USE OF APPARENT ELECTRICAL CONDUCTIVITY AS SECONDARY INFORMATION FOR SOIL ORGANIC CARBON SPATIAL CHARACTERIZATION

Gonzalo Martínez[1]*, Karl Vanderlinden[1], J. V. Giráldez[2], Antonio J. Espejo[1], Esther Rodríguez[1], Rafaela Ordóñez[3], José L. Muriel[1]

1: Grupo de investigación suelo y Agua.
Área de Producción Ecológica y Recursos Naturales
IFAPA, Junta de Andalucía
Centro Las Torres-Tomejil, Crtra. Sevilla-Cazalla, km 12.2. 41200 Alcalá del Río (Sevilla)
e-mail: gonzalo.martinez@juntadeandalucia.es, web: http://www.agroehidroecologia.org

2: Departamento de Agronomía,
Universidad de Córdoba e Instituto de Agricultura Sostenible, CSIC,
Campus de Rabanales, Edificio da Vinci. Ctra. Madrid, km 396, 14071 Córdoba

3: Área de Producción Ecológica y Recursos Naturales
IFAPA, Junta de Andalucía
Centro Alameda del Obispo, Av. Menéndez Pidal, sn. 18001. Córdoba

Palabras clave: Soil Organic Carbon, Apparent electrical conductivity, Soil management, Fuzzy k-means, Simple Kriging with varying local means

RESUMEN. *La conductividad eléctrica aparente del suelo (EC_a) puede mejorar la estimación espacio-temporal de algunas propiedades del suelo, pero ¿puede caracterizar también el carbono orgánico (SOC) en un ensayo a largo plazo de sistemas de manejo? Los resultados mostrados en este informe así lo prueban. La EC_a y el SOC fueron mayores en las parcelas de Siembra directa que en las de laboreo tradicional. Los mapas de EC_a mostraron las diferencias atribuidas al sisema de manejo y a la topografía. El mapa obtenido por clasificación difusa de la diferencia normalizada de la EC_a de la superficie del suelo (ECas) y del suelo profundo (ECad) (FKM1), así como el obtenido a partir de EC_{as} y EC_{ad}, representaron el 30 % de la variabilidad total del SOC, mientras que el valor medio de cada parcela y de cada sistema de manejo representaron el 44 y 41 %. El krigeado simple con media local variable empleando FKM2 o el SOC promedio de una parcela como información secundaria mejoraron la estimación del SOC con respecto al krigeado ordinario. A pesar de la reducida correlación entre el SOC y la EC_a, ésta fue útil para mejorar la estimación espacial del SOC.*

ABSTRACT. *Ancillary information, such as apparent electrical conductivity (EC_a), can improve the spatial and temporal estimation of some soil properties, but can it also infer the soil organic carbon contet, SOC? The results of this report confirm this hypothesis in a long-term tillage experiment. Both EC_a and SOC were higher in the DD plots. EC_a maps showed tillage and topographic effects on soil spatial variability. A normalized difference of shallow and deep EC_a, ΔEC_a (FKM1) and EC_{ad} and EC_{as} (FKM2) classified by fuzzy k-means accounted for 30% of the total SOC variability, whereas the individual plots and the soil management system explained 44 and 41%, respectively. Simple kriging with local varying means using either FKM2 or plot-average SOC as secondary information improved the SOC estimation compared with ordinary kriging. Despite the low point-to-point correlation between EC_a and SOC, EC_a was shown to be useful for the spatial estimation of SOC.*

