POSTPRINT of the article: Uribeetxebarria, A., Arnó, J., Escolà, A., Martínez-Casasnovas J.A. 2018. Apparent electrical conductivity and multivariate analysis of soil properties to assess soil constraints in orchards affected by previous parcelling. *Geoderma*. 319, 185-193. https://doi.org/10.1016/j.geoderma.2018.01.008

Apparent electrical conductivity and multivariate analysis of soil properties to assess soil constraints in orchards affected by previous parcelling

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Abstract
Fruit production is relevant to the European agricultural sector. However, orchards in semi-arid areas of southern Europe may contain soils with constrains for tree development. This is the case of soils with high $CaCO_3$ content or limiting layers at variable depth. To assess spatial and in-depth variation of these soil constraints, an apparent electrical conductivity (ECa) survey was conducted in an orchard by using a galvanic contact soil sensor (Veris 3100). Different soil properties were randomly sampled at two depths (topsoil and subsoil) in 20 different sampling points within the plot. ECa raster maps were obtained for shallow (0-30 cm) and deep (0-90 cm) soil profile depths. In addition, an inversion modelling software was used to obtain horizontal ECa slices corresponding to 10 cm thick soil layers from 0-10 cm to 80-90 cm in depth. Concordance analysis of ECa slices allowed the soil profile to be segmented into four homogeneous horizons with different spatial conductivity pattern. Then, a multivariate analysis of variance (MANOVA) was key, i) to better interpret the specific soil properties that mainly contributed to the spatial variation of ECa ($CaCO_3$ and organic mater (OM) contents), and ii) to delimit the soil layer and the specific spatial pattern of ECa that allows potential management areas to be delineated by presenting the same trend in $CaCO_3$ and OM for topsoil and subsoil simultaneously. Moreover, assessing 3D variation of ECa made it possible to identify different soil areas that, linked to previous earthworks to optimize the parcelling of the farm, are the main cause of spatial variability within the orchard.

Keywords
Soil sensing, ECa inversion, MANOVA, Precision fruticulture, Spatial analysis

1. Introduction
Fruit production and quality are affected to some extent by soil properties given the plant-soil interaction (Pedrera-Parrilla et al., 2014; Unamunzaga et al., 2014; Khan et al., 2016). As soil can vary spatially and at different scales, knowledge of spatial patterns within the plots could help farmers to make better management decisions based on the delimitation of areas with different soil conditions and agronomic needs (Ping et al., 2005; Vitharana et al., 2008; Pedrera-Parrilla et al., 2014; Córdoba et al., 2016). This is particularly relevant in semi-arid fruit growing areas of southern Europe. Soils in these areas are characterized by a high and spatially variable content of carbonates with clear incidence in nutritional deficiencies and chlorosis that affect growth and the

normal foliar development. Accordingly, orchards usually show spatial variability in the canopy volume within the plot. In addition, this lack of homogeneity is particularly remarkable in plots that have been affected by successive earthworks over the years to reshape and optimize the parcelling of the farm. Fruit growers are therefore especially interested in locating and delimiting areas within the orchards that can be a major constraint for management (Fulton et al., 2011).

Soil sensors for mapping the apparent soil electrical conductivity (ECa in mS/m) are increasingly used to understand and evaluate how soil varies spatially (Corwin and Lesch, 2003; Abdu et al., 2008; Fulton et al., 2011) to delineate ECa-based management zones (Moral et al., 2010; Peralta and Costa, 2013). At present, it begins to be applied as a key sensing system in the framework of precision fruticulture (Käthner and Zude-Sasse, 2015). As ECa varies on a similar spatial scale as many soil physico-chemical properties (Sudduth et al., 2003; Carroll and Oliver, 2005), these soil monitoring systems have been widely accepted. Specifically, good correlations with soil salinity, soil water content and soil texture have been widely documented (Corwin and Lesch, 2005; Heil and Schmidhalter, 2012). Even, other soil properties affecting conductivity may be the organic C (Sudduth et al., 2003; Martinez et al., 2009), the cation exchange capacity (Sudduth et al., 2005) and the $CaCO_3$ content (Kühn et al., 2009). However, despite these good predictive characteristics, there are few studies that refer the use of such sensors in horticulture and, more specifically, in fruit orchards located in Mediterranean latitudes. One reason could be the small size of many fruit orchards. This induces farmers to think that tree plantations are rather homogeneous, and spatial variability is not enough to justify investing in this technology. By contrast, Käthner and Zude-Sasse (2015) show that even in small orchards there may be differences in soil properties that relate to tree growth and fruit size. Two soil sensing systems are commonly used in agriculture (Corwin and Lesch, 2005). In both cases (galvanic contact with the soil and electromagnetic induction), sensors measure the ECa on a soil volume basis including both topsoil and subsoil. This is very interesting since soil influences fruit trees at least to the depth covered by the roots, and ECa measurements should cover the same depth. Depending on the system, soil sensors provide with several electrical signals corresponding to several explored depths. When two signals are provided, they are known as shallow and deep ECa, and may correspond to the topsoil and whole profile depending on the sensor range. Farmers can get maps of both signals to evaluate the spatial variation of ECa, and indirectly the spatial pattern of soil related properties. Moreover, by overlapping maps they can also assess whether the soil is uniform or varies in depth. The problem occurs when the interest is to determine exact depths at which changes in the soil profile are produced (e.g. petrocalcic horizons) using such averaging procedures that encompass all or part of the soil profile (Heege, 2013).

Mapping the thickness or depth to a contrasting textural layer using ECa has been also referenced in several studies to detect clay horizons (Doolittle et al., 1994; Saey et al., 2009), or estimate topsoil depth explored by roots (Khan et al., 2016). Depth estimates may be based on empirical equations (using a single ECa signal that integrates the relative contribution of soil at each depth) or by combining data from multiple ECa sensors in both two- and three-layer models (Sudduth et al., 2010, 2013). Electromagnetic conductivity imaging (EMCI) of soil is another option that has been recently investigated (Triantafilis et al., 2013). Combining conductivity data and an inversion modelling software, a two-dimensional model of the ECa can be generated to assess soil variation (i.e. horizons) at discrete depth intervals (Triantafilis and Monteiro Santos, 2013). Researchers can take advantage of this additional information regarding the signal variation probably caused by layers of different thickness and composition. In short, soil properties sampled at varying depths may be better interpreted if a model indicating the variation of ECa with soil depth is available.

