Precision Agriculture (2019) 20:1000–1014
https://doi.org/10.1007/s11119-018-09631-9

Using low-cost geophysical survey to map soil properties and delineate management zones on grazed permanent pastures

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Published online: 5 January 2019

Abstract

Usually, soils utilised for livestock production have similar high spatial variability as those for agricultural or forest use. As a consequence, it is necessary to determine the spatial patterns of the main soil properties as the first stage to implement site-specific management. However, this has to be performed using an inexpensive technique because the profitability in these types of farm are very low, so owners need a cheap, effective, and reliable method to know which zones have similar production potential. Using soil apparent electrical conductivity (ECa) measurements, obtained with a contact sensor at many locations, as the basis to perform a directed soil sampling, 10 samples were taken at two depths (0–0.25 m and 0.25–0.50 m) in a 2.3 ha field in Évora (southern Portugal). Firstly, relationships between ECa and many soil properties were analysed using regression analysis. Six soil properties (clay, silt, fine sand, soil moisture content, pH, and cation exchange capacity) were significantly correlated with ECa. Consequently, spatial distributions of these variables were visualised using map algebra techniques. Later, a fuzzy clustering algorithm was utilised to delineate management zones, resulting in two subfields to be managed separately. Finally, a principal component analysis was conducted to analyse the influence of the soil properties and elevation on the soil variability. It was determined that elevation and clay were the most important contributing properties. Therefore, these can be regarded as key latent variables in this soil. Results showed that low-cost data based on ECa surveys can be used to implement site-specific management in soils with permanent pastures, such as those in the montado or dehesa ecosystems, in the southwest of the Iberian Peninsula.

Keywords Site-specific management · Contact sensor · Soil apparent electrical conductivity · Principal component analysis

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Introduction

The spatial variability of soil properties across a field has to be determined when potential benefits of adopting site-specific crop management (SSCM) are evaluated (e.g. Bullock et al. 2009). Soil sampling of the field and laboratory work are necessary to obtain the raw information to map the main soil properties. However, at the farming scale, this task is labour intensive, expensive and time consuming, as traditional techniques require many samples to be taken and analysed. Consequently, quicker and cheaper methods for measuring variability of soil properties are needed. Soil apparent electrical conductivity (ECa) is a property which can be intensively measured in an inexpensive and easy way; in fact, it has been used in many previous studies to characterise within-field variability of some soil properties in agricultural fields and delimit homogeneous zones, often referred to as management zones (MZs), which are subfields of similar production potential (e.g. Moral et al. 2010; Peralta et al. 2015).

Electrical conductivity sensors can be divided into two types. The first one uses electrodes, usually in the shape of coulters that make contact with the soil to measure ECa. Veris sensor systems are the contact type of electrical conductivity measuring device (e.g. Moral et al. 2010). Alternatively, other sensors are based on the principle of electromagnetic induction, and they do not contact the soil directly. One popular model of these non-contact sensors is the DUALEM system (e.g. Serrano et al. 2014).

For the last two decandes, ECa has been considered an efficient ground-based sensing technology for SSCM (Corwin and Lesch 2003). It can be used to delimit MZ (e.g. Peralta et al. 2015) or to estimate several soil properties and their spatial patterns, such as soil texture (Moral et al. 2010), soil moisture (Fortes et al. 2015), cation exchange capacity (CEC; Kitchen et al. 2000), and soil organic matter (OM; Corwin and Lesch 2005). However, the fact that ECa depends on many soil properties, over different spatial scales (e.g. Saey et al. 2013; Stadler et al. 2015), and in a complex way, has given place to inconsistent relationships between ECa and other soil variables (e.g. Sudduth et al. 2005). Moreover, when there are few soil samples, modelling the relationships between primary soil variables and ECa is not an easy task.

Although sampling is often done at points with a previous basic design, sometimes, the results are no less accurate than those obtained from a stratified sampling technique (Marchant et al. 2012). The variation of the soil properties across a field cannot be properly determined at a low resolution from composite soil samples. To properly map a soil property, multiple soil samples have to be taken within the field, the sampling location recorded, and each sample analysed separately (e.g. Fu et al. 2013). Often those soil samples are taken on a grid, but they might be allocated according to MZs or other prior knowledge of the spatial pattern of the soils. One example of a situation in which soil property mapping is essential is variable rate application of fertiliser. Later, using a geostatistical method, one can obtain accurate estimates and map the soil property, but kriging needs a minimum number of measurements to estimate the variogram (or covariance function) for the studied variable, which could be around 100 (Goovaerts 1997). However, the measurement of any soil property using many laboratory samples is expensive and the money saved by locally varying the application of the fertiliser or other inputs to match the requirements of the crop or the pasture can be less than the cost of sampling and measurement.