1. INTRODUCTION

Soil organic carbon (SOC) plays an important role in a wide variety of biogeochemical fluxes. However, SOC stores are not well defined while an increasing demand for its accurate characterization at different scales is required. This information can help to understand SOC cycles and determine under which circumstances soils act as either a C source or sink (Smith, 2004) and evaluate the effects of different management strategies on soil properties and CO_2 emissions. Direct SOC spatial characterization, however, requires a large number of soil samples. As an alternative, Kravchenko and Robertson (2007) integrated secondary information such as topographic attributes or yield to improve SOC spatial characterization. These variables did not improve significantly the spatial characterization of SOC. Nowadays, the availability of modern remote and proximal sensors provides other sources of secondary information that are useful for the characterization of different soil properties at different scales and depths. Proximal sensors have a better performance for studying soil-depth relationships and distribution of soil physical and chemical properties at small to medium scales, while remote sensors are especially useful for vegetation-related properties at medium to large spatial scales and at the soil surface (Robinson *et al.* 2008). Electromagnetic induction proximal sensor has been used to explore vadose zone relationships between apparent electrical conductivity (EC_a) and soil properties at small scale research (Kachanoski *et al.* 1988; Carrol and Oliver, 2005; Vitharana *et al.* 2006, Weller *et al*. 2007; Abdu *et al*. 2008). Linear relationships between EC_a and other soil properties were not always strong enough to use Co-Kriging. As an alternative, EC_a has been used to assist the spatial classification of EC_a -related soil properties to define homogeneous areas (Cockx *et al*. 2005; Vitharana *et al.* 2006) and management-induced changes (McCutcheon *et al.* 2006). These alternatives offer a chance to apply EC_a on the spatial characterization of soil organic carbon and to discriminate the effects of management on SOC. The objective of this work was to analyze whether EC_a–based secondary information improves SOC spatial estimation in a tillage experiment.

2. MATERIALS AND METHODS

2.1 Study Site

The study was conducted in a 3.5-ha parcel of the Tomejil Experiment Station (37°24’ N, 5°35’ W, 79 m above sea level) not far from Seville. Clay is the predominant size fraction (60% on average) in the 0-0.15-m horizon, with small differences in particle size distribution within the field. In the fall of 1982, a management experiment was initiated to compare the agronomic consequences and the evolution of soil physical and chemical properties under conventional tillage (CT), minimum tillage, and Direct Drilling (DD) (Ordóñez *et al.* 2007). Figure 1 shows the layout of three replicates of CT and DD plots, distributed in three blocks, with individual dimensions of 15 by 65 m. The crop rotation was wheat-sunflower-legume. The field was left fallow between the harvest of wheat in June 2005 and the drilling of sunflower in April 2006.

Soil sampling and sensing.

In fall 2005 soil samples from the upper horizon (0-0.15m) were collected, 71 according to a stratified random design and 24 randomly located to get a wide range of distances between sampling points (Fig. 1). Apparent electrical conductivity was sensed using an EM38-DD (Geonics Ltd., Missisauga, ON, Canada) at two depths: shallow (EC_{as}) and deep (EC_{ad}). The sensor integrates the readings of two sensors placed in opposite orientations, vertical and horizontal and soil depth sensed by each EM38 depends on soil EC_a (Callegary *et al.* 2007). The estimated depths for EC_{as} and EC_{ad} can be around 0.5 and 0.7 m respectively. Soil EC_a sensing was carried out coupled to soil sampling on the Fall of 2005 and more intensively on March 2006, when soil was moister, to create EC_a-related maps. Soil samples were dried crushed and sieved prior to SOC analysis following the method of Walkley and Black (Sparks *et al.* 1996).

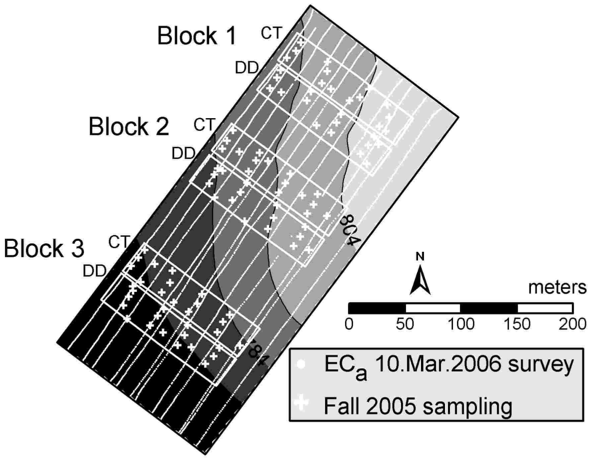

Figure 1. Topographic field-map. Overlaid appear subplots in white, SOC and EC_a sample points of Fall 2005 (crosses) and EC_a dense survey of March 2006 (dots).

