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Delineation of site-specific management units in a saline region at the Venice Lagoon margin, Italy, using soil reflectance and apparent electrical conductivity

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ABSTRACT

Site-specific crop management utilizes site-specific management units (SSMUs) to apply inputs when, where, and in the amount needed to increase food productivity, optimize resource utilization, increase profitability, and reduce detrimental environmental impacts. It is the objective of this study to demonstrate the delineation of SSMUs using geospatial apparent soil electrical conductivity (EC_a) and bare-soil reflectance measurements. The study site was a 21-ha field at the southern margin of the Venice Lagoon, Italy, which is known to have considerable spatial variability of soil properties influencing crop yield. Maize (*Zea mais* L.) yield maps from 2010 and 2011 showed high spatial heterogeneity primarily due to variation in soil-related factors. Approximately 53% of the spatial variation in maize yield was successfully modeled according to the variability of four soil properties: salinity, texture, organic carbon content, and bulk density. The spatial variability of these soil properties was characterized by the combined use of intensive geospatial EC_a measurements and bare-soil normalized difference vegetation index (NDVI) survey data. On the basis of the relationships with these soil properties, EC_a and NDVI were used to divide the field into five *SSMUs* using fuzzy c-means clustering: one homogeneous with optimal maize yield, one unit affected by high soil salinity, one characterized by very coarse texture (i.e., sandy paleochannels), and two zones with both soil salinity and high organic carbon content. Yield monitoring maps provide valuable spatial information, but do not provide reasons for the variation in yield. However, even in cases where measurements like EC_a and bare-soil NDVI are not directly correlated to maize yield, their combined use can help classify the soil according to its fertility. The identification of areas where soil properties are fairly homogeneous can help managing diverse soil-related issues optimizing resource use, lowering costs, and increasing soil quality.

1. Introduction

The southern margin of the Venice Lagoon in Italy is a highly heterogeneous environment subject to both natural changes and anthropogenic pressures (De Franco et al., 2009). The area is part of the Po River alluvial plain and is characterized by high spatial geomorphologic variability with highly permeable sandy paleochannels crossing soils rich in organic matter (Rizzetto et al., 2003). Due to the presence of peat, the area has been subsiding since its reclamation for agricultural purposes at the beginning of the 20th century (Teatini et al., 2007; Zanello et al., 2011). Furthermore, saltwater intrusion is a major threat to crop production (De Franco et al., 2009; Viezzoli et al., 2010) because the area lies down to 4 m below average sea level (asl) and continuous drainage causes the saltwater–freshwater interface to rise close to the soil surface (Bear, 1988).

Spatial and temporal variations in edaphic properties cause within-field crop yield variation due to various crop stresses that cannot be managed effectively with conventional farming strategies (Robert, 2002). Site-specific crop management (i.e., application of resources when, where, and in the amount needed) represents the best option to manage within-field spatial variation of crops and soils. In particular, the use of site-specific management units (SSMUs; i.e., the delineation of sub-sections of a field that are managed the same in order to achieve a specific goal) has proved to be a reliable solution for managing heterogeneous farmlands (Robert, 2002).

Abbreviations: EC_a, soil apparent electrical conductivity; NDVI, normalized difference vegetation index; $EC_{1:2}$, soil salinity electrical conductivity of a soil-water extract ratio 1:2; ρ_b, soil bulk density; SOC, soil organic carbon.

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Spatial variation of yield is affected by a large range of factors, including topographic, edaphic, biological, meteorological, and anthropogenic factors (Corwin and Lesch, 2005a). However, only a portion of these can be practically managed in order to increase crop productivity. Indeed, as suggested by Corwin and Lesch (2010), a simplified and effective way of designing SSMUs is to analyze the effect of a single factor (e.g., edaphic) on yield spatial variability. The extent of yield variation specifically related to changes in soil properties can be substantial (Corwin et al., 2003; Li et al., 2007; Savabi et al., 2013).

Intensive and relatively inexpensive spatial measurements of soil apparent electrical conductivity (EC_a) are commonly used to characterize the spatial variability of a vast group of soil properties (Corwin and Lesch, 2005a). Apparent soil electrical conductivity is influenced by, and therefore correlated with, soil properties, including soil salinity, water and organic matter content, texture, and bulk density (Corwin and Lesch, 2005a). Unfortunately, in most cases EC_a measurements are not sufficient to describe the spatial distribution of all the soil properties influencing yield. Often, EC_a measurements in a field are dominated by one or two soil properties (Johnson et al., 2005; Corwin, 2008). In such cases other types of ancillary information could be used to complement EC_a. Several types of sensors have been recently used to provide ancillary data for characterizing large farmlands based on a limited number of soil samples (Adamchuk et al., 2004; Mulder et al., 2011; Viscarra Rossel et al., 2011), including optical and radiometric sensors in the visible (400–700 nm) and near-infrared (700–2500 nm) regions.

In particular, radiometric sensors in the visible range provide reflectance measurements which are closely related to soil color (Post et al., 2000). Dark soils are generally characterized by high organic matter and/or iron oxides contents (FitzPatrick, 1986; Leone and Escadafal, 2001). A lighter color can identify areas rich in carbonate (Ellis and Mellor, 2002), or areas affected by high salinity (Metternicht and Zinck, 2003), or sandy areas (Rizzetto et al., 2002; Goovaerts and Kerry, 2010). Soil color also depends on water content, as moisture increases color intensity (Post et al., 2000). Near-infrared reflectance is primarily related to the presence of –OH, –CH, and –NH groups (Gomez et al., 2008). Nevertheless, near-infrared reflectance has been correlated with a wide range of soil properties, including total C, total N, water content, and texture (Chang et al., 2001; Viscarra Rossel et al., 2006). An improved benefit on describing soil properties comes when visible and near-infrared data are combined (e.g. calculating the so called "*vegetation indices*" as done in vegetation remote sensing) to enhance their relationships with soil organic carbon (Gomez et al., 2008; Zhang et al., 2012) and, in general, soil color (Singh et al., 2004).