The main objective of the present research was to analyse the capacity of a galvanic contact soil sensor (Veris 3100) to be used as a diagnostic tool in fruit growing areas with high calcium carbonate content, and plots affected by previous parcelling works. Special attention was devoted to assess the spatial variability of physico-chemical soil properties to properly define differential management zones within an orchard. For that, we focused our research on i) evaluating the sensing system and its signal mapping, ii) inverting the ECa signal to obtain electrical imaging of ECa variation with soil profile, and iii) applying not conventional statistical methods i.e. multivariate analysis of variance (MANOVA) for a better interpretation of ECa and soil data.

2. Materials and methods

2.1. Study area

The study was carried out at the IRTA Experimental Station (Lon. 0.392017, Lat. 41.654413, Datum WGS84), located in Gimenells, 24 km west from Lleida (Catalonia, Spain). The research was focused on a 0.65 ha plot that was planted in 2011 with peach trees (*Prunus persica* L. Stokes var. platycarpa) according to a 5 x 2.80 m plantation pattern (Fig. 1). Soil was classified as Petrocalcic Calcixerept (Soil Survey Staff, 2014), and it is a well-drained soil without salinity problems. The climate, typical of semi-arid areas of the Mediterranean region, is characterized by strong seasonal temperature variations (cold winters and hot summers), and an annual precipitation that is usually below 400 mm, although with significant interannual variability.

However, the most important feature of the plot was the presence of a petrocalcic horizon at a variable depth from 40 cm to 80 cm. This spatial variation in depth could be explained by the successive earthworks made in recent years in order to improve or adapt the parcelling of the farm. Probably, the petrocalcic layer was broken over time due to soil tillage and now appears even at shallow depths in certain areas. In fact, the history of transformation and land uses of this plot has been relatively complex as shown in Figure 1. Since 1946, when the Experimental Station was created, the plot has been cultivated with different crops and was modified in shape and size in several occasions (at least, the plot undergone a minimum of four major transformations in recent years, Fig. 1).

https://doi.org/10.1016/j.geoderma.2018.01.008

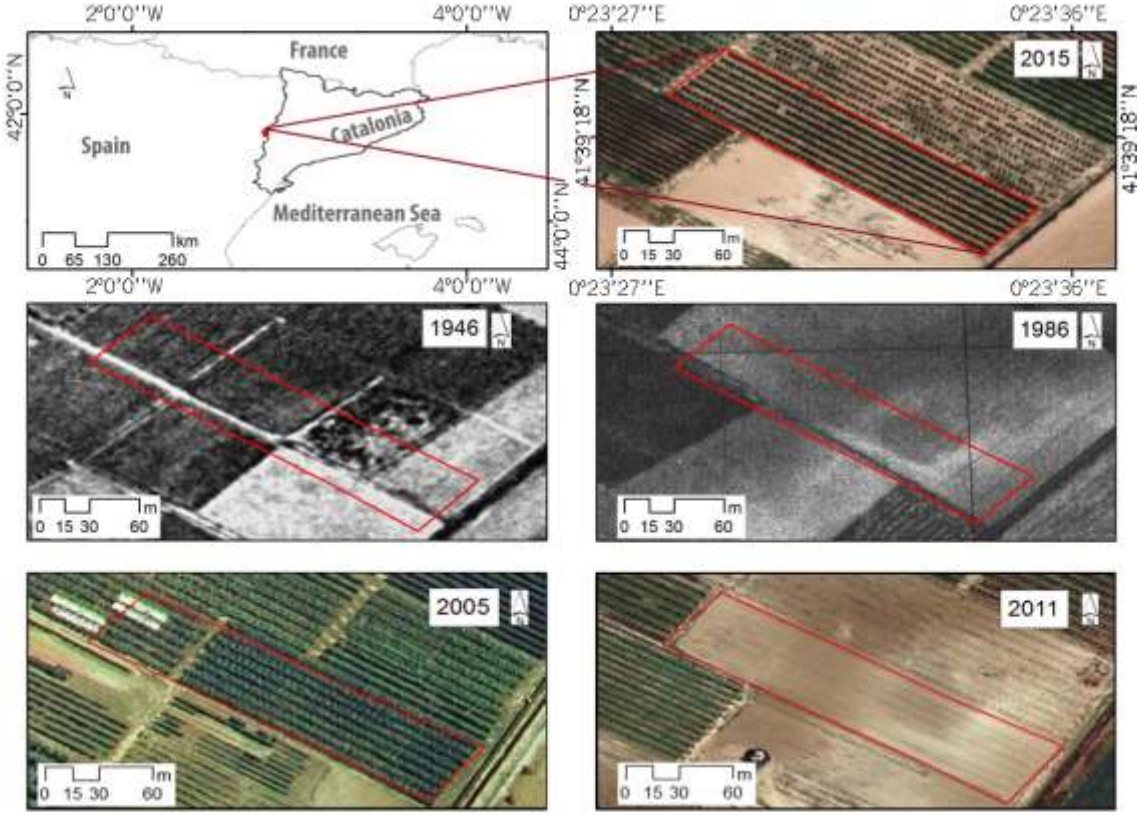

Fig. 1 Location of the study area and recent orthophoto (2015) of the experimental peach orchard (top). Other pictures: ancient orthophotos of the same area corresponding to different years since 1946.