2.3. Data analysis.

As a way to merge EC_{ad} and EC_{as} information we calculated a normalized difference between them (Eq. 1). The normalized difference filters common variability in EC_{ad} and EC_{as} from the signals and elucidates differences between the soil surface and the deeper soil horizons.

$$\Delta EC_a = \left(\frac{EC_{ad}}{\overline{\overline{EC_{ad}}}}\right) - \left(\frac{EC_{as}}{\overline{\overline{EC_{as}}}}\right) \tag{1}$$

Geostatistical analysis

A random function (RF) can be decomposed as a sum of three components, the expected value of the RF, a stochastic spatially dependent term, and a spatially uncorrelated noise term (Goovaerts 1997). The trend or local mean, was calculated as (i) the spatial average SOC of the individual experimental plots, (ii) the average SOC of each management type, or (iii) the average SOC of the different classes obtained by classification. The residuals were then obtained as the difference between the RF and its local mean. The spatial correlation structure of the total SOC data set and its residuals were calculated using the variogram. Depending on the model selected for the local mean, different forms of the kriging estimator can be distinguished. Ordinary kriging (OK) accounts for local fluctuations of the mean but considers the global mean an unknown constant and uses the variogram of the RF, while in simple kriging with varying local means (SKlm), the mean is a known, stationary value and the residual variogram is used instead. Cross validation assesses the performance of the Kriging and consists of successive elimination of each data value and its estimation from the remaining points. To give quantitative indexes of cross validation the root mean square error (RMSE) and the Nash-Sutcliffe efficiency index (E) were used. Ordinary kriging and SKlm of SOC were computed using the kt3d program from the Geostatistical software library (GSLIB) of Deutsch and Journel (1998). The EC_{ad}, EC_{as}, and ΔEC_a values (from the March 2006 survey) were interpolated by OK using VESPER (Minasny *et al*. 2002a), which is especially useful for interpolating large data sets since it allows the use of local variograms.

Classification procedure.

Classification was performed by the Fuzzy k-means (FKM) algorithm using the program FuzME (Minasny and McBratney 2002b). Data used for FKM were (i) OK-interpolated ΔEC_a data (FKM1) and (ii) OK-interpolated

EC_{ad} and EC_{as} data (FKM2) from the March EC_a data set, selecting only those points located inside the CT and DD subplots. Fuzzy *k*-means is an unsupervised classification method that splits the data set in random groups and clusters data by iterating the calculation of distances or dissimilarities, between individual data points and a class center. Grouping is achieved minimizing intraclass variation and maximizing interclass variation. Fuzzy *k*-means is a method that allows for the overlapping of classes, determined by its fuzzy exponent (φ), where φ = 1 represents no overlap and φ > 1 represents an increasing overlap between clusters or classes. The optimal number of classes is given by two functions involved in FKM classification, the fuzziness performance index (FPI) and normalized classification entropy (NCE) (Odeh *et al.* 1992). The FPI function estimates the degree of segregation generated by a specified number of classes, while the NCE estimates the degree of disorganization created by a specified number of classes. The confusion index (CI) is a measure of the sharing of a point between classes. The minimum of both FPI and NCE give the optimal number of continuous and structured classes. For FKM1, the optimal φ was 2.4 and two classes yielded less segregation and disorganization of groups, while for FKM2, the optimal φ was lower, 1.9, and four classes yielded less segregation and disorganization of groups.

3. RESULTS AND DISCUSSION

3.1. Exploratory data analysis.

In general, SOC was lower than 13 g kg^{-1} and had a slightly skewed distribution (Table 1). Due to the high clay content of this soil and the positive correlation between clay and EC_a reported by several authors (Vitharana *et al.* 2006; Weller *et al*. 2007; Abdu *et al.* 2008), mean EC_{ad} and EC_{as} values observed in October 2005 and March 2006 were higher than for other soils (Cockx *et al.* 2005; Vitharana *et al.* 2006; McCutcheon *et al.* 2006). Skewness was higher for EC_{ad} than for EC_{as}, reflecting the presence of areas with large EC_{ad} values, extending far beyond the mean. From a management point of view, the CT plots contained less SOC than the DD plots (9.16 and 11.7g kg^{-1}, respectively) and exhibited, on average, lower EC_{ad} (79.6 and 86.0 mS m^{-1}, respectively) and EC_{as} values (50.7 and 62.1 mS m^{-1}, respectively).