The delineation of SSMUs driven by ancillary data from proximal soil sensors has become a common practice (Corwin et al., 2003; Johnson et al., 2008; Morari et al., 2009; Roberts et al., 2012). Previous delineation of SSMUs driven by soil proximal sensor data has generally relied on a single type of sensor, mainly on geospatial EC_a measurements (Corwin et al., 2003; Corwin and Lesch, 2010). It is hypothesized that the combined use of proximal sensing techniques, such as electromagnetic induction and radiometric measurements on bare-soil, provides complementary data that augment the ability to define SSMUs. Indeed, the response of a single sensor is influenced by several soil properties making the measurements difficult to interpret. Conversely, multi-sensor data represent an effective mean of separating out edaphic influences on crop yield. In this context, the objective of this study was to use a combination of EC_a and bare-soil NDVI to delineate SSMUs in a highly contrasting coastal basin affected by saltwater intrusion at the southern margin of the Venice Lagoon.

2. Materials and methods

The basic approach for delineating *SSMU*s followed the procedure introduced by Corwin and colleagues (Corwin et al., 2003; Corwin and Lesch, 2010). The first step of the procedure consisted of investigating the effect of soil salinity and other soil properties on the spatial variability of crop yield. Secondly, the suitability of proximal-sensing data for characterizing the spatial distribution of soil properties influencing yield was tested. Finally, a relationship between edaphic properties and yield was developed from which SSMUs were derived.

2.1. Study site

The study site (Fig. 1) is a ca. 21 ha field located at Chioggia, Venice, Italy (45°10′57″N; 12°13′55″E) along the southern margin of the Venice Lagoon. With an elevation ranging between 1 and 3.3 m below asl, the soil is mainly silt–clay (*Molli-Gleyic Cambisols,* FAO-UNESCO, 1989) with the presence of peat and sandy drifts (i.e. paleochannels). In particular, two well preserved-paleochannels (i.e. western and eastern), generally characterized by coarse texture, cross the study site in a SW–NE direction (Donnici et al., 2011). A pumping station and a dense network of ditches control the depth to the water table, which is generally maintained at ~0.6 m during the summer season in order to promote subirrigation.

Maize (*Zea mais* L.) was cultivated in the years 2010 (seeding April 22nd and harvest September 10th) and 2011 (seeding April 4th and harvest September 2nd). Soil tillage was an autumn plowing at 30 cm, followed by standard seedbed preparation operations. Maize was fertilized with a base-dressing of 64 kg N ha^{-1} and 94 kg P_2O_5 ha^{-1} and a top-dressing of 184 kg N ha^{-1} (urea). Meteorological data were recorded by a nearby automatic station (Regional Agency for Environmental Protection, Veneto). From a meteorological point of view, the two cropping seasons were characterized by contrasting conditions with higher rainfall (540 mm) and lower reference evapotranspiration (497 mm) in 2010 than 2011 (200 mm and 599 mm, respectively).

2.2. Soil sampling and analyses

Both undisturbed and disturbed soil samples were collected in May 2010 at 41 points selected according to an EC_a-directed sampling scheme based on simulated spatial annealing (Scudiero et al., 2011). Disturbed samples were taken at 4 depth increments: 0–0.15, 0.15–0.45, 0.45–0.8, and 0.8–1.2 m. Undisturbed cores were extracted with a hydraulic sampler from the upper 1-m profile and then analyzed at 0–0.15, 0.15–0.45, 0.45–0.8, and 0.8–1.00 m for bulk density (ρ_b, Mg m^{-3}). The ground elevation Z at the sampling points was obtained by a Trimble FM 1000 CNH (Trimble Navigation Ltd., Sunnyvale, CA, USA) with a ±0.02 m vertical accuracy.

Disturbed soil was analyzed for texture (Mastersizer 2000, Malvern Instruments Ltd., Great Malvern, UK), pH and electrical conductivity (i.e. $EC_{1:2}$, soil–water extract ratio 1:2) (Rhoades et al., 1999), total carbon (TC), organic carbon (SOC), total N (TN), and total sulfur (TS) (CNS Vario Macro elemental analyzer, Elementar, Hanau, Germany). Inorganic carbon was converted to $CaCO_3$ percentage.

2.3. Soil proximal-sensing

2.3.1. Apparent electrical conductivity

A number of EC_a surveys were carried out during the experiment with a frequency-domain electromagnetic induction sensor (CMD-1, GF Instruments, Brno, Czech Republic). In particular, the