There are many studies in which the efficacy of alternative and reduced-cost soil sampling strategies suitable for mapping and site-specific management has been analysed. Thus, for instance, Nanni et al. (2011), Hu et al. (2015), and Muhammed et al. (2017)

utilised different sampling approaches and assessed their efficacy to describe the spatial patterns of some nutrients and other soil properties with the aim of establishing a variable-rate fertilisation. De Bruyn and Andrews (2016) and Loescher et al. (2014) analysed sampling strategies for the management and improvement of soil health. Moreover, the use of different sensors has been proposed to optimise the soil sampling and improve the mapping of different soil properties (e.g. Shaner et al. 2008; Wetterlind et al. 2008; Fortes et al. 2015). Additionally, different sampling designs and algorithms have been applied to improve digital soil maps and calibrate spatial models (e.g. Stumpf et al. 2017; Biswas and Zhang 2018; An et al. 2018). However, similar studies performed in soil used for livestock production are scarce and those found in the scientific literature (e.g. Shi et al. 2000; McCormick et al. 2009) were performed in ecosystems very different from those existing in the south of the Iberian Peninsula.

Sampling along transects placed strategically across a field could be an essential source of information to examine the spatial patterns of soil properties. Nevertheless, ancillary data have to be used to determine the most appropriate direction to sample along a transect which takes into account the maximum spatial variability throughout the field.

Although studies in agricultural fields devoted to analyse different techniques to define MZ are numerous (e.g., Shaddad et al. 2016; Gavioli et al. 2016; Fortes et al. 2015), there has been little research in pasture systems (Trotter et al. 2014), and, particularly, there are no studies in the Mediterranean evergreen oak woodlands (called montados in Portugal or dehesas in Spain). However, the appropriate management of this ecosystem requires the identification of areas with similar permanent characteristics (Schellberg et al. 2008), which can help farmers in making important decisions such as the planning of grazing and variable fertilisation.

In this context, the general objective of this study was to determine if ECa could be used to guide MZ delineation in montados or dehesas used for livestock grazing. The specific objectives were to: (1) determine which soil characteristics are most closely correlated with ECa in these soils, and (2) identify the principle sources of variation in defining the MZs. The hypotheses to be tested are: (1) based on ECa in other soils, the main determinate of ECa in montados or dehesas is soil moisture content (SMC), and (2) the principal sources of variation driving MZ delineation are clay content and elevation. Thus, this study contributes to scientific knowledge by showing how reduced-cost sampling strategies for mapping can be used for attaining a site-specific management of pasture fields.

Materials and methods

Experimental field

This research was conducted at a farm called Mitra (38°32.2′ N, 8°1.1′ W), located in the proximity of Valverde, 10 km southwest from Évora (southern Portugal). The area of study is 2.3 ha and an overview of the boundary of the site is given in Fig. 1. Some previous studies have been performed in this field (Sales-Baptista et al. 2016; Serrano et al. 2017, 2018).

The climate of this area is Mediterranean, modified by the interior location and by oceanic influences from the Atlantic. According to the Köppen–Geiger classification, it is a climate type Csa (Peel et al. 2007). It is characterised by dry and hot summers, mild winters, and variable intraannual rainfall. The monthly average temperature is between 8 and 26 °C. Minimum temperatures are close to 0 °C between December and February, and