TABLE 1. Descriptive statistics of soil organic carbon samples, shallow and deep apparent electrical conductivity sensed in October and for the intensive EC_a survey of March 2006 using only points located within the plots. Q25 is the lower quartile, Q50 the median, Q75 the upper quartile and CV is the coefficient of variation.

	SOC (g kg^{-1})	EC_{ad}^{Fall} (mS m^{-1})	EC_{as}^{Fall} (mS m^{-1})	EC_{ad}^{March} (mS m^{-1})	EC_{as}^{March} (mS m^{-1})
N	93	69	69	1609	1609
Mean	10.4	82.7	56.3	122.	59.6
Q_{25}	8.81	75.4	50.1	115.	50.6
Q_{50}	10.0	82.1	56.4	121.	61.3
Q_{75}	11.7	85.8	62.6	127.	65.8
Min.	6.90	63.1	38.4	96.9	25.4
Max	16.3	119.	88.5	170.	95.8
Variance	4.38	141.	94.7	137.	105.
CV	0.201	0.14	0.17	0.10	0.17
Skewness	0.738	1.06	0.44	1.25	0.44
Kurtosis	0.003	1.66	0.87	2.68	0.54

Although organic matter loading increased by 18 Mg ha^{-1} during the long-term experiment as a consequence of the minimization of tillage (Ordóñez *et al.* 2007), the SOC content remained low. The SOC variance was four times higher under DD than under CT (4.62 and 1.03 g^2 kg^{-2}, respectively), contrary to the findings of Perfect and Caron (2002) who found less variability under DD for a silt loam soil. This difference can be a consequence of the presence of areas in which crop residue accumulates when harvest operations are done. In contrast, the EC_a variance was lower in the DD than in the CT plots, both for EC_{ad} (122 and 144 mS^2 m^{-2}, respectively) and EC_{as} (48.8 and 75.3 mS^2 m^{-2}, respectively). Correlation coefficients between SOC and EC_{ad}, EC_{as}, and ΔEC_a were 0.175, 0.331, and −0.404, respectively. These correlations were weak; therefore, we did not expect cokriging to improve SOC estimation using EC_a data. These low correlations might be caused by (i) differences in the soil volume explored by the EM38-DD and manual augering, (ii) the small range of SOC values, (iii) the weight-based SOC observations against volumetric EC_a measurements, and (iv) the bulk influence of other soil properties on EC_a. In March, higher EC_{ad} and EC_{as} values (122 ± 0.29 and 59.6 ± 0.25 mS m^{-1}, respectively) were observed than in October due to the higher soil moisture content and possible solubility of salts. Skewness was again higher in EC_{ad} while the interquartile range was similar for EC_{ad} and EC_{as} (12.3 and 15.1 mS m^{-1} respectively). The mean EC_{ad} and EC_{as} values for DD were 128 ± 0.44 and 67.8 ± 0.27 mS m^{-1} respectively, and for CT 118 ± 0.32 and 53.4 ± 0.25 mS m^{-1}, respectively.

3.2. Apparent Electrical Conductivity Maps.

Ordóñez *et al.* (2007) reported management-induced changes in the soil physical and chemical properties of this field as a consequence of the different tillage systems. The CT and DD plots could be best distinguished on the ΔEC_a map (Fig. 2); however, big differences can be distinguished on the EC_{ad} and EC_{as} maps. Positive ΔEC_a values corresponded generally with the CT plots, while negative values were mainly observed within the DD plots. This same pattern was also observed for the EC_a measurements in October. According to Eq. [1], positive ΔEC_a values occur when the normalized EC_{ad} exceeds the normalized EC_{as}, which might be a consequence of the denser and wetter subsoil and a higher Electrical conductivity of the subjacent soil (Lozano 2008). Vanderlinden *et al.* (2008) found persistently higher soil water content in DD plots during the growing season, with a permanently drier surface horizon.