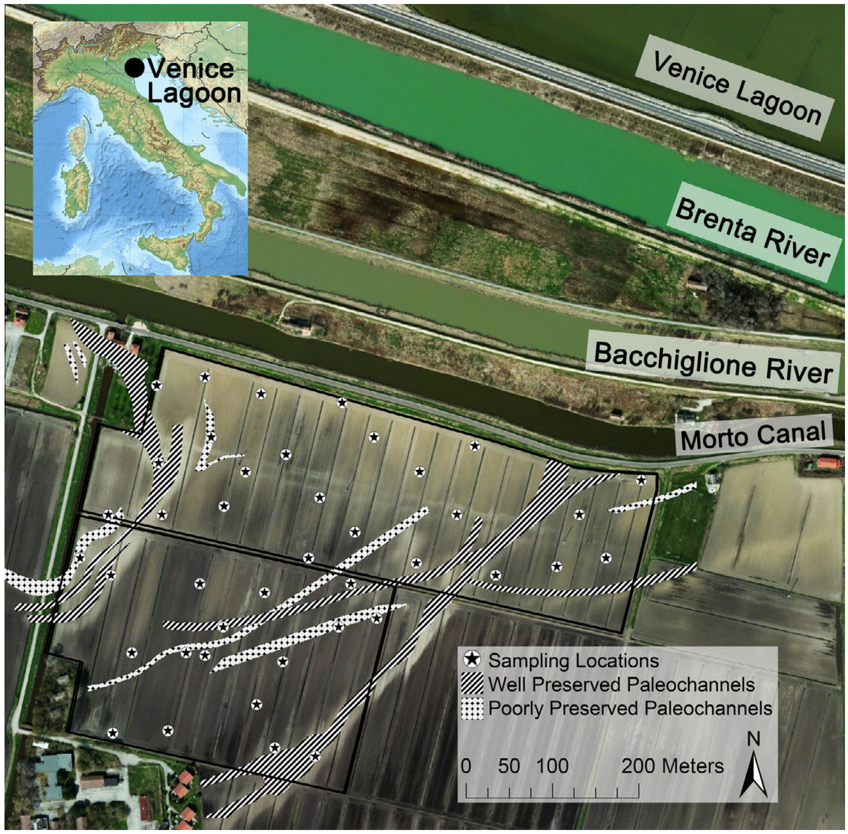

Fig. 1. Map of the study area with highlights on local poorly and well preserved paleochannels (after Donnici et al. (2011)) and soil sampling locations.

CMD-1 probe provides two different depths of investigation, named *Low* and *High*, corresponding respectively to 0–0.75 m (EC_a *Low*) and 0–1.5 m (EC_a *High*). For continuous measurements, the CMD-1 probe was placed on a mobile platform and connected to a GPS, using a 0.5 s acquisition time interval.

The surveys revealed a similar EC_a pattern irrespective of the acquisition time. Due to the largest number of monitoring points, equal to 18,053 and 20,470 for EC_a *Low* and EC_a *High*, respectively, the survey carried out in April 20, 2011, was used in the present analysis. On the same day, gravimetric water content (θ_g) was also assessed in the soil profile at the 41 sampling locations.

2.3.2. Bare-soil reflectance

In spring 2012 bare-soil reflectance at 590 nm (VIS) and at 880 nm (NIR) was measured with a handheld active spectrometer (APS1-CropCircle, Holland Scientific, Lincoln, NE, USA) linked with a GPS. A number of 10,214 locations covered the site using a 1 s time acquisition interval. The well-known normalized difference vegetation index (NDVI) (Rouse et al., 1973) was calculated as follows:

$$\mathrm{NDVI} = \frac{\mathrm{NIR} - \mathrm{VIS}}{\mathrm{NIR} + \mathrm{VIS}} \quad (1)$$

2.3.3. Interpolation of soil proximal-sensing data

Proximal-sensing data did not exactly overlay the soil sampling locations. Consequently, EC_a and reflectance measurements were interpolated to estimate their values at the 41 locations. The spatial correlation structure of each dataset (δ_i) was modeled by an isotropic spherical semivariogram:

$$v(\delta_i) = (\eta + \sigma) \times \left(\frac{1.5h}{r} - \frac{0.5h^3}{r^3}\right) \quad (2)$$

where η represents the nugget variance, σ the spatial variance component (partial sill), h the lag distance, and r the range. Because the EC_a distribution was not normal, the dataset was preliminary normalized by the normal score transformation (Deutsch and Journel, 1992). Data were interpolated by ordinary kriging and tested with leave-one-out cross validations using ArcMap 10.0 (ESRI, Redlands, CA, USA).

2.4. Yield data

Maize yield was measured in 2010 and 2011 by a combine harvester equipped with a yield monitor (Agrocom, Claas, Harsewinkel, Germany) and a DGPS. Raw data were corrected for values below a threshold equal to 2 Mg ha^{-1}. The operation eliminated very low yield readings that were almost exclusively due to field-edge effect.

2.5. Delineation of Site-Specific Management Units (SSMUs)

A simple methodological approach was developed to delineate and validate the *SSMUs* at the study site. Fig. 2 is a schematic outlining the steps involved. As suggested by Corwin et al. (2003), the soil properties significantly influencing yield spatial variability were identified with a spatial linear model using the yield maps and the soil properties measured by lab tests on samples collected in the field. The second step investigated the possibility of representing the variability of the soil properties selected in the previous step by using soil proximal-sensing measurements (Lesch and Corwin, 2008). In particular, we tested the use of soil apparent electrical conductivity (EC_a) and a possible improvement of the characterization accuracy using bare-soil reflectance. Finally, proximal-sensing maps were used to classify the study site into management units by a fuzzy c-means clustering (Fridgen et al.,

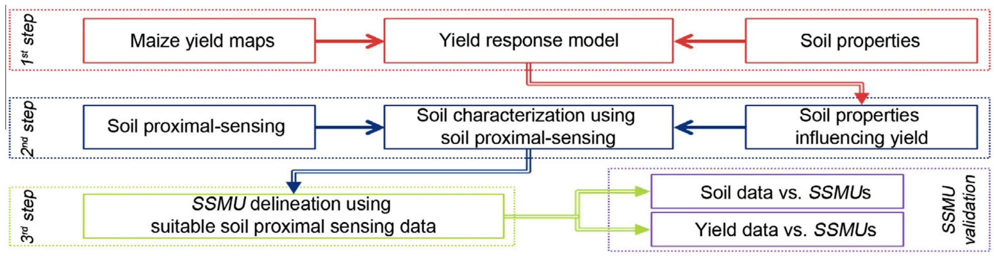

Fig. 2. Schematic of the workflow for the delineation of site-specific management units (*SSMUs*).