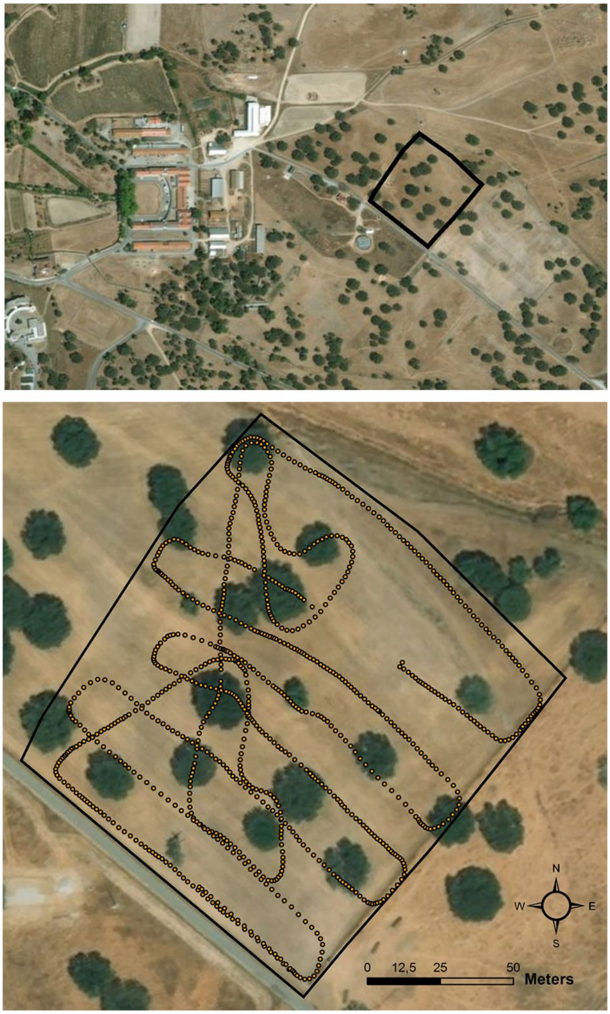

Fig. 1 Study site. Map of the area in which the experimental field is located (above) and overview of the boundary of the site (below) with the transects of the measurements of soil apparent electrical conductivity

maximum occasionally reaches more than 40 °C in summer. The annual rainfall is between 400 and 600 mm. However, one of the most important characteristics of the precipitation is its interannual variability. There is a dry season, from June to September, and a wet season, from October to May (more than 80% of the precipitation falls between these months). Periodical droughts with duration of two or more years are frequent, occurring approximately once in each decade.

Figure 2 shows the monthly precipitation and temperature between November 2015 and October 2016. Accumulated rainfall between March and May was 239 mm, higher than the average expected value, 186 mm. However, during the summer, there was practically no precipitation. October was very rainy, exceeding around 35% the expected rainfall (Serrano et al. 2017). The rainfall in April and May is important for maintaining the growth of the pasture and lengthening its vegetative cycle, and, in June, the lower rainfall and higher temperature severely impacts on the productivity and quality of the pasture (Serrano et al. 2017).

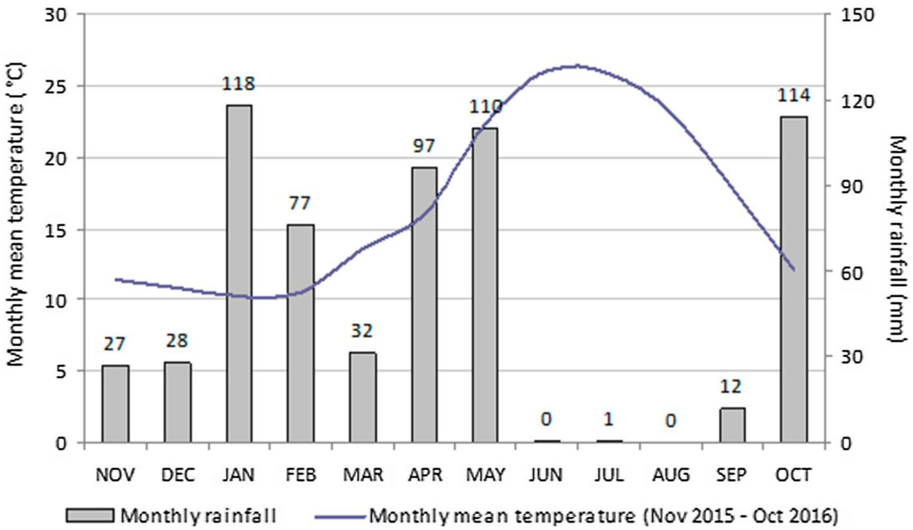

Fig. 2 Monthly mean temperature and monthly precipitation in the Évora Meteorological Station between November 2015 and October 2016

The predominant soil of this field is classified as a Cambisol derived from granite (IUSS Working Group WRB 2015). Cambisols are characterised by slight or moderate weathering of parent material and by absence of appreciable quantities of illuviated clay, OM, aluminium, and/or iron compounds. These soils are not very fertile, being used for mixed arable farming and as forest and grazing land.

Data collection

Soil ECa measurements were made using the Veris 2000 XA contact-type sensor (Veris Technologies, Salina, KS, USA) in October 2016. The Veris 2000 XA unit has four disks (one pair passes electrical current into the soil while the other pair measures the voltage drop). It measures soil ECa from one depth, but it can be adjusted, varying the distance between the emitting and receiving coulter-electrodes, to read ECa for the topsoil, 0–0.45 m, or for a deeper soil profile, 0–0.90 m. In this case study, the ECa was measured at 0–0.50 m because this information was used for soil sample selection and the pasture roots are almost completely found at this depth. The Veris 2000 XA, equipped with a global positioning system (GPS) antenna, was pulled by an all-terrain vehicle at an average speed of 1.3 m s^{-1} and successive passages were made across the field (Fig. 1). The sensor was programmed to register the measurements each second and generated one set of geo-referenced ECa data with 923 values.