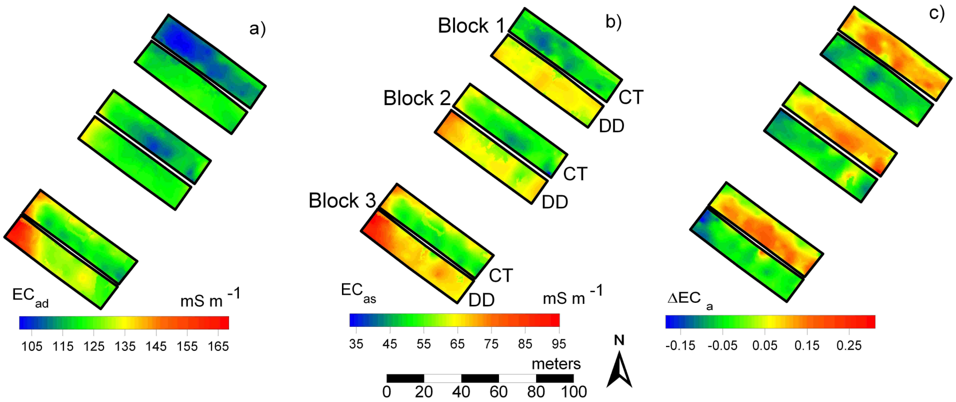

Figure 2. Ordinary kriging maps of (a) deeper soil apparent electrical conductivity (EC_{ad}), (b) shallower soil apparent electrical conductivity (EC_{as}), and (c) normalized apparent electrical conductivity difference (ΔEC_a), for the intensive survey of March 2006 under conventional tillage (CT) and direct drilling (DD).

The maps in Fig. 2 show the heterogeneous nature of the CT plots, with a transition to DD values near the edge of the plots where the tillage operations might have been less effective. Topographic influences on the spatial EC_a distribution were also found and are displayed in figure 2, but are not visible with ΔEC_a. Generally, high EC_a values occur in the lowest parts of the field (Fig. 1a and 1b), which could be a coupled effect of the accumulation of nutrients, water, and sediments in the lowest part of the field. The EC_a values were related not only to the tillage system, but depended also on their location within the field. For example, plots located in Block 3 had higher EC_a values since they were situated in the lowest part of the field.

3.3. Fuzzy *k*-Means Classification.

Normalized Apparent Electrical Conductivity Difference Classification

Figure 3a shows the distribution of FKM classes and, as it also occurs with the ΔEC_a map, CT are clearly separated from the DD plots. Areas with CI higher than 0.5 were mainly located near plot edges, showing an intermediate behavior between Classes 1 and 2. To simplify, these areas were included in the class for which their membership was highest. Class 1 mainly delimited areas managed under CT, except for a small spot in the DD plot of Block 3, close the CT plot. Class 1 showed low SOC (9.5 g kg^{-1}), a positive ΔEC_a value (0.09), and mean EC_{ad} and EC_{as} values of 116 and 52 mS m^{-1}. Class 2 generally corresponds to DD plots and several borders of the CT plots. This class showed higher values for both EC_{ad} and EC_{as} (126 and 67 mS m^{-1}) and for SOC (11.4 g kg^{-1}) than class 1.

Vertically and Horizontally Sensed Apparent Electrical Conductivity Classification