2.2. Soil sampling

A simple random soil sampling was carried out in 20 different points within the plot (Fig. 2). Soil was sampled on March 15th, 2015. Samples were collected with the aid of a manual auger-hole at three different depths (0-30, 30-60, 60-90 cm). It is necessary to clarify that only in 4 of these sampling points it was possible to take a sample of the deepest layer, since the soil was shallow at most of the sampled sites. Sample locations were also georeferenced with submetric precision using a Trimble GPS Geo XH receiver and SBAS differential correction based on EGNOS. Soil samples were air-dried and sieved, and different physicochemical properties were analysed in laboratory according to the standard procedures. Specifically, data were obtained on the following properties: calcium carbonate content ($CaCO_3$), cation exchange capacity (CEC), electrical conductivity in a 1:5 soil-water solution ($EC_{1:5}$), organic matter (OM), pH measured in a 1:2.5 soil-water ratio, soil texture, total nitrogen (TN) in soil, and water holding capacity (WHC).

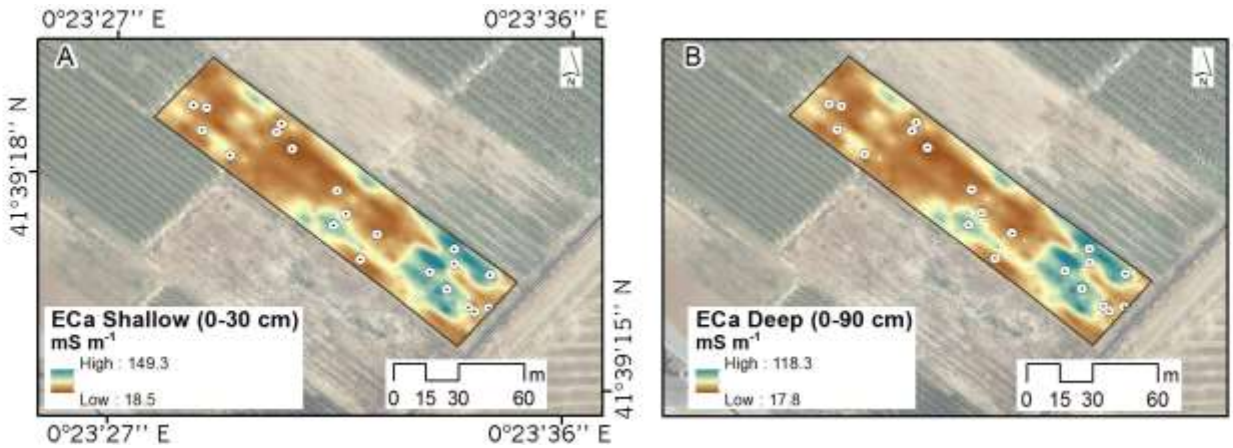

Fig. 2 ECa maps obtained by spatial interpolation and random soil sampling points within the plot. A) shallow ECa (0-30 cm). B) deep ECa (0-90 cm).

In addition to manual soil sampling, an ECa survey was conducted by using the Soil EC Surveyor Veris 3100 (Veris Technologies, Inc., Salina, KS, USA). The Veris 3100 implement is a simple and effective tool to acquire on-the-go information on soil bulk electrical conductivity for subsequent mapping. Its advantage lies in using two electrical arrays that allows ECa readings to be obtained at two different soil depths simultaneously and free of metal interference. Equipped with six heavy-duty coulter-electrodes, a pair of electrodes inject electrical current into the soil while the other two pairs measure the voltage drop. The penetration of the electrical current into the soil and, by extension, the volume of soil explored increases as the inter-electrode spacing increases. In our case, the array configuration allowed 0-30 cm (shallow ECa lecture) and 0-90 cm (deep ECa lecture) soil depths to be explored.

The ECa survey was carried out on March 23rd, 2015. For that, the Veris 3100 system was pulled by a 4-wheel drive vehicle passing along all the alleyways of the peach orchard. As tree rows were spaced 5 m, parallel ECa measurements were spaced this same distance. On the other hand, the soil sensor was connected to a Trimble AgGPS332 receiver for georeferencing purposes, and SBAS differential correction based on EGNOS was used. Regarding the spatial sampling resolution, data were recorded every second providing a total of 644 georeferenced ECa readings within the orchard (990 sampling points per hectare).

2.3. Apparent electrical conductivity maps and quasi-3D inversion modelling

Both ECa values (shallow and deep) were mapped by ordinary kriging. Maps were obtained after checking the normality of the acquired data and having removed extreme outliers from the analysis. Regarding the latter, ECa values lower than $Q_1 - 3 \times IQR$ or greater than $Q_3 + 3 \times IQR$ were not considered in the spatial interpolation (Q_1 and Q_3 were the first and third quartiles, and IQR was the interquartile range of the distribution). ArcMap 10.4.1 Geostatistical Analyst (Environmental Systems Research Institute, Redlands, CA, USA) was then used to finally interpolate shallow and deep ECa values by kriging on a 1 m grid. Geometric anisotropy along peach rows was taken into account when adjusting the experimental variograms (exponential model for the shallow ECa, and stable model for the deep ECa). A strong spatial variation was also found on both maps (Fig. 2) (Cambardella et al., 1994).

In addition to raster ECa maps (0-30 cm and 0-90 cm depth profile), inversion modelling was applied in order to estimate ECa values at different specific soil depths. The software invVERIS 1.1 (EMTOMO Lda, Lisbon, Portugal) was used for this purpose. Specifically, invVERIS enables the inversion of ECa data acquired by galvanic contact soil sensors such as Veris 3100. The inversion procedure consists in a 1-dimensional laterally constrained technique to evaluate the ECa for a given soil transect (Quasi-2D inversion). The technique of signal inversion is based on a nonlinear, smoothness-constrained algorithm described by Monteiro Santos et al. (2011) and Monteiro Santos (2004). As the Veris 3100 sensor was used passing along all the alleyways of the orchard (different transects), the possibility of inversion in each of these profiles makes it possible to obtain a soil layer model from the set of 1D models distributed according to the locations of the ECa measurement sites. The program finally allows horizontal slices (maps) of soil layers of the same thickness to be displayed at selected depths and covering the whole area of the plot (quasi-3D inversion modelling). In our case, we chose to model and visualize 9 layers of ECa of 10 cm in thickness from 0-10 cm to 80-90 cm in depth.