After measuring ECa, soil variability was assessed across the field. Soil samples were collected in a transect based on the maximum variability direction of the ECa survey, in October 2016, just after these ECa measurements. Consequently, 10 points (Fig. 2) were sampled at 2 depths, 0–0.25 m and 0.25–0.50 m, and their coordinates were determined with a real time kinematic (RTK) GPS instrument (Trimble RTK/PP-4700 GPS, Trimble

Navigation Limited, USA). The soil samples were collected using a gouge auger and a hammer.

Several soil characteristics were measured: texture, moisture content, CEC, pH, OM content, nitrogen, phosphorus, and potassium. Each composite sample was the result of five sub-samples. The soil samples were air-dried and analysed for particle-size distribution using a sedimentographer (Sedigraph 5100, manufactured by Micromeritics), after passing the fine components through a 2 mm sieve. The soil was also analysed for pH in 1:2.5 (soil:water) suspension, using the potentiometric method. OM was measured by combustion and CO_2 measurement, using an infrared detection cell. The CEC was measured by the neutral ammonium acetate method. The NO_3 was measured using the selective ion method. P_2O_5 and K_2O were extracted by the Egner–Riehm method, and P_2O_5 was measured using colorimetric method, while K_2O content was measured with a flame photometer (Egner et al. 1960). The soil samples were weighed, dried at 70 °C for 48 h, and then weighed again to establish the SMC.

Data treatment

With the aim of analysing the raw data, different software packages were used. Previously, an exploratory analysis of data was performed. Consequently, the data were studied without considering their geographical distribution. Statistics were applied to check data consistency, removing outliers, and identifying the statistical distribution of data.

Estimating ECa at unsampled locations was done with the ordinary point kriging method, integrating the spatial correlation structure described with the variogram. The kriged map showing the spatial distribution of ECa in the experimental field was obtained from the estimated values. The geostatistical analysis was carried out with the extension Geostatistical Analyst of the GIS software ArcGIS (version 10.3, ESRI, Inc., Redlands, California, USA). The kriged map of ECa was produced with the ArcMap module of the ArcGIS, after conducting the geostatistical study. A 5 m × 5 m grid cell size was chosen to define the final raster ECa map.

Linear regressions between ECa and soil properties were computed with the Spatial Analyst Tools in ArcGIS using the ordinary least squares technique. When any linear regression was statistically significant (at the 5% significance level), spatial distribution of the soil property was mapped with the Raster Calculator tool in ArcGIS, considering 5 m resolution cells.

A topographic survey of the area was carried out using the aforementioned GPS instrument, simultaneously with the ECa survey. The elevation data were sampled in the field with the GPS assembled on an all-terrain vehicle. The digital elevation model surface was created using the triangulated irregular network (TIN) interpolation tool from ArcGIS. The TIN algorithm uses sample points to create a surface formed by triangles based on nearest neighbour point information. This vector information was converted into a grid surface using the Spatial Analyst Tools.

Homogeneous subfields were delineated using a fuzzy cluster algorithm (e.g., Höppner et al. 1999), considering soil properties which were significant and modelled with map algebra techniques. The MZ Analyst (MZA) software was utilised in this study. This software provides procedures for delineating MZs in a field and evaluating the number of homogeneous zones (Fridgen et al. 2004). Consequently, the fuzzy c-means, an unsupervised continuous classification procedure, which is implemented in the MZA program, was used to divide the field into different cluster classes. This classification algorithm is very adequate for grouping properties in the soil continuum, because it produces a continuous grouping of objects by assigning partial class membership.

Some clustering parameters need to be specified in the MZA program. The fuzziness exponent was set at the conventional value of 1.3 and the Mahalanobis measure of similarity was chosen as it is the most suitable for multivariate data classification (e.g., Tagarakis et al. 2013). The classification was repeated for a range of classes between 2 and 6, taking into account that more than three homogeneous zones would not be manageable. The optimal number of cluster classes were evaluated with two indices: the fuzziness performance index (FPI) and the normalized classification entropy (NCE; Fridgen et al. 2004). Both indices have values between 0 and 1. FPI is a measure of the degree of membership sharing among classes: 0 indicates different classes with no membership sharing and 1 reflects a strong sharing of membership. NCE is an estimate of the amount of disorganization created by a number of classes: 0 indicates high organization and 1 represents a strong disorganization. When each index is at minimum, which indicates the least membership sharing (FPI) and greatest amount of organization (NCE) as a result of the clustering process, the optimum number of classes is achieved (Fridgen et al. 2004).

Finally, with the aim of determining the variables that summarize the principal sources of variability in the data, a principal component analysis (PCA) was carried out. PCA is a dimension reduction method which uses correlated variables and identifies orthogonal linear recombination of them. The number of principal components (PCs) is the same that the number of considered variables, but usually the first few components explain most of the total variance in the data set (Li et al. 2007). PCA was computed with the Spatial Analyst Tools in ArcGIS.