The FKM1 and FKM2 maps (Fig. 3a and 3b) showed differences between CT and DD plots. However, only FKM2 could show a topographic effect with differences between Block 3 and the other blocks. Areas with a high confusion index were situated near the plot edges like in FKM1 and within Block 3 where the hydrologic behavior of the field changes. Class 1 delimited areas, with high SOC and medium EC_{as}, were mainly within the DD plots of Blocks 1 and 2, with higher slope and altitude. Class 2 showed the lowest EC_a values and SOC content. This class was mainly located in the CT plots of Blocks 1 and 2, which have similar topographic attributes (Fig. 1). Class 3 showed medium SOC and medium EC_a (Table 3). This class covered some areas of Block 3, especially near plot edges. Average SOC in this class (10.1 ± 0.57 g kg−1) was lower than the average value of the DD plots (11.7 ± 0.31 g kg−1). These low-altitude areas and plot edges showed medium values of EC_a, probably due to higher nutrient and moisture contents than Classes 1 and 2. Areas included in Class 4 had a similar SOC content and had been managed in the same way as most of Class 1. The differences found were probably a consequence of topographic effects (Fig. 1), as also observed by Kravchenko and Robertson (2007). Other researchers have also concluded that low-altitude areas and edges or headlands are moister and show higher EC_a values (Cockx *et al.* 2005; Vitharana *et al.* 2006).

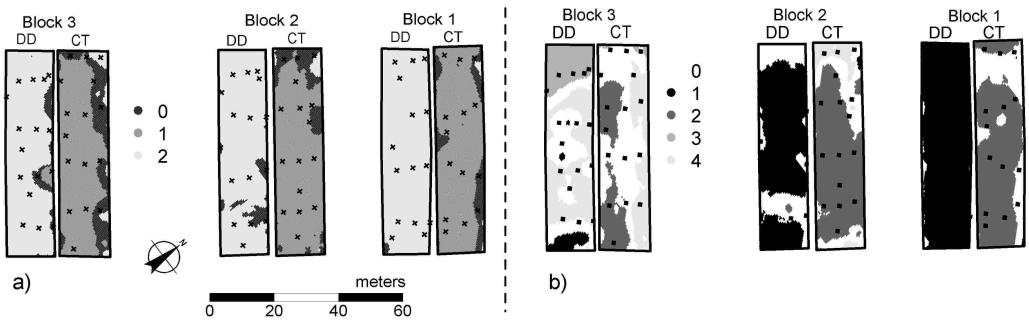

Figure 3. Class maps obtained by Fuzzy k-means classification using: a) normalized apparent electrical conductivity difference (FKM1) and b) surface and deep soil apparent electrical conductivity (FKM2). Class 0 represents zones where the confusion index is higher than 0.5. Superposed points are the soil sampling locations.

3.4 Soil Organic Carbon Estimation

The spherical models fitted to the SOC and residual variograms are shown in Fig. 4. Variogram sills reflect the total variability or the unstructured variability of SOC and its residuals. Sills of the FKM1, FKM2, plot, and management residual variograms were 29, 30, 44, and 41% smaller, respectively, than the SOC sill. These differences between the residual variograms and the SOC variogram indicate that a large part of the SOC variance in the field can be explained by ECa and management. For the FKM2 and plot residual variograms, the nugget/sill ratio exceeded 0.80, showing that short-range variation and procedural errors were the most important sources of residual variation. The variogram ranges, that gives a measure of up to what extent there exist a structured spatial variation, were close to the plot width (15 m). This indicates that most of the structured variance occurred within individual plots and blocks, and that points from blocks 1 and 2 are not compared to those of block 3. The SOC variogram sill was reached at larger lag distances, for which data pairs were formed by points from adjacent plots with different soil management systems.

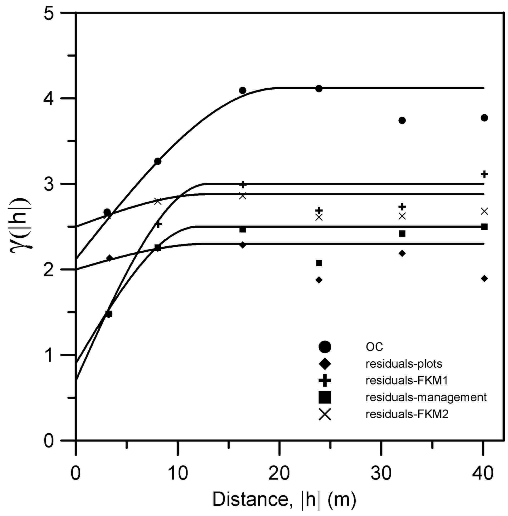

Figure 4. Variograms for soil organic carbon (SOC) and SOC residuals calculated using local means obtained from fuzzy *k*-means classification for normalized apparent electrical conductivity data (FKM1) and for vertically and horizontally sensed apparent electrical conductivity data (FKM2) and plot and management mean values.