2.4. Data analysis

2.4.1. Clustering and map comparison

A cluster analysis was performed to classify ECa maps. Once the shallow and deep ECa maps were created, each map was clustered into two classes (low and high EC_a) using the Iterative Self-Organizing Data Analysis Technique (ISODATA) implemented in ArcGIS 10.4.1 (IsoCluster function). The procedure is based on an iterative algorithm that begins assigning an arbitrary mean to each class. Pixels are then successively reassigned based on minimizing the Euclidean distance of each pixel to the mean value of the class. In each iteration, class means are recalculated and pixels are reallocated until the last iteration is reached, or the number of pixels that change from one class to another does not exceed a certain threshold (Guastaferro et al., 2010). Classified conductivity maps were then used to assess whether the soil was significantly different depending on the ECa in each area. Multivariate analysis of variance (MANOVA) of the sampled soil properties according to conductivity classes (high and low) was used to evaluate this effect.

This same procedure was repeated for the horizontal slices (maps) resulting from the quasi-3D inversion modelling of ECa values. However, to avoid redundant analysis, maps from the 9 inverted ECa layers were first compared with each other using the Map Comparison Kit (MCK) software (Visser & de Nijs, 2006). The degree of similarity between maps was quantified by the Kappa coefficient (Cohen, 1960) and, as a result of the comparison, the nine layers previously established were finally grouped into four different homogeneous horizons.

2.4.2. Multivariate analysis of variance (MANOVA)

Separate analysis of each sampled soil property according to different levels of ECa (ANOVA) may lead to misleading and inconsistent results. In fact, ECa reflects the combined effect of soil properties as a whole, and delimitation of areas within the plot based on ECa maps should be checked from a multivariate approach. To detect the specific soil properties that mainly contributed to the spatial variation of EC_a, a multivariate analysis of variance (MANOVA) was performed. The method is slightly more complex and scarcerly used in soil science (Taylor and Whelan, 2011). However, it has proved to be an effective technique to delineate differential management zones in precision agriculture (Ping et al., 2005). In our case, the effect of ECa was then evaluated by performing a MANOVA using soil sampled properties as dependent variables and classes of EC_a (high and low) as the factor under analysis.

The problem arises when a significant result must be interpreted, since there is no unanimity as to the most appropriate post hoc procedures to be used (Warne, 2014). In this research, a descriptive discriminant analysis (DDA) was used to interpret significant MANOVAs (Thomas, 1992). DDA is a statistical procedure that, in our case, provided a linear combination of the soil properties (discriminant function) that managed to separate the two classes of ECa in a meaningful way. Standardized coefficients of the discriminant function and structure coefficients were used for interpretation. Standardized discriminant function coefficients (SDFCs) were indicative of the contribution of each soil variable to the discriminant function, whereas the structure coefficients (SCs) were the correlations between each observed variable and the discriminant function scores. The most important soil variables affecting the differential ECa were finally identified through the so-called parallel discriminant ratio coefficients (parallel DRCs) by multiplying SDFCs by the corresponding SCs. So parallel DRCs were used to assess non-redundant soil variables contributing to discriminate two types of soil in terms of ECa.

3. Results and discussion

3.1. Soil characterization

Table 1 shows the main descriptive statistics for the soil properties. Only soil properties analysed at both depths (0-30 cm and 30-60 cm) were included in the analysis (total nitrogen was excluded for this reason). Soils in the study plot were found to have an average depth of about 60 cm, basically limited by the petrocalcic horizon. As the standard deviation was 18 cm, soil depth showed a considerable spatial variability within the plot (CV of 30%). Other soil properties that showed spatial variability were the electrical conductivity at the two sampling depths and, with much lower incidence, the water holding capacity at the deepest layer. Regarding the latter, average WHC did not vary significantly between soil and subsoil, and a rather low value of 64.23 mm was obtained as an average for the whole soil profile. Carbonates also varied spatially (CV of 20%), but the most significant was the high value of the carbonates content in the soil (27% at the top layer and 33% at the bottom layer). Probably, the observed enrichment of $CaCO_3$ in the second layer (6% higher) could be explained by the near presence of the petrocalcic horizon and its breakage over the years by tillage operations. Derived from this, a moderately basic pH was expected in the soil. Finally, the organic matter was lower in the subsoil but at the expense of a strong spatial variation. The soil could be considered as well-drained, not saline, and with a loam soil texture. No other consideration was noteworthy.

Table 1 Soil properties for two sampling depths (N=20 sampling points)

Soil property	Mean	Standard deviation	CV (%)	Minimum	Maximum
Soil depth* (cm)	59.75	17.91	29.99	42.0	90.0
		Sampling depth 0- 30 cm			
pH	7.92	0.10	1.26	7.90	8.10
$EC_{1:5}$ (dS/m)	0.93	0.51	54.83	0.23	1.84
$CaCO_3$ (%)	26.95	5.61	20.81	16.27	35.32
CEC (meq/100 g)	13.97	1.02	7.30	11.50	15.90
OM (%)	2.70	0.64	23.70	0.89	3.93
Sand (%)	42.45	3.66	8.62	37.60	54.40
Silt (%)	30.38	3.38	11.12	18.30	35.60
Clay (%)	27.18	1.99	7.32	23.80	31.50
WHC (%)	10.95	0.94	8.58	9.00	13.00
		Sampling depth 30- 60 cm			
pH	7.57	0.12	1.58	7.30	7.80
$EC_{1:5}$ (dS/m)	1.92	0.96	50.00	0.50	3.46
$CaCO_3$ (%)	33.04	6.00	18.15	19.29	41.71
CEC (meq/100 g)	11.61	1.47	12.66	8.96	14.10
OM (%)	1.22	0.62	50.81	0.16	3.24
Sand (%)	42.12	4.50	10.68	35.80	53.10
Silt (%)	31.22	6.22	19.92	14.20	39.90
Clay (%)	26.21	3.15	12.01	19.40	31.10
WHC (%)	10.55	1.63	15.44	8.00	14.00

*Soil depth refers to the depth needed to reach the petrocalcic horizon.