Results and discussion

Data exploratory analysis

An initial analysis of all soil properties considered at each sampling location was carried out and results are shown in Table 1. The soil has a sandy loam texture class. The mean sand, silt, and clay contents calculated for samples from the 10 locations were around 75, 13, and 12% for 0–0.25 m depth and 66, 15, and 20% for 0.25–0.50 m depth, respectively, that is, the finest soil fraction increases in depth.

Mean pH values were quite similar (around 5.5) in both depths. These soils are typically acid (Guevara-Escobar et al. 2007), a consequence of nutrient extraction and nitrate leaching. The mean OM content for the topsoil, 1.65%, was three times larger than the mean OM content in the deeper layer. Potassium levels were high in both depths (199.20 ± 114.36 mg kg^{-1} and 102.40 ± 63.22 mg kg^{-1}), particularly in the topsoil; phosphorus levels were also high in the topsoil (68.20 ± 31.37 mg kg^{-1}) and lower in the subsoil (24.44 ± 24.67 mg kg^{-1}); nitrogen content was very low (lower than 0.1 g kg^{-1}). These values were very similar to those reported by Serrano et al. (2017) in the same soil. Mean CEC increased in depth, from 8.40 cmol kg^{-1} in the topsoil to 10.01 cmol kg^{-1} in the subsoil. These low values are typical of soils in which the sand content is high. Soils with a low CEC are more likely to develop deficiencies in nutrients.

The mean SMC during the time of sampling increased from 6.89% in the topsoil to 8.52% in the subsoil, which was expected due to the clay layer in depth. Soil samples were taken after the beginning of the rainy season (Fig. 2). SMC is highly variable in

Table 1 Descriptive statistics of the sample data (soil physical–chemical properties) in the study area

Variables	Mean	Median	SD	Min	Max	CV (%)
0–0.25 m						
Coarse sand (%)	48.09	47.65	3.11	42.90	53.20	6.47
Fine sand (%)	27.63	27.20	1.89	25.10	32.10	6.84
Silt (%)	12.57	12.65	1.87	9.30	15.90	14.88
Clay (%)	11.71	12.05	1.49	9.40	13.60	12.72
pH	5.45	5.43	0.36	4.90	6.00	6.61
CEC (cmol kg^{-1})	8.40	8.20	0.76	7.32	9.44	9.05
OM (%)	1.65	1.63	0.43	1.10	2.40	26.06
P_2O_5 (mg kg^{-1})	68.20	66.00	31.37	25.00	114.00	45.99
TN (g kg^{-1})	0.07	0.06	0.02	0.03	0.12	28.57
K_2O (mg kg^{-1})	199.20	176.00	114.36	80.00	440.00	57.40
SMC (%)	6.89	6.59	1.82	3.64	9.05	26.42
0.25–0.50 m						
Coarse sand (%)	42.39	42.35	4.75	31.50	47.80	11.20
Fine sand (%)	23.60	24.00	2.72	16.70	26.50	11.52
Silt (%)	14.55	14.85	2.06	10.60	16.90	14.16
Clay (%)	19.47	17.05	5.23	15.10	31.60	26.86
pH	5.54	5.35	0.65	4.80	6.50	11.73
CEC (cmol kg^{-1})	10.01	9.18	2.33	8.08	15.56	23.28
OM (%)	0.53	0.50	0.16	0.40	0.80	30.19
P_2O_5 (mg kg^{-1})	24.44	13.50	24.67	8.40	84.00	100.94
TN (g kg^{-1})	0.01	0.01	0.01	0.00	0.03	100.00
K_2O (mg kg^{-1})	102.40	72.00	63.22	36.00	240.00	61.74
SMC (%)	8.52	7.49	3.39	4.96	15.99	39.79

In each one of the 10 locations, samples were taken at two depths

SD standard deviation, *CV* coefficient of variation, *CEC* cation exchange capacity, *OM* organic matter, *TN* total nitrogen, *SMC* soil moisture content

Mediterranean climates due to the aforementioned intraannual precipitation variability, so the measured SMC is related to the preceding meteorological conditions.

The coefficients of variation for some soil properties were large, particularly with regard to OM, nitrogen, phosphorus, potassium, and SMC (Table 1). The other soil properties show lower coefficients of variation but they are also important. Moreover, the coefficients of variation were higher in the deeper soil layer for all soil properties than in the topsoil, except for the silt content, denoting a general high spatial variability. Consequently, it can be suggested the appropriateness of site-specific management in the field. This soil variability has been also reported in other studies involving the soil–tree–pasture ecosystem (e.g., Serrano et al. 2013; Bernardi et al. 2016).