The cross-validation of the kriging estimation showed that SKlm performed better than OK in all cases except SKlm–FKM1. The improvement of the RMSE ranged from −2% for SKlm–FKM1 to 19% for SKlm–plots. Compared with OK, both SKlm–FKM2 and SKlm–management reduced the RMSE by 8%, indicating that, in this case, EC_a–based secondary information is as efficient as soil management-based knowledge for interpolating SOC. The improvement of SKlm-FKM2 and SKlm-management are in the same order of magnitude than that of Kravchenko and Robertson (2007) who obtained a reduction of the RMSE of 10% using topography and yield as secondary information in regression kriging. Although here the improvement of SOC estimation is lower than 10%, maybe using an EC_a dataset with more sampling dates can achieve a better improvement. Despite the low correlation found between EC_a and SOC, FKM classification based information could improve the SOC estimation. Although the FKM1 and management classification were very similar, poorer results were obtained by SKlm–FKM1. This was due to the classification of nine singular points, generally situated near the edges of the plots. The FKM1 classes where these points were included did not coincide with the management classification, according to the plots to which they belonged. The Nash and Sutcliffe index was generally lower than 0.5, but increased by almost 70% for SKlm–FKM2 compared with OK, similar to the results obtained for SKlm–management. These findings indicate that EC_a is capable of capturing the spatial variability in SOC, mainly attributed to different management systems in this uniform clay soil. Other sources of within-plot variability of SOC could not be identified successfully, however, so that only 30% of the variability in SOC could be accounted for. Possibly changing from one point observation in time to average EC_a patterns can improve SOC estimation.

4. CONCLUSIONS

Apparent electrical conductivity surveys can provide a cheap and useful information to capture soil spatial variability at small to medium scales, and to assist the quantitative spatial characterization of SOC. The ECa data elucidated differences in soil properties as a consequence of topography and management and explained >25% of the SOC spatial variation. The FKM1 and FKM2 classifications of ECa could successfully delimit homogeneous soil units related to soil management and the spatial distribution of SOC. Plot edges and accumulation areas introduced some bias and SKlm–FKM1 could not improve the spatial estimation of SOC. The use of ECad and ECas as secondary information in SKlm–FKM2 reduced the RMSE of the SOC interpolation by 8%, similar to SKlm–management. The FKM2 classification was also able to differentiate plots from the same treatment and showed variations within plots caused by other factors like tillage, topography, erosion or compaction. The results of this work can be useful for similar experiments on the assessment of soil C dynamics under different tillage systems. Even in our homogeneous clay soil, uniform management units could be identified using ECa and FKM, where different experimental treatments can be best compared

Acknowledgements. This work was funded by the Spanish Ministry of Education and Science and the National Institute of Agricultural Research through Grants RTA2006-00058-CO3-01/02, PRE-2005, and by the Junta de Andalucía though Grant AGR2349. Complementary funding by the IFAPA through Grant FIC07-06 is also acknowledged. We thank J. García-Baquero and the personnel of the soils laboratory at IFAPA-Alameda del Obispo for helping with the soil analysis. Also special thanks to J. Osuna (University of Cordoba) and M. Morón (IFAPA) for setting up the mobile configuration of the equipment.

REFERENCES

Abdu H., D.A. Robinson, M. Seyfried y S.B. Jones. 2008. Geophysical imaging of watershed subsurface patterns and prediction of soil texture and water holding capacity. *Water Resour. Res.* 44, W00D18, doi:10.1029/2008WR007043.

Cockx, L., M. Van Meirvenne, and G. Hofman. 2005. Characterization of nitrogen dynamics in a pasture soil by electromagnetic induction. *Biol. Fertil. Soils,* 42: 24–30.

Deutsch, C. V., and A.G. Journel. 1998. Gslib. Geostatistical software library and user's guide. 2nd ed. Oxford Univ. Press. Oxford.