3.2. Soil horizons delimited by ECa patterns at different depths

Figure 3 shows the interpolated maps of ECa (shallow and deep) and the corresponding maps where ECa was classified into two classes (high ECa and low ECa). Comparing the shallow and deep ECa maps (Fig. 3), one realizes that the pattern of spatial variation is quite similar. In theory, this was indicative of a uniform soil in depth. However, classified maps are not so similar (Fig. 3), occupying the high conductivity class a larger area (59% of the plot area) when the plot was classified based on the deep signal compared to 38% for the case of shallow signal.

To assess in more detail the variation of ECa within depth, inversion modelling software invVERIS 1.1 was used to obtain electrical conductivity maps (ECM) or horizontal slices every 10 cm in depth. In this respect, nine different maps were obtained corresponding to depths from 0-10 cm to 80-90 cm (Fig. 4). Maps corresponding to the topsoil layers (0-30 cm in depth) showed higher ECa values and greater spatial variability than the deeper layers (CV of 45% for layer 0-10 cm was reduced to CV of 15% for layer 80-90 cm). The attenuation of the conductivity signal was therefore evident, hindering differentiation of soils although there was considerable spatial variation in certain soil properties at greater depth (Table 1). This same result was observed by Sudduth et al. (2005).

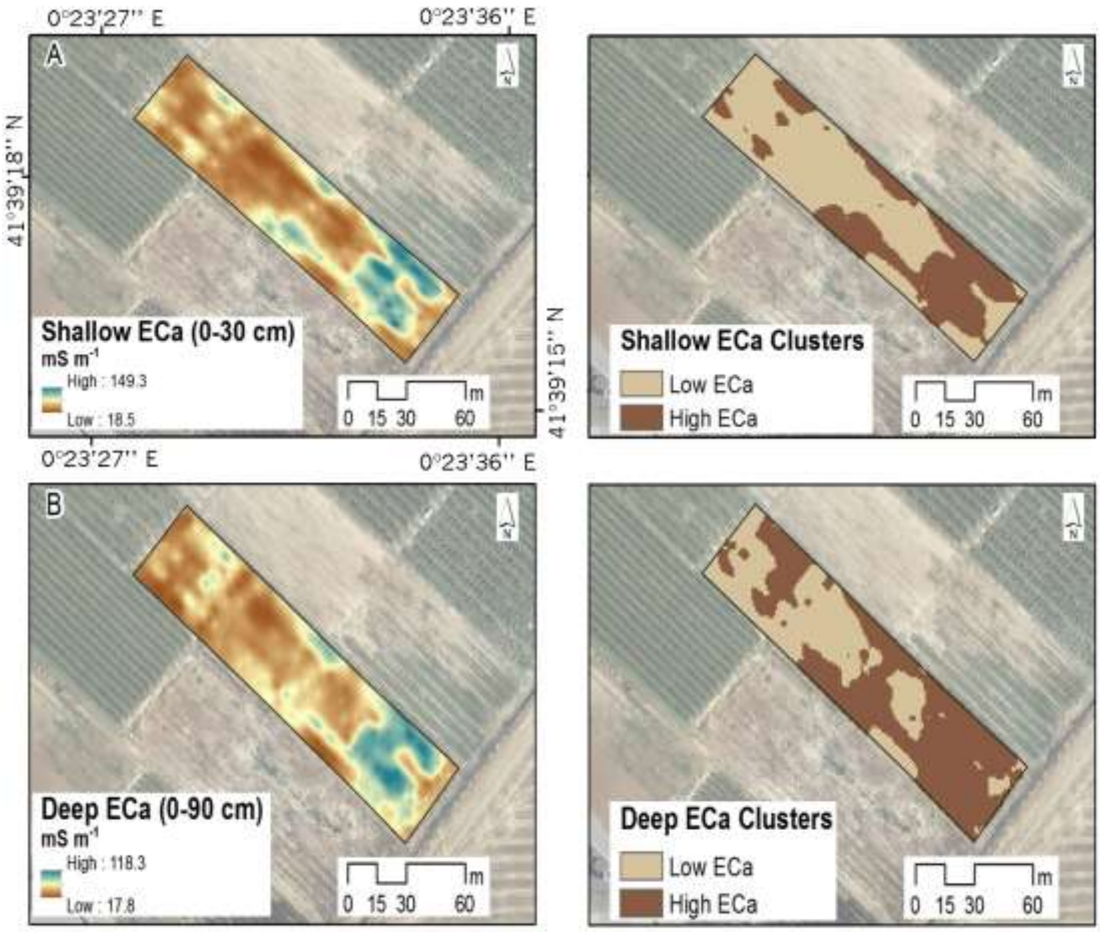

Fig. 3 A) Shallow interpolated ECa map (left), and shallow clustered map with low and high ECa classes (right). B) Deep interpolated ECa map (left), and deep clustered map with low and high ECa classes (right).

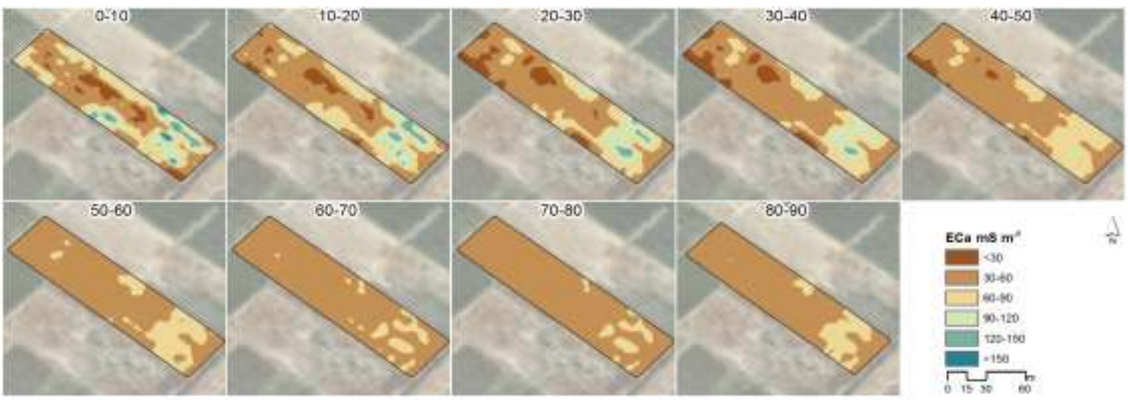

Fig. 4 Horizontal slices 10 cm thick at different depths obtained by inversion of the ECa values with invVERIS 1.1.