Figure 3 shows the elevation and ECa surfaces. Although the topography is smooth, with gentle slopes, it is apparent that ECa has an important spatial variability, with a high coefficient of variation (130.25%). It is known that elevation has an important influence on soil forming processes and, consequently, on soil water movement and salinity distribution (e.g., Corwin and Lesch 2005). Thus, ECa and elevation can be correlated (e.g., Serrano et al. 2010; Peralta et al. 2015) but, in this case study, there is no a

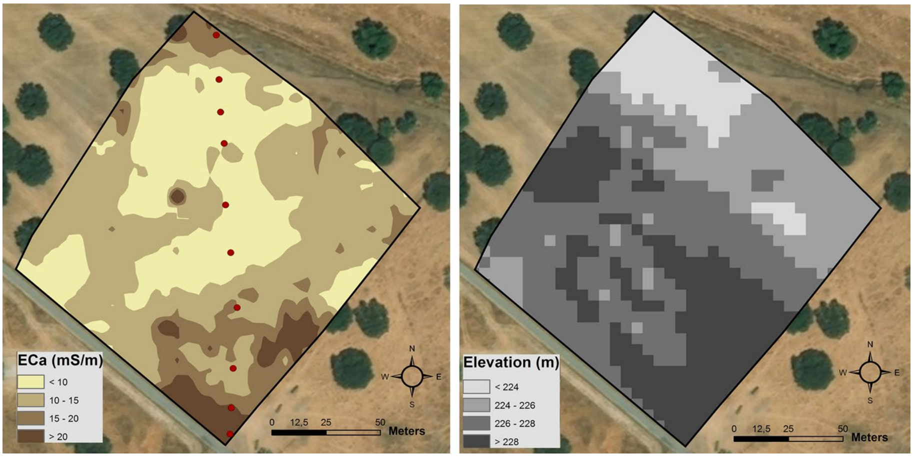

Fig. 3 Maps of soil apparent electrical conductivity (ECa) and elevation. Soil samples are indicated as dots in the ECa map

significant correlation between them (correlation coefficient is 0.16). High and low ECa values are in zones where elevation is either high or low (Fig. 3).

Table 2 shows all significant relationships between soil properties and ECa. Considering the textural fractions, only coarse sand was not correlated with ECa. In this soil, where sand is the most important textural fraction, the other finer components, clay and silt, were positively correlated with ECa, and the fine sand was negatively correlated with ECa. Similar results were obtained elsewhere (e.g. Serrano et al. 2014; Moral et al. 2010).

With respect to the other soil properties, SMC, pH, and CEC showed significant and positive correlation coefficients with ECa. The rest of the soil properties were uncorrelated with ECa. In the experimental field, where the soil has a high sand content, it might be important to delimit the zones in which clay content is higher.

According to Friedman (2005), the major factor affecting the ECa of unsaturated soils is SMC, and other factors, which are relatively time-invariable, are the solid particle quantifiers, which include texture and CEC. Of course, the soil variables which affect the ECa do not act independently and the most important influence of SMC can obscure the effects of other variables. Consequently, the highest coefficient of determination obtained when SMC was the dependent variable (Table 2) was expected. However, the lowest coefficient of determination for the clay content was probably due to its

Table 2 Linear relationships (Y = aX + b) between ECa (X) and soil texture variables (Y)

Y	a	b	R^2
Clay	14.533	0.354	0.38
Fine sand	27.145	− 0.254	0.73
Silt	16.968	− 0.173	0.59
SMC	3.947	0.328	0.78
pH	4.851	0.049	0.48
CEC	6.943	0.220	0.74

low percentage in the soil of the experimental field and, consequently, its influence on ECa is less important than it has been reported in other soils with more clay (e.g. Moral et al. 2010).

Spatial distribution maps of soil properties and delineation of management zones

Initially, geostatistics was used to estimate ECa at unsampled points, utilising as previous information all ECa data obtained with the Veris 2000 XA sensor at sample locations. Thus, the experimental variogram was computed, assuming isotropy conditions because the anisotropy ratio (quotient between ranges of the directional variograms in the major and minor anisotropy directions) was very low, around 1.53 (e.g. Goovaerts 1997). After computing the experimental variogram, a spherical theoretical variogram was fitted to the points. The ratio of nugget to sill was 46.28%, which, according to Cambardella et al. (1994), denotes strong spatial dependence of the variable, ECa. The kriged map of ECa (Fig. 3) was obtained using ordinary kriging as the estimation method, integrating the spatial correlation structure described with the variogram. The final raster ECa map has a 5 m × 5 m grid resolution.