Callegary, J.B., T.P.A. Ferré, and R.W. Groom. 2007. Vertical spatial sensitivity and exploration depth of low-induction-number electromagnetic-induction instruments. *Vadose Zone J.* 6,158–167.

Carroll, Z.L., and M.A. Oliver. 2005. Exploring the spatial relations between soil physical properties and apparent electrical conductivity. *Geoderma* 128:354-374.

Goovaerts, P. 1997. *Geostatistics for natural resources evaluation*. Oxford Univ. Press, Oxford

Kravchenko, A.N, and G.P. Robertson. 2007. Can topographical and yield data substantially improve total soil carbon mapping by regression kriging? *Agron. J.* 99:12-17.

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

Lozano, B. 2008. *Estudio del comportamiento hídrico en ZNS de un vertisol del Valle Medio del Guadalquivir*. Tesis Doctoral, Dpto. de Química Agrícola, Universidad de Córdoba.

McCutcheon, M.C, H.J. Farahani, J.D. Stednic, G.W. Buchleiter and T.R. Green. 2006. Effect of soil water on apparent soil electrical conductivity and texture relationships in a dryland field. *Biosyst Engng.* 94:19-32.

Minasny, B., A.B. McBratney, and B.M. Whelan. 2002a. Vesper (variogram estimation and spatial prediction plus error) version 1.6. Aust. Ctr. for Precision Agric., Sydney

Minasny, B., and A.B. McBratney. 2002b. FuzME version 3.0, Australian Centre for Precision Agriculture. Available at http://www.usyd.edu.au/su/agric/acpa (Verified 12 Dec. 2008)

Odeh, I.O.A, A. B. McBratney, and D.J. Chittleborough. 1992. Soil pattern recognition with Fuzzy-c-means: Application to Classification and Soil-Landform Interrelationships. Soil Sci. Soc. Am. J. 56:505-516.

Ordóñez, R., P. González, J.V. Giráldez, and F. Perea. 2007. Soil properties and crop yields after 21 years of direct drilling trials in southern Spain. *Soil Till. Res*. 94, 47–54.

Perfect, E., and J. Caron. 2002. Spectral analysis of tillage-induced differences is soil spatial variability. *Soil Sci. Soc. Am. J.* 66:1587-1595.

Robinson D.A., A. Binley, N. Crook, F.D. Day-Lewis, T.P.A. Ferré, V.J.S. Grauch, R. Knight, M. Knoll, V. Lakshmi, R. Miller, J. Nyquist, L. Pellerin y K. Singha. 2008. Advancing process-based watershed hydrological research using near-surface geophysics: a vision for, and review of, electrical and magnetic geophysical methods. *Hydrol. Proc.*. 22, 3604-3635.

Smith, P. 2004.Soil as a carbon sink: the global context. *Soil Use Manag*. 20:212-218.

Sparks, D.L., A.L. Page, P.A. Helmke, R.H. Loeppert, P.N. Soltanpour, M.A. Tabatai, C.T. Johnston, and M.E. Sumner (Eds.), 1996. Methods of Soil Analysis. Part 3: Chemical Methods. Soil Sci. Soc. Am. Book Series no. 5. 3rd ed. Soil Science Society of America, Madison.

Vanderlinden , K., J.A. Jiménez, J.L. Muriel, F. Perea, I. García and G. Martínez. 2008. Interpolation of soil moisture content aided by FDR sensor observations. Soares, A., M. J. Pereira and R. Dimitrakopoulos: *GeoENV VI - Geostatistics for Environmental Applications*, 397-407. Springer, Berlín.

Vitharana, U.W.A., M. Van Meirvenne, L. Cockx, and J. Bourgeois. 2006. Identifying potential management zones in a layered soil using several sources of ancillary information. *Soil Use Manage*. 22:405-413.

Weller, U., M. Zipprich, M. Sommer, W. Zu Castell and M. Wehran. 2007. Mapping clay content across boundaries at the landscape scale with electromagnetic induction. *Soil Sci. Soc. Am. J*. 71: 1740-1747.