2004). The variance of soil properties and crop production within the management units was lastly analyzed to verify the goodness of the *SSMU* delineation.

2.5.1. Spatial linear models

The identification of the soil properties influencing yield spatial variability and the soil spatial characterization using proximal sensing data were both carried out using spatial linear models (Corwin et al., 2003; Lesch and Corwin, 2008).

Ordinary least square (*OLS*) multiple linear regressions (*MLRs*) can reliably estimate a spatially distributed random variable when the regression residuals are spatially uncorrelated (Lesch et al., 1995; Corwin et al., 2003; Schabenberger and Gotway, 2004; Lesch and Corwin, 2008). Multiple linear regression represents a special case of geostatistical mixed linear models, which represent a more general family of models including many well-known geostatistical techniques, such as universal kriging (Lesch and Corwin, 2008). According to Corwin et al. (2003) and Lesch and Corwin (2008), the *MLR* residuals were examined for outliers, normal distribution (Shapiro–Wilk Normality Test; Shapiro and Wilk, 1965) and spatial autocorrelation (Moran's I Test for Residual Spatial Autocorrelation; Cliff and Ord, 1981). The regression models showing a significant residual spatial autocorrelation were then recalculated using the *spdep* library (Bivand et al., 2011) in R (R Development Core Team, 2012) with the maximum-likelihood approach (Corwin et al., 2003; Lesch and Corwin, 2008) to avoid biased parameter estimates (Cressie, 1993).

Preliminarily to the formulation of the yield response model, the soil properties were tested for multicollinearity, which was observed between clay and sand and silt, and between SOC and TC and TN and TS. Hence, based on this exploratory correlation analysis, the primary (independent) soil properties considered for the yield model were Z, $EC_{1:2}$, θ_g, clay, ρ_b, pH, SOC, and $CaCO_3$. The yield response model was calibrated with backward stepwise procedure, allowing both linear and quadratic relationships between yield and soil properties (Corwin et al., 2003). The approach was performed on each depth intervals (i.e., 0–0.15, 0.15–0.45, 0.45–0.8, and 0.8–1.2 m) and the weighted average of increasing-depth soil profiles (i.e., 0–0.45, 0–0.80, and 0–1.2 m). The best model performances were obtained with the averaged 0.8 m profile, suggesting that 0–0.8 m was the most representative of the maize root zone in the study site. A sensitivity analysis was carried out by calculating the yield variation by individually shifting up each soil property by 1 standard deviation from its mean value.

Multiple linear regressions were also used to test the suitability of proximal-sensing data for characterizing the spatial distribution of soil properties identified by the yield response model.

2.5.2. Site-specific management units: delineation and validation

Management units were delineated using a fuzzy c-means unsupervised clustering algorithm (Odeh et al., 1992) implemented in the Management Zone Analyst (MZA) software (Fridgen et al., 2004). The c-means clustering aims to identify a continuous group of ancillary data values, minimizing the sum of square distances of all the data points in the cluster domain from the cluster centroid. The fuzzy element allows one location to belong to different clusters at different degrees. This membership sharing is controlled by a weighting exponent that is conventionally set to 1.35 (Odeh et al., 1992). Management Zone Analyst was used with the same settings (e.g., iterations, etc.) as provided by Morari et al. (2009), for a range of *SSMUs* between 4 and 7. The optimum number of *SSMUs* was identified according to the minimization of the fuzziness performance index (FPI) and the normalized classification entropy index (NCE) (Odeh et al., 1992). The FPI ($0 \leqslant \text{FPI} \leqslant 1$) is a measure of the amount of membership-sharing that occurs among management zones. The larger the FPI, the strongest is the sharing of membership between the selected *SSMUs*. The NCE ($0 \leqslant \text{NCE} \leqslant 1$) models the degree of disorganization created by dividing the data set into *SSMUs*. The lower the NCE, the higher is the amount of organization between management zones.

Moreover within-unit variance of soil properties was calculated to check if the *SSMUs* were characterized by a soil spatial variability lower than the entire field. The variance at each unit was calculated as (Fraisse et al., 2001):

$$S_U^2 = \frac{1}{n_U} \times \sum_{i=1}^{n_U} (\mu_i - \hat{\mu})^2 \times \frac{n_U}{n_T} \tag{3}$$

where S_U^2 is the weighted variance for the management unit U, μ_i the measured value of the soil property μ at the position i, $\hat{\mu}$ the mean value of μ in U, n_U the number of soil samples in U, and n_T the total number of soil samples in the entire field. Total within-unit variance of a *SSMU* configuration was defined as the sum of weighted within-unit variances of each management unit.

The best *SSMU* delineation was validated by an analysis of variance (ANOVA) between management units. The analysis was carried out on the soil properties identified by the yield response model and the 2010 and 2011 production maps. If observed, spatial correlation among the ANOVA residuals was adjusted with generalized least square method using the *spdep* library in R.

3. Results and discussion

3.1. Relationship between maize yield and soil properties

Maize yield in 2010 (2896 data points) and 2011 (2973 data points) showed high variability across the study site (Fig. 3). Yield data in 2010 was characterized by lower average (5.78 Mg ha^{-1}) and maximum (11.97 Mg ha^{-1}) values than in the following year (average: 8.76 Mg ha^{-1}; maximum: 14.99 Mg ha^{-1}). Maize production in 2010 was severely compromised in some monitored points by a heavy wind-hail storm occurred on the 13th of August (ca. 60 mm of rainfall). Consequently only the 2011 yield data at the 41 sampling location was used to fit the maize yield response model. Nevertheless, as the two yield maps showed a similar spatial pattern, the 2010 yield data was retained for the *SSMUs* validation at field scale.