Later, considering the linear regressions between ECa and soil properties shown in Table 2, maps of each soil property were generated with 5 m resolution cells (Fig. 4).

Serrano et al. (2017) analysed the variability of soil properties in this experimental field, considering the influence of trees on the spatial patterns. It was found that soil under the tree canopy had significantly higher levels of OM, nitrogen, phosphorus, and potassium, and no significant differences were found in texture and pH. Similar results have been also verified by Marcos et al. (2007) in the same ecosystem; moreover, they indicated that there

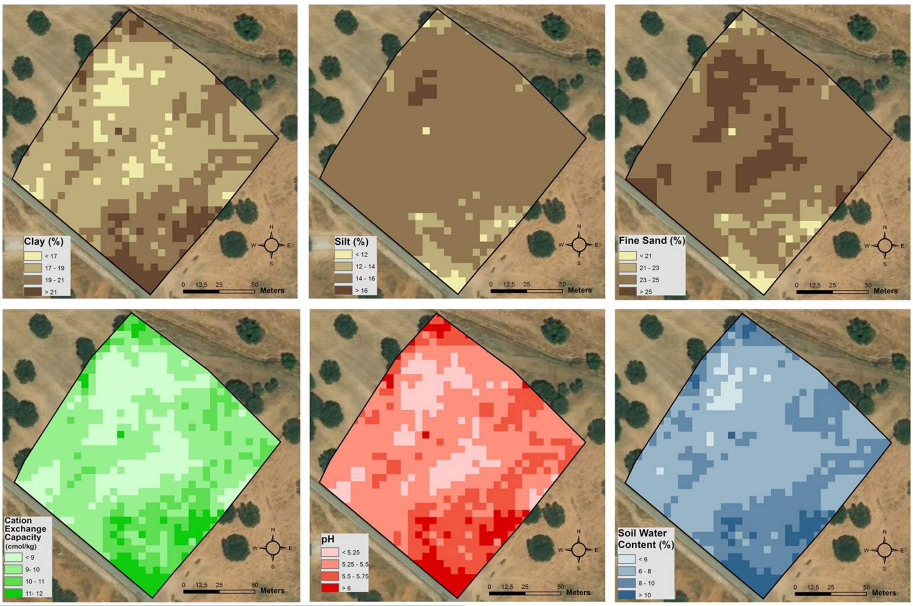

Fig. 4 Raster maps (with 5 m resolution cells) of those soil properties significantly correlated with soil apparent electrical conductivity

are positive effects of trees on soil nutrient contents, soil water storage capacity, and pasture production. Benavides et al. (2009) also found similar soil texture for open pasture and under trees. Scattered trees lead to a great spatial variation of soil conditions, generating islands of higher soil quality, improving soil physical properties, and affecting productivity in understory vegetation compared with surrounding open zones (Gómez-Rey et al. 2012).

Serrano et al. (2017) also reported significant differences in SMC under and outside the tree canopy in this field, and throughout the entire vegetative cycle of the plants. Thus, SMC tends to be higher outside the tree canopy in winter and early spring, but when temperature increases and precipitation decreases, the situation reverses. It reflects the effect of the canopy, acting as a barrier to the penetration of rain under the tree canopy and, when temperature increases, acting as a shade and maintaining higher SMC. SMC distribution shown in Fig. 4, with lower values in zones where there are trees, confirms the previous findings.

Zones where there are trees tend to be associated with lower ECa values (Fig. 4). As ECa is influenced by the SMC, their patterns are similar. The same can be visualised when the spatial distributions of CEC and pH are considered which, in turn, are significantly related to ECa (Table 2). As Pedrera-Parrilla et al. (2014) indicated, variations in ECa are mainly related with variations in SMC and soil texture, and zones with the lowest ECa values are optimal for tree growth because of their better drainage conditions, avoiding saturation and water logging during wet spells.

The attribute data of raster images of fine sand, clay, pH, CEC, and elevation were taken as the input of the clustering analysis. After specifying the clustering parameters in the MZA program, results indicated that the best option was two clusters as the FPI and NCE indices were at minimum. According to Fridgen et al. (2004), the concordance of the two indexes is an indication of the goodness of the classification, so it was not necessary to perform further analysis to verify the results. In consequence, two MZs were delimited. Thus, taking the partition results and spatial locations under two zones as data sources, the MZ map (Fig. 5) was generated in ArcGIS. Although there is a zone that is divided into two separate parts, both zones are concentrated, which has an advantage of being easily treated. The few small spots within each zone could be removed from a practical site-specific management point of view.