Concordance analysis between ECa maps allowed the horizontal layers of 10 cm to be grouped according to 4 soil horizons that were homogeneous but different from each other in both signal intensity and spatial pattern. Only layers with high spatial agreement were grouped (Kappa coefficient greater than 0.6, data not shown; Landis and Koch, 1977), resulting in a soil profile that could be segmented into (i) a first horizon occupying the first 10 cm (0 to 10 cm), (ii) a second horizon of the same thickness, from 10 to 20 cm), (iii) a third horizon with a greater thickness to a depth of 50 cm (20 to 50 cm), and (iv) a deeper and homogeneous layer up to 90 cm (50-90 cm). The representative conductivity map of each horizon was classified into two ECa classes (high and low) following the same procedure as for the original maps (Fig. 5). Multivariate analysis of variance (MANOVA) of soil properties was then performed for each of the identified soil horizons (Table 2).

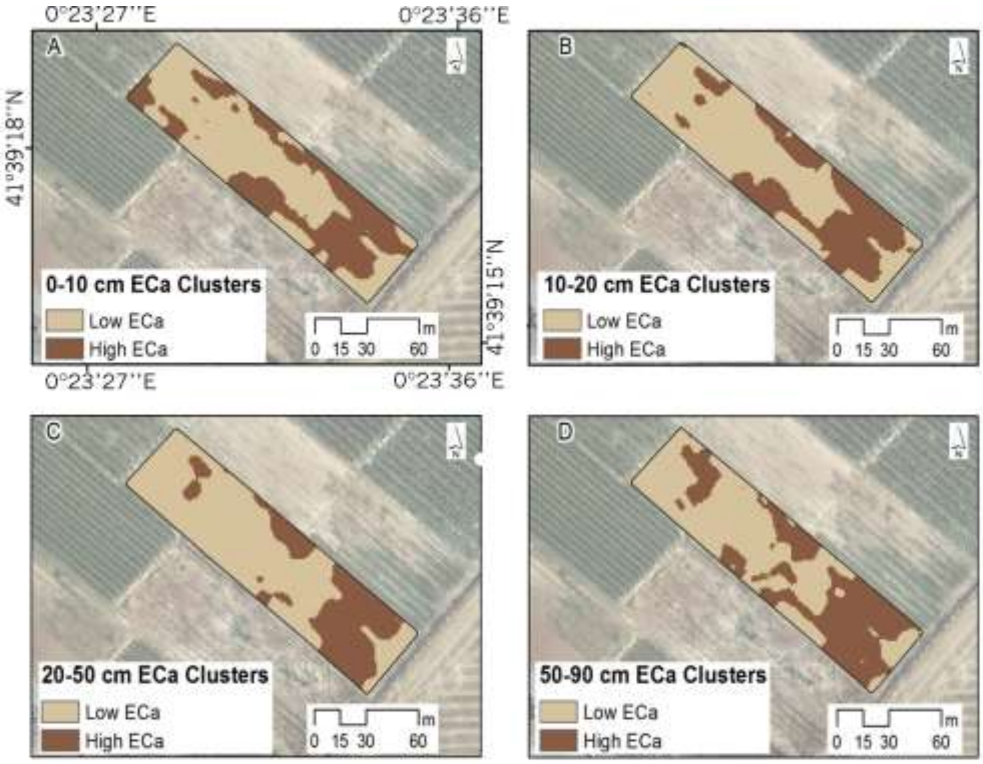

Fig. 5 Clustered maps (high and low ECa) for the four soil horizons delimited by concordance analysis.

3.3. Soil properties influencing the spatial and in-depth variation of the ECa

A series of multivariate analysis of variance (MANOVAs) were performed to determine specific soil properties mainly linked to the spatial variation of ECa measured with the Veris 3100 sensor. Results are shown in Table 2. For topsoil properties (0-30 cm), pH, $CaCO_3$ and organic matter (OM) were the properties that contributed most to the spatial variation of the ECa. This result was somehow unexpected since, besides carbonates, organic matter appeared as a soil property that influenced the ECa signal. Descriptive discriminant analysis (DDA) highlighted the importance of OM through the so-called parallel discriminant ratio coefficient (parallel DRC), that indicates the relative contribution of each soil property in the canonical (discriminant) function. Even more, the influence of OM on the ECa was evident for both the shallow values and for the discretized values for the first three soil horizons (Table 2). Among the latter, discriminant function of soil properties corresponding to the 10-20 cm soil layer was able to better differentiate low and high electrical conductivity. However, good discrimination between low and high signals was also achieved by using the soil layer conductivity corresponding to a depth of 20-50 cm. This soil classification was especially interesting given the strong contribution of both $CaCO_3$ and OM in the corresponding discriminant function (Table 2). On the other hand, contribution of water holding capacity (WHC) did not seem to significantly influence ECa, and the original idea that water holding capacity could be behind the spatial variation of ECa was no longer supported.

A similar trend occurred for the subsoil (30-60 cm) and, again, $CaCO_3$ and OM were the properties that contributed most to explain the variability of ECa. Discriminant function for the deeper layer (50-90 cm) provided the best differentiation between low and high electrical conductivity. But, as with topsoil, it was necessary to classify the ECa for a boundary horizon between topsoil and subsoil (20-50 cm) to detect such differences with almost exclusive contribution of $CaCO_3$ and OM (Table 2). Another possibility would be to focus the deep soil management on the carbonates content and, in this case, areas could be delimited using the deep ECa. The relationship between soil variables and ECa coincided with that reported by other authors. Thus, there was an increase in electric conductivity with increasing carbonates content (Kühn et al., 2009), while the effect of organic matter was just the opposite (Moral et al., 2010).