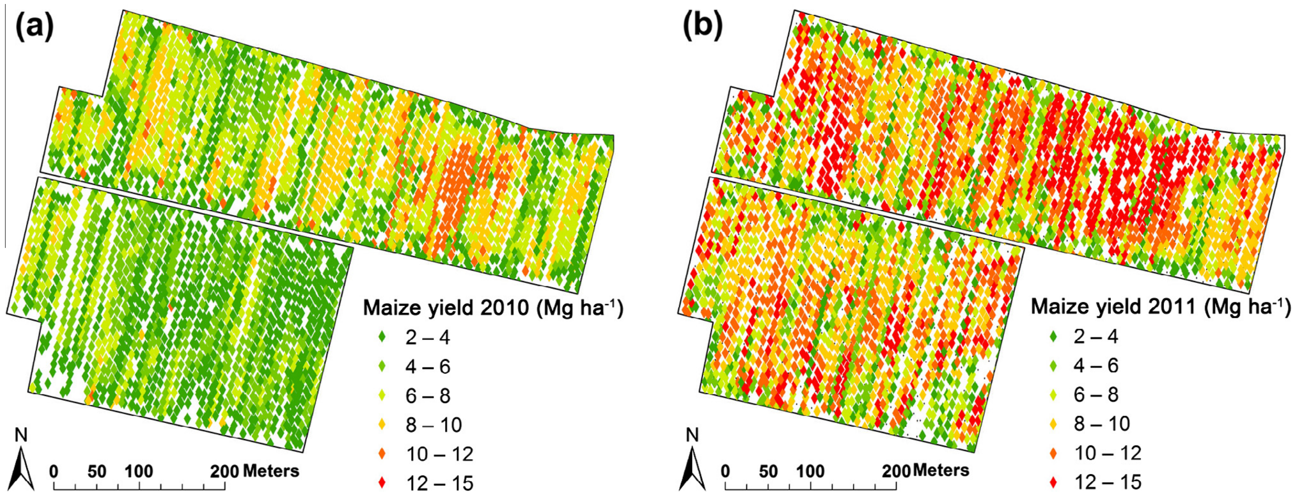

Fig. 3. Maize yield data points for (a) 2010 and (b) 2011.

The average ground elevation amounted to −2.58 m asl (Table 1), with the northern portion of the field ranging between −2.50 and −1.40 m asl, and a gradual southward decrease, where a minimum −3.15 m asl was observed. Soil texture was very coarse in the paleochannels (Fig. 1), except in the upper part of the eastern paleochannel where finer texture (loam) was observed. Outside the sandy morphological structures, texture was contrastingly different with clay percentage that decreased gradually from high contents in the North (silty-clay loam) to lower values in the very South of the study area (sandy loam). On average, soil samples were characterized by medium to high salinity (Abrol et al., 1988). The lowest salinity values (<0.4 dS m^{-1}) were recorded in the coarser portions of the paleochannels, and the highest values (>1.5 dS m^{-1}) in the northern part of the study area, outside the paleochannels. Soil pH varied drastically in the area, from a minimum of 4.45 in the south to slightly-medium alkaline (>7.5) associated with the well preserved paleochannels and the high clay contents observed along the northern margin of the study site. Soil organic carbon content, which strongly influenced several physical properties, was generally very high (average: 9.8%). Although in mineral soils the organic matter generally accumulates where texture is finer (Lugato et al., 2009), spatial variability of SOC and texture can be unrelated in organic soils (as those addressed by the present study) (Shimada et al., 2001). The northern part of the study site, where clay content was the highest, was generally characterized by low SOC (<4%), the well preserved paleochannels also showed low SOC, with a slightly wider range (2–9%). The saline areas and most of the southern portion of the study site were characterized by high SOC, generally in the 11–22% range. As a consequence, higher bulk density (ρ_b > 1.2 Mg m^{-3}) were observed in sandy soil with relatively low SOC content, whereas low ρ_b values (ρ_b < 0.7 Mg m^{-3}) were observed in soils with high SOC.

No significant correlations were observed between soil properties and the 2010 crop production likely due to the unfavorable meteorological conditions (Table 2). In contrast, the 2011 yield correlated positively with clay content and negatively with soil salinity, TC, SOC, TN, and TS. Even though organic matter is generally known to be beneficial for soil productivity (Baldock and Nelson, 2000), high contents of acidic peat can be an inhospitable environment for most crops (Andriesse, 1988). Moreover, being more prone to land subsidence than mineral soils (Schothorst, 1977; Gambolati et al., 2005), organic soils are characterized by a lower elevation and, consequently, in coastal farmlands they generally lay very close to the saline groundwater.

3.2. Maize yield response model

Eq. (4) shows the backward stepwise *OLS MLR* that provided the best maize response model according to the spatial variability of the soil properties in the 41 sampling locations:

Table 1
Soil topographic and physicochemical properties mean and range statistics of the average over the 0–0.8 m depth increment at the 41 sampling locations.

