1989. 50 pp; 4 map photo; scale 1:50.000.

Isaaks, E. H. and Srivastava, R. M. 1989. An introduction to applied geostatistics. Oxford University Press, New York, NY. 561 pp.

Johnson, C. K., Doran, J. W., Wienhold, B. J. and Shanahan, J. F. 2001. Field-scale electrical conductivity mapping for delineating soil condition. Soil Sci. Soc. Am. J. **65**: 1829–1837.

Kachanoski, R. G., Gregorich, E. G. and Van Wesenbeeck, I. J. 1988. Estimating spatial variations of soil water content using noncontacting electromagnetic inductive methods. Can. J. Soil Sci. **68**: 715–722.

Kaffka, S. R., Lesch, S. M., Bali, K. M. and Corwin, D. L. 2005. Site-specific management in salt-affected sugar beet fields using electromagnetic induction. Comp. Elect. Agric. **46**: 329–350.

Kitchen, N. R., Drummond, S. T., Lund, E. D. and Sudduth, K. A. 2003. Soil electrical conductivity and topography related to yield for three contrasting soil-crop systems. Agron. J. **95**: 483–495.

Kühn, J., Brenning, A., Wehrhan, M., Koszinski, S. and Sommer, M. 2009. Interpretation of electrical conductivity patterns by soil properties and geological maps for precision agriculture. Precis. Agric. **10**: 490–507.

Lal, R. 2004. Soil carbon sequestration impacts on global change and food security. Science **304**: 1623–1627.

Ministry of Agriculture, Fishing and Food. 1986. Official analysis methods (soils). Ministry of Agriculture, Fishing and Food, Madrid, Spain.

Martínez, G., Vanderlinden, K., Giráldez, J. V., Espejo, A. J. and Muriel, J. L. 2010. Field-scale soil moisture pattern mapping using electromagnetic induction. Vadose Zone J. **9**: 871–881.

Melchiori. 2002. Spatial variability of wheat yield, association with edaphic parameters and assessment of application of nitrogen for specific sites. Thesis for Master of Science degree. National University of Mar del Plata, Balcarce, Argentina.

Moral, F. J., Terrón, J. M. and Marques da Silva, J. R. 2010. Delineation of management zones using mobile measurements of soil apparent electrical conductivity and multivariate geostatistical techniques. Soil Tillage Res. **106**: 335–343.

Mueller, T. G., Hartsock, N. J., Stombaugh, T. S., Shearer, S. A. and Barnhisel, R. I. 2003. Soil electrical conductivity map variability in limestone soil overlain by loess. Agron. J. **95**: 496–507.

Muñoz, J. D., Martinez, L. J. and Giraldo, R. 2006. Spatial variability of edaphic properties and their relationship to the yield of a potato crop (*Solanum tuberosum* L.). Columbian Agron. **24**: 1–16.

Pazos, M. S. and Mestelan, S. A. 2002. Variability of depth to tosca in Udolls and soil classification, Buenos Aires Province, Argentina. Soil Sci. Soc. Am. J. **66**: 1256–1264.

Pye, K. 1987. Aeolian dust and dust deposits. Academic Press, London, UK. 334 pp.

Rhoades, J. D., Manteghi, N. A., Shouse, P. J. and Alves, W. J. 1989. Soil electrical conductivity and soil salinity: New formulations and calibrations. Soil Sci. Soc. Am. J. **53**: 433–439.

SAS Institute, Inc. 2002. SAS user's guide. SAS Institute, Inc., Cary, NC.

Satorre, E. H. and Slafer, G. A. 1999. Wheat production systems of the Pampas. Pages 333–348 *in* E. M. Satorre and G. A. Slafer, eds. Wheat ecology and physiology of yield determination. The Haworth Press Inc., New York, NY.

Shainberg, I., Rhoades, J. D. and Prather, R. J. 1981. Effect of low electrolyte concentration on clay dispersion and hydraulic conductivity of a sodic soil. Soil Sci. Soc. Am. J. **45**: 273–277.

Shaner, D. L., Brodahl, M. K. and Buchleiter, G. W. 2008. How well does zone sampling based on soil electrical conductivity maps represent soil variability? Agron. J. **100**: 1472–1480.

Soil Conservation Service. 1972. Soil survey laboratory. Methods and procedures for collecting soil samples. Soil Survey Report 1. USDA, Washington, DC.

Stevenson, F. J. 1982. Origin and distribution of nitrogen in soil. Pages 1–42 *in* F. J. Stevenson, ed. Nitrogen in agricultural soils. Agron. Monogr. 22. ASA, CSSA, and SSSA, Madison, WI.

Sudduth, K. A., Drummond, S. T. and Kitchen, N. R. 2001. Accuracy issues in electromagnetic induction sensing of soil electrical conductivity for precision agriculture. Comp. Elect. Agric. **31**: 239–264.

Sudduth, K. A., Kitchen, N. R., Bollero, G. A., Bullock, D. G. and Wiebold, W. J. 2003. Comparison of electromagnetic induction and direct sensing of soil electrical conductivity. Agron. J. **95**: 472–482.

Suero, E. E., Santa Cruz, J. N., Busso, A. S., Della Maggiora, A. I., Irigoyen, A. I., Costa, J. L. and Gardiol, J. M. 1990. Characterization of natural resources in low-watering systems of the Southeastern Pampas. RIA **30**: 71–90.

Teruggi, G. 1957. The nature and origin of the Argentinian loess. J. Sediment. Petrol. **27**: 322–332.

Veris Technologies. 2001. Frequently asked questions about soil electrical conductivity. [Online] Available: http://www.veristech.com [2011 Oct. 15].

Walkley, A. and Black, I. A. 1934. An examination of Degtjareff method for determining soil organic matter and a proposed modification of the chromic acid titration method. Soil Sci. **3**: 29–37.

Webster, R. 1985. Quantitative spatial analysis of soil in the field. Adv. Soil Sci. **3**: 1–70.

Zhang, R. and Wienhold, B. J. 2002. The effect of soil moisture on mineral nitrogen, soil electrical conductivity and pH. Nutr. Cycl. Agroecosyst. **63**: 251–254.