Spatial and in-depth variation of $CaCO_3$ and OM made it possible to propose a site-specific management within the plot based on applying chelates and organic amendments in a differentiated way. Two basic issues need to be addressed. Should the plot be managed based on the differences between topsoil and subsoil, or is it more advisable to consider the entire profile globally? And, faced with the delineation of potential management zones, should areas be defined using the shallow ECa, the deep ECa, or the discretized ECa for a particular soil layer? MANOVA provided very interesting information to assist in such decision making process (Table 2). First, differential management should primarily focus on the $CaCO_3$ spatial distribution because this property clearly influenced the ECa for the entire soil profile. The petrocalcic horizon would probably be behind this spatial variation as a result of previous parcelling and earthworks in recent years. Secondly, the delimitation of areas of low and high conductivity by respectively matching low and high $CaCO_3$ contents for both topsoil and subsoil would be ideal for differential management. The soil layer covering a depth between 20 and 50 cm has shown a spatial pattern of electrical conductivity that meets this requirement. OM was also important, and its spatial variation in the topsoil also seems to be linked to the variation in the subsoil in view of discriminant functions obtained for the soil layer from 20 to 50 cm depth (Table 2). Probably, the boundary condition between topsoil and subsoil of this intermediate layer allowed to use it as representative of the whole soil profile. Contrary to the post hoc interpretation of MANOVAs, separate ANOVAs for each of the most relevant soil properties led to somewhat different results (Table 3). Specifically, spatial pattern of ECa for this horizon (20 cm to 50 cm) would only be justified to delimit potential zones of topsoil management. However, this same ECa pattern can be applied to the subsoil according to the MANOVA results, highlighting the need for a multivariate approach when deciding on potential management areas.

Table 2 Descriptive discriminant analysis (DDA) of soil properties affecting ECa for different soil depths

ECa classified map	Discriminant analysis (DDA)	*Soil properties sampled in the topsoil (0-30 cm)*							
		pH	$EC_{1:5}$	$CaCO_3$	OM	CEC	Clay	Sand	WHC
Shallow ECa	SDFC	1.02	0.26	-1.04	1.19	-0.32	0.45	1.08	-0.03
	SC	0.37	-0.23	-0.36	0.23	0.06	-0.09	0.08	-0.20
	Parallel DRC	**0.38**	-0.06	**0.37**	**0.27**	-0.02	-0.04	0.09	0.01
Depth 0-10 cm	SDFC	1.21	1.85	1.26	-1.60	0.35	-0.01	0.27	0.19
	SC	-0.35	0.50	0.22	-0.14	0.05	0.12	-0.13	0.16
	Parallel DRC	-0.43	**0.93**	**0.27**	**0.22**	0.02	0.00	-0.04	0.03
Depth 10-20 cm	SDFC	0.57	-0.66	-1.42	1.68	-0.28	0.74	1.60	-0.11
	SC	0.27	-0.22	-0.25	0.15	0.03	-0.07	0.09	-0.15
	Parallel DRC	0.15	0.15	**0.36**	**0.25**	-0.01	-0.05	0.14	0.02
Depth 20-50 cm	SDFC	1.21	1.36	-1.14	1.83	-1.77	-	-0.21	0.13
	SC	0.27	-0.12	-0.46	0.26	0.08	-	0.06	-0.19
	Parallel DRC	**0.33**	-0.16	**0.53**	**0.48**	-0.13	-	-0.01	-0.02
ECa classified map	Discriminant analysis (DDA)	*Soil properties sampled in the subsoil (30-60 cm)*							
		pH	$EC_{1:5}$	$CaCO_3$	OM	CEC	Clay	Sand	WHC
Deep ECa	SDFC	0.97	0.35	1.56	-0.02	-	-	-1.42	0.69
	SC	-0.26	0.35	0.42	-0.09	-	-	-0.21	0.26
	Parallel DRC	-0.26	0.12	**0.65**	0.00	-	-	**0.30**	0.18
Depth 20-50 cm	SDFC	1.19	-	2.20	-0.87	-	-	-	-
	SC	0.04	-	0.26	-0.45	-	-	-	-
	Parallel DRC	0.04	-	**0.58**	**0.39**	-	-	-	-
Depth 50-90 cm	SDFC	-	0.48	1.04	-0.48	0.66	-1.36	-0.75	0.58
	SC	-	0.37	0.38	-0.38	0.02	-0.05	-0.07	0.18
	Parallel DRC	-	**0.18**	**0.40**	**0.18**	0.01	0.07	0.06	0.10

Hyphens indicate variables that were removed to obtain significant discriminant functions. Parallel DRC in bold indicates soil properties with greater contribution in the discriminant function from MANOVA. SDFC: standardized discriminant function coefficient; SC: structure coefficient; parallel DRC: parallel discriminant ratio coefficient. $EC_{1:5}$: electrical conductivity in a 1:5 soil-water solution (dS/m); $CaCO_3$ (%); OM: organic matter content (%); CEC: cation exchange capacity (meq/100 g); Clay (%); Sand (%); WHC: water holding capacity (%).

Table 3 Relevant soil properties with significant differences according to ECa classes

ECa classified map	ECa classes	*Soil properties sampled (0-30 cm)*			
		pH	$EC_{1:5}$	$CaCO_3$	OM
Shallow ECa	Low	7.98	-	25.09	-
	High	7.84	-	31.73	-
Depth 0-10 cm	Low	7.98	0.69	-	-
	High	7.83	1.52	-	-
Depth 10-20 cm	Low	7.98	0.70	25.09	-
	High	7.83	1.40	31.11	-
Depth 20-50 cm	Low	7.95	-	24.01	2.78
	High	7.85	-	31.87	2.22

ECa classified map	ECa classes	*Soil properties sampled (30-60 cm)*			
		pH	$EC_{1:5}$	$CaCO_3$	OM
Deep ECa	Low	-	-	29.28	-
	High	-	-	35.47	-
Depth 20-50 cm	Low	-	-	-	-
	High	-	-	-	-
Depth 50-90 cm	Low	-	1.29	29.05	1.57
	High	-	2.26	35.09	0.93

Hyphens indicate variables that did not show significant differences ($p<0.05$) in the corresponding ANOVAs. $EC_{1:5}$: electrical conductivity in a 1:5 soil-water solution (dS/m); $CaCO_3$ (%); OM: organic matter content (%). CEC, clay, sand and WHC are not shown in the table, because they were not significantly different in any of the soil layers.