Soil properties[a]	Mean	Minimum	Maximum	Standard deviation	Standard error	Coefficient of variation	Skewness
Z, m	−2.58	−3.15	−1.40	0.39	0.06	−0.15	0.96[b]
$EC_{1:2}$, dS m^{-1}	1.14	0.21	3.30	0.72	0.11	0.63	1.05[b]
θ_g, kg kg^{-1}	0.27	0.08	0.44	0.09	0.01	0.31	−0.06
Sand, %	44.09	14.77	73.09	14.87	2.32	0.34	0.42
Silt, %	39.74	19.86	56.32	9.09	1.42	0.23	−0.72
Clay, %	16.17	6.03	31.38	6.43	1.00	0.40	0.22
ρ_b, Mg m^{-3}	0.90	0.51	1.44	0.21	0.03	0.24	0.30
pH	7.04	4.45	7.99	0.85	0.13	0.12	−1.54
TC, %	11.03	3.97	22.22	4.70	0.73	0.43	0.89[b]
$CaCO_3$, %	9.99	0.29	27.07	7.27	1.14	0.73	0.49
SOC, %	9.83	1.92	22.19	5.14	0.80	0.52	0.88[b]
TN, %	0.75	0.22	1.54	0.33	0.05	0.44	0.68
C:N	12.49	6.26	16.72	2.04	0.32	0.16	−0.72
TS, %	0.52	0.11	1.20	0.26	0.04	0.51	0.64

[a] *Z*, elevation; $EC_{1:2}$, electrical conductivity of a soil extract with a soil to water ratio of 1:2; θ_g, gravimetric water content; ρ_b, bulk density; TC, total carbon; SOC, soil organic carbon; TN, total nitrogen; C:N, SOC to TN ratio; TS, total sulfur.
[b] Significant. Skewness is significant if skewness divided by standard error of skewness (SES) > 2. SES was calculated according to Tabachnick et al. (2001).

Table 2
Correlation matrix for the soil properties[a] and maize yield in the study area. Bold numbers are significant at the $P \leqslant 0.05$ level.

[a]Soil properties	Z	$EC_{1:2}$	θ_g	Sand	Silt	Clay	ρ_b	pH	TC	SOC	$CaCO_3$	TN	C:N	TS
Z	–													
$EC_{1:2}$	−0.09	–												
θ_g	−0.19	**0.64**	–											
Sand	−0.22	−0.23	**−0.35**	–										
Silt	0.14	0.26	**0.42**	**−0.97**	–									
Clay	**0.32**	0.16	0.21	**−0.94**	**0.83**	–								
ρ_b	0.24	**−0.36**	**−0.72**	**0.43**	**−0.50**	−0.29	–							
pH	**0.57**	−0.08	**−0.36**	0.11	−0.16	−0.04	**0.38**	–						
TC	**−0.34**	0.20	**0.31**	0.04	−0.04	−0.05	−0.20	**−0.67**	–					
SOC	**−0.40**	0.21	**0.40**	0.00	0.01	−0.02	−0.28	**−0.73**	**0.98**	–				
$CaCO_3$	**0.57**	−0.17	**−0.56**	0.18	−0.22	−0.10	**0.54**	**0.70**	**−0.49**	**−0.62**	–			
TN	**−0.39**	0.23	**0.39**	−0.03	0.04	0.00	−0.29	**−0.72**	**0.98**	**0.98**	**−0.61**	–		
C:N	**−0.53**	0.13	0.28	**0.37**	**−0.32**	**−0.42**	−0.18	**−0.51**	**0.56**	**0.62**	**−0.65**	**0.56**	–	
TS	−0.29	0.20	0.29	−0.01	0.02	−0.01	−0.24	**−0.61**	**0.95**	**0.93**	**−0.48**	**0.94**	**0.49**	–
Yield 2010	−0.18	−0.19	−0.29	−0.01	0.03	−0.01	−0.19	−0.29	0.22	0.24	−0.28	0.24	0.20	0.22
Yield 2011	0.24	**−0.34**	−0.16	−0.28	0.19	**0.36**	−0.18	0.23	**−0.38**	**−0.36**	0.00	**−0.33**	**−0.33**	**−0.35**

[a] Z, elevation; $EC_{1:2}$, electrical conductivity of a soil extract with a soil to water ratio of 1:2; θ_g, gravimetric water content; ρ_b, bulk density; TC, total carbon; SOC, soil organic carbon; TN, total nitrogen; C:N, SOC to TN ratio; TS, total sulfur.

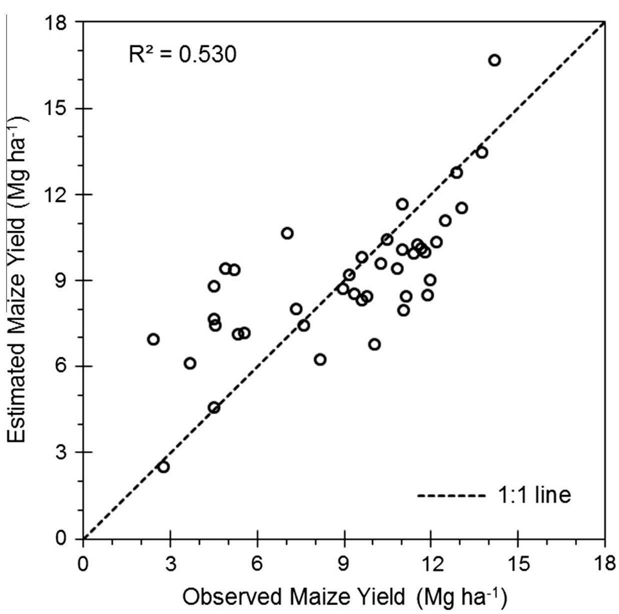

Fig. 4. Observed maize yield vs. predicted estimates using Eq. (4). Dashed line represents a 1:1 relationship.

$$Y = 18.70 - 0.48 \times EC_{1:2}^2 - 3.62 \times \rho_b^2 - 0.18 \times SOC - 0.71 \times clay + 0.02 \times clay^2 + \varepsilon \quad (4)$$

where Y is the estimated 2011 yield and ε is the random error component, which was confirmed to be normally distributed and spatially independent. This latter implies that the *OLS* fitting technique provided optimal and unbiased estimates of the regression parameters. The regression was characterized by $R^2 = 0.530$ (Fig. 4) and a root mean square error RMSE = 2.22 Mg ha^{-1}. All the soil parameters were significant at $P < 0.05$ or below. The analysis of variance indicated that the $F = 7.88$ was significant ($P > F$ at <0.001).