When the MZ map was visually compared with the elevation map, it was apparent that lower elevations predominate in one zone and higher elevations in the other one. The influence of the soil properties on each zone was less evident. As a significant relationship between some soil properties and ECa was found, a PCA was conducted to evaluate the contribution of each variable. The three first PCs are shown in Table 3. PCs with eigenvalues greater than one should be considered as they explain a significant amount of the total variance (e.g., Peralta and Costa 2013). In this study, the first and second PCs (PC1 and PC2) had an eigenvalue greater than one. The eigenvalue for PC1 has a high value (16.188), which supposes 83.253% component loading, so it explained this percentage of the total variance. If PC2 is considered, both PC1 and PC2 explained almost completely (99.999%) the total variance.

As soil properties with loading factors lower than 0.4 have an insignificant influence on the variance (e.g., Peralta et al. 2015), clay content is the only property to be considered key latent variable, taking into account PC1, and elevation is another key latent variable considering PC2.

However, although PC1 is mainly influenced by clay content, some other soil properties (CEC and fine sand) have a loading factor near 0.4, so globally they are also important. In the case of PC2, elevation is clearly the predominant property. Consequently, elevation

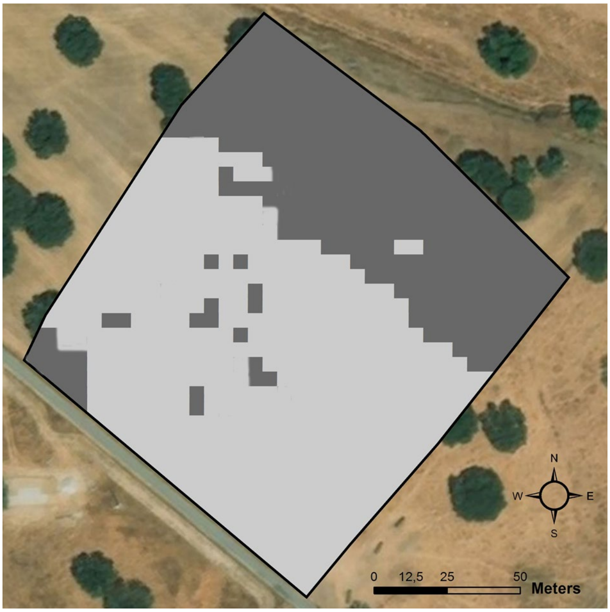

Fig. 5 Management zones map for optimum clusters in the study area

Table 3 Results of the principal component analysis for the nine soil properties

Principal components	Eigenvalues	Component loading	Cumulative loading
PC1	16.188	83.253	83.253
PC2	3.156	16.746	99.999
PC3	0.001	0.001	100.00

PC loadings for each variable

	Elevation	Clay	Fine sand	CEC	pH
PC1	0.058	0.667	− 0.387	0.366	0.055
PC2	1.254	− 0.035	0.021	− 0.015	− 0.005

contributes to around 17% of the total variance, clay content being the other important contributing property, around 83%, of the variance. This is the reason of the similarity between the elevation map and the MZ map, as it was previously denoted.

Conclusions

A fast and low-cost technique to obtain soil information with high resolution is the combination of a GPS system and a Veris 2000 XA electrical conductivity sensor, measuring georeferenced soil ECa in many locations. Initially, ECa can be used for a guided sampling, reducing the necessity of many soils samples, which, in turn, leads to an important cost reduction. Later, if significant correlations are found between ECa and some soil properties, ECa can be auxiliary variable in geostatistical analysis. Thus, in the case study, using map algebra techniques in a GIS, the spatial distributions of soil texture variables (clay, silt, and fine sand) and other soil properties related to soil fertility, such as pH and CEC, were visualised throughout the field.

Further analysis of the soil properties GIS layers can generate more additional information. A fuzzy c-means classification procedure, in which the GIS layers are the input data, can be used to define homogeneous zones. In the present study, two homogeneous zones were delimited, considering elevation and the other aforementioned soil properties as the input information. This is the first stage to implement precision farming in the studied field, which could lead to a more cost-effective field management.

Additionally, PCA can be also conducted to find the main variability sources, as it was performed in the experimental field, in which elevation and clay content were the most important contributing properties, that is, the key latent variables in this field.

Acknowledgements This research was funded by the Junta de Extremadura and the European Regional Development Fund (ERDF) through the Project GR15050 (Research Group TIC008), by ERDF through the Operational Programme for Competitiveness Factors: COMPETE and National Funds through FCT: Foundation for Science and Technology under the Strategic Project PEst-C/AGR/UI0115/2011 and under the FCT Project: EXCL_AGR-TEC_0336_2012, and also by ERDF and the Spanish Ministry of Economy and Competitiveness through the Project AGL2015-65036-C3-3-R. The authors are also very grateful to two anonymous reviewers for providing constructive comments which contributed to improve the final version of this paper.

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