3.4. Spatial pattern of the ECa as a result of previous parcelling: consequences for management

As previously mentioned, the plot under study had been subjected to different parcelling processes in recent decades. Figure 1 shows the evolution from 1946. By overlapping the ECa map derived from the Veris 3100 sensor readings (deep signal) (Fig. 6), it is interesting to observe how it clearly reproduces the edges and divisions of previous plots. Depending on the use and the parent material, the soil of the present plot is the result of all these transformations affecting productivity and causing the current spatial variability. From this point of view, the use of combined information from soil sensors and historical orthophotos becomes an interesting tool for better soil interpretation and better diagnosis of management actions to be performed.

As showed in Fig. 6, the two transverse subdivisions (paths) in 1946, one of which was still in place in 2005, are relatively marked as areas of highest conductivity in the ECa cluster map for the reference horizon corresponding to 20-50 cm depth (Fig. 5). On the other hand, a more compact area with also high ECa values appears as a consequence of incorporating a piece from another different plot in 1986. This area has remained different from the rest of the plot until today (perfectly marked on the cluster map), and corresponds to the area where problems commonly due to high carbonates contents are done. Our management proposal for this plot could then be established making use of the classified map for the aforementioned reference horizon, that matches the joint differential needs for topsoil and subsoil. Therefore, in areas with potential chlorosis and soil fertility problems (high ECa), the farmer could implement a fertilization plan by adding chelates and organic fertilizers to correct these nutritional imbalances more optimally.

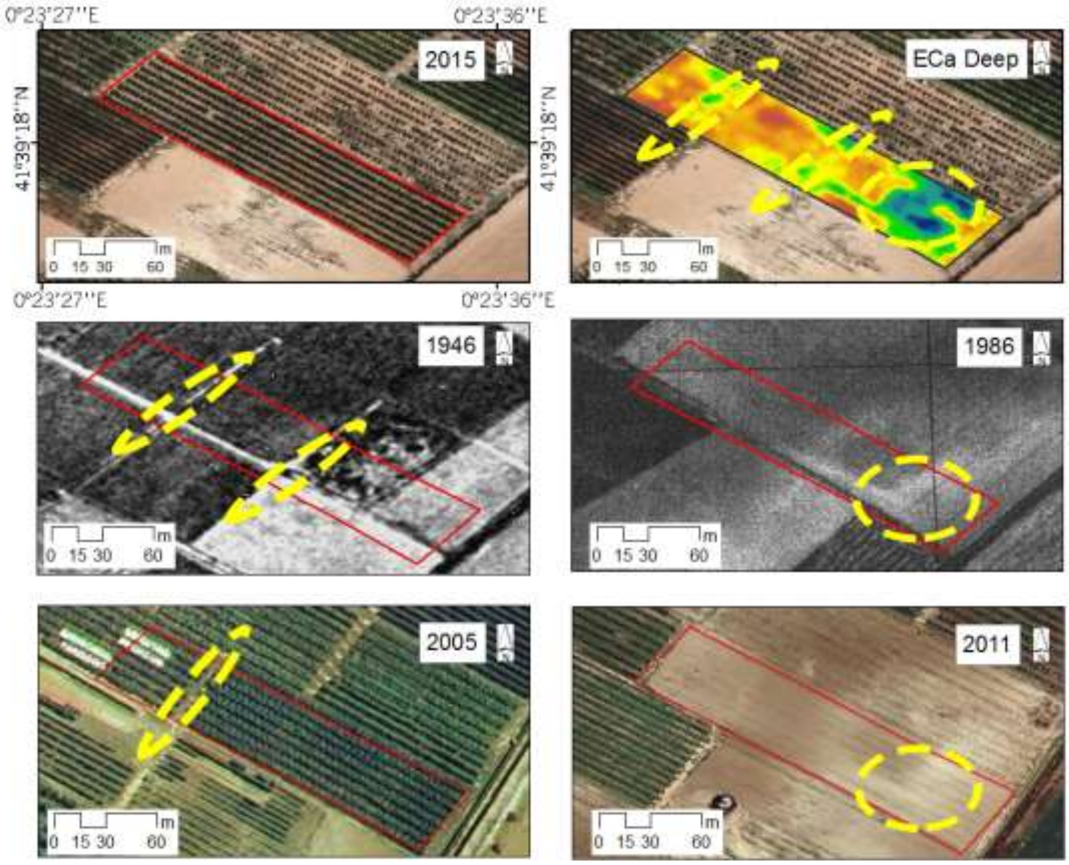

Fig. 6 Evolution of historical parcelling until 2015 and current design. The overlapping of the deep ECa map shows where the transformations occurred.

4. Conclusions

The acquisition and mapping of apparent electrical conductivity (ECa) allowed areas with potential chlorosis problems to be delimited in the study plot. These areas were characterized by high $CaCO_3$ content due to the presence of a petrocalcic horizon at variable depth. On the other hand, parcelling carried out over the years has been revealed as a key factor in understanding the soil spatial variability that is then reproduced by the electrical conductivity sensor. Since carbonates and organic matter are behind much of the variability detected by the conductivity signal, site-specific organic amendment and chelate application is a management option to be taken into account. Regarding the information analysis procedure, ECa analysis should not focus exclusively on shallow and deep signals. Signal inversion allowing ECa measures to be estimated in depth at discrete intervals makes it possible to divide the soil profile into homogeneous horizons by comparing classified maps of ECa at different depths. Then, multivariate analysis of variance (MANOVA) based on the previous maps offers interesting outputs in agronomy because, i) the overall relationship between ECa and soil properties is better interpreted, and ii) potential management zones can be validated knowing in detail the specific causes behind the variation of ECa, in our case, both $CaCO_3$ and organic matter contents.

Acknowledgements
This work was funded by the Spanish Ministry of Economy and Competitiveness through the project AgVANCE (AGL2013-48297-C2-2- R). We are also grateful to the University of Lleida for funding PhD scholarship for the first author

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