According to Eq. (4), a higher soil salinity, bulk density, and organic carbon content would decrease maize production; on the other hand, yield would increase with increasing clay content. The *one-at-a-time* sensitivity analysis reported in Table 3 indicates that clay and bulk density are the most significant soil properties influencing yield in 2011. Ostensibly, the significance and correlation of yield to clay content and bulk density is a consequence of smaller available water associated with soils with little clay and/or SOC contents (hence with high ρ_b) because available water directly influences crop yield.

Table 3
Degree of predicted yield sensitivity to 1 standard deviation (SD) change in each soil property (highlighted in bold) of Eq. (4).

Parameter sensitivity[a]	$EC_{1:2}$ dS m^{-1}	ρ_b kg m^{-3}	SOC %	Clay %	Calculated yield Mg ha^{-1}	Percentage change %
Baseline (Eq. (4))	1.14	0.9	9.83	16.17	8.43	–
$EC_{1:2}$ + 1 SD	**1.86**	0.9	9.83	16.17	7.4	12.16
ρ_b + 1 SD	1.14	**1.11**	9.83	16.17	6.87	18.5
SOC + 1 SD	1.14	0.9	**14.97**	16.17	7.51	10.93
Clay + 1 SD	1.14	0.9	9.83	**22.6**	10.03	19.05

[a] Average over the root zone (0–0.8 m). $EC_{1:2}$, electrical conductivity of a soil extract with a soil to water ratio of 1:2; ρ_b, soil bulk density; *SOC*, soil organic carbon.

The model described about 53% of the total yield variability, suggesting that other factors (e.g., biological, meteorological, and anthropogenic factors) influenced the crop production in 2011 aside from the investigated soil properties. Moreover, the robustness of this type of yield response model is limited because of the noise in the yield data, which is commonly biased by within-cell variability and combine dynamics (Corwin et al., 2003; Simbahan et al., 2004).

3.3. Soil spatial characterization driven by proximal-sensing

Apparent soil electrical conductivity and bare-soil NDVI spatial data displayed high variability across the study site, described by the experimental semivariograms showed in Fig. 5. The *a posteriori* cross-validation provided very low RMSEs for the three datasets: 0.01 dS m^{-1} for EC_a *Low*, 0.03 dS m^{-1} for EC_a *High*, and 0.004 for bare-soil NDVI.

The EC_a *Low* and EC_a *High* maps showed nearly identical spatial patterns (see Fig. 6a; EC_a *High* map is not shown), yet they differed in values and ranges. The EC_a *Low* map (Fig. 6a) was characterized by an average (0.65 dS m^{-1}) lower than that of EC_a *High* (1.07 dS m^{-1}). The lowest EC_a values were observed in the paleochannels, with minimum values equal to 0.12 and 0.31 dS m^{-1} for EC_a *Low* and EC_a *High*, respectively, recorded in the western paleochannel (low clay and SOC, high ρ_b). Conversely, the maximum EC_a values (1.75 and 2.78 dS m^{-1} for EC_a *Low* and EC_a *High*, respectively) were

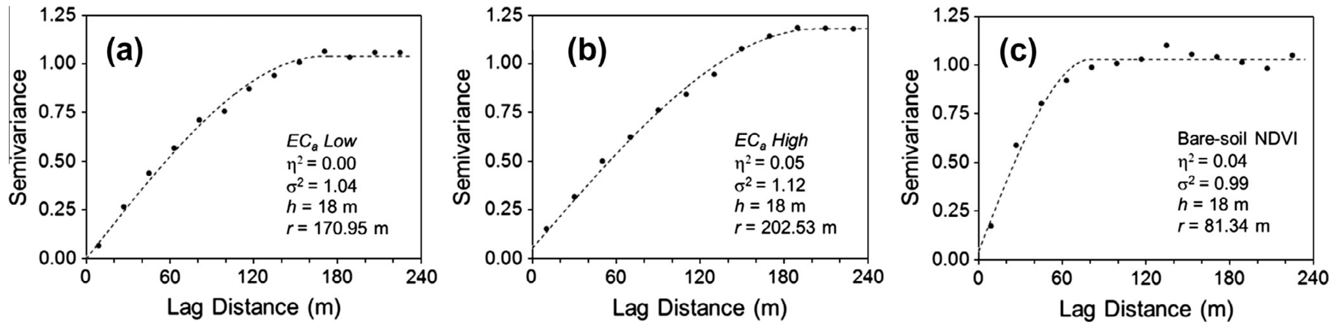

Fig. 5. Experimental (points) and fitted (dashed line) isotropic semivariograms of (a) EC_a *Low*, (b) EC_a *High*, and (c) NDVI. EC_a, apparent soil electrical conductivity (dS m^{-1}); NDVI, normalized difference vegetation index; η^2, nugget variance; σ^2, spatial variance component (partial sill); *h*, lag; *r*, range.

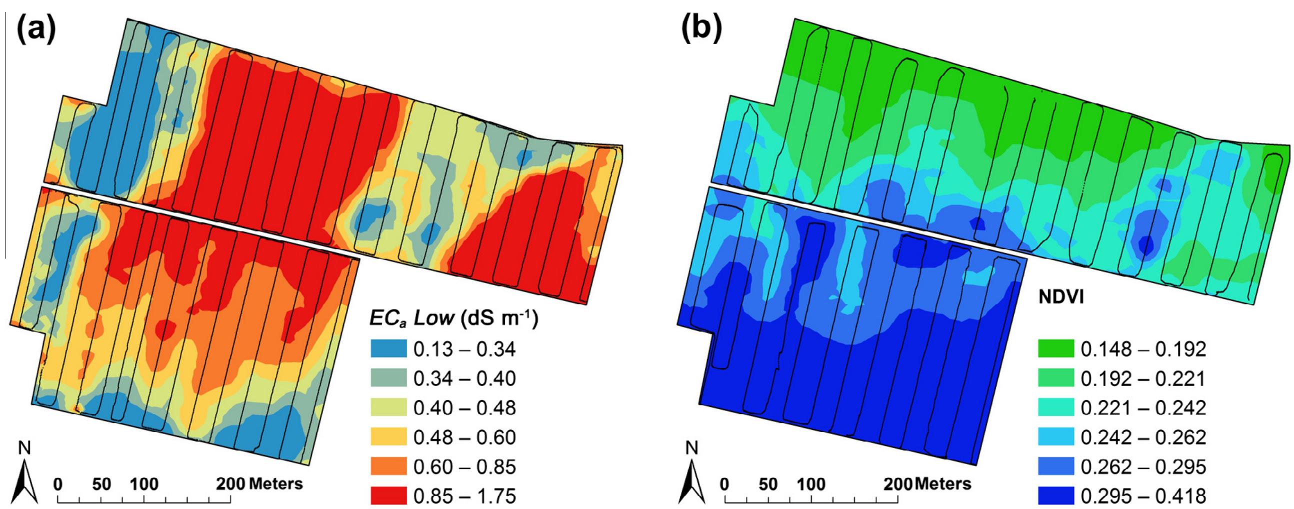

Fig. 6. Kriged maps for (a) EC_a *Low* and (b) bare soil NDVI. The dots in the maps represent the EC_a survey grids. EC_a, apparent soil electrical conductivity (dS m^{-1}); NDVI, normalized difference vegetation index.

associated with saline loamy soils in the northern part of the study site.

Bare-soil NDVI (Fig. 6b) also varied greatly across the area, with a north–south gradient: in the northern part of the study site, where texture was finer, NDVI ranged between 0.148 and 0.242. The NDVI increased gradually southward reaching a maximum value of 0.418.

The EC_a *Low* and EC_a *High* measurements showed similar correlations with soil properties (Table 4). The EC_a was significantly correlated with salinity and bulk density, as commonly observed in similar studies (Corwin and Lesch, 2005a). As sometimes can occur (Corwin et al., 2003), EC_a was not correlated with maize yield. High EC_a values were observed in the salt-affected portions of the field, whereas low EC_a readings were found within the paleochannels characterized by high ρ_b (hence low clay and SOC contents). Consequently, as suggested by Eq. (4), both high and low EC_a, i.e. high $EC_{1:2}$ and high ρ_b, respectively, were associated to low crop production. This evidence indicated that EC_a should be considered a parameter to characterize soil spatial variability rather than a mean to predict yield dynamics (Corwin and Lesch, 2010).

Table 4
Correlation coefficients for the soil proximal- and remote-sensing data with selected soil properties and the 2010 and 2011 maize yield data. Bold numbers are significant at the $P \leqslant 0.05$ level.

Soil properties[a]	$EC_{1:2}$	Clay	ρ_b	SOC	Yield 2010	Yield 2011
EC_a *Low*	**0.52**	0.24	**−0.46**	0.15	0.05	0.01
EC_a *High*	**0.49**	0.27	**−0.53**	0.12	0.13	0.11
Bare-soil NDVI	−0.06	**−0.51**	−0.12	**0.52**	−0.23	**0.45**

[a] $EC_{1:2}$, electrical conductivity of a soil extract with a soil to water ratio of 1:2; ρ_b, bulk density; SOC, soil organic carbon.

Significant correlations were observed between texture, organic content, and maize yield in 2011 with bare-soil reflectance, confirming the results from other Authors (Torrent and Barron, 1993; Chang et al., 2001; Singh et al., 2004; Viscarra Rossel et al., 2006; Gomez et al., 2008). A SOC increase reduced both VIS and NIR reflectance (Uno et al., 2005). However, VIS, which was always smaller than NIR (Lillesand et al., 2004; Uno et al., 2005), decreased with a higher slope than NIR, yielding larger values of NDVI.

These outcomes were also confirmed by spatial linear model analyses. The EC_a, both in *Low* or *High* configuration, was not sufficient to characterize the spatial variability of the four soil properties, describing variability in $EC_{1:2}$ and ρ_b only.

The EC_a *Low* and EC_a *High* measurements were normalized to their natural logarithm, as commonly done with EC_a data calibration (Lesch et al., 1992). Both regressions leaded to very similar regression models. The first for EC_a *Low* was

$$ln(EC_a\ Low) = -0.38 + 0.21 \times EC_{1:2} - 0.61 \times \rho_b + \varepsilon \quad (5)$$

and was characterized by a $R^2 = 0.415$ (adjusted $R^2 = 0.385$) and RSME = 0.22 dS m^{-1}. Soil salinity and bulk density were both significant to the <0.01, whereas the intercept resulted non-significantly different from zero.

The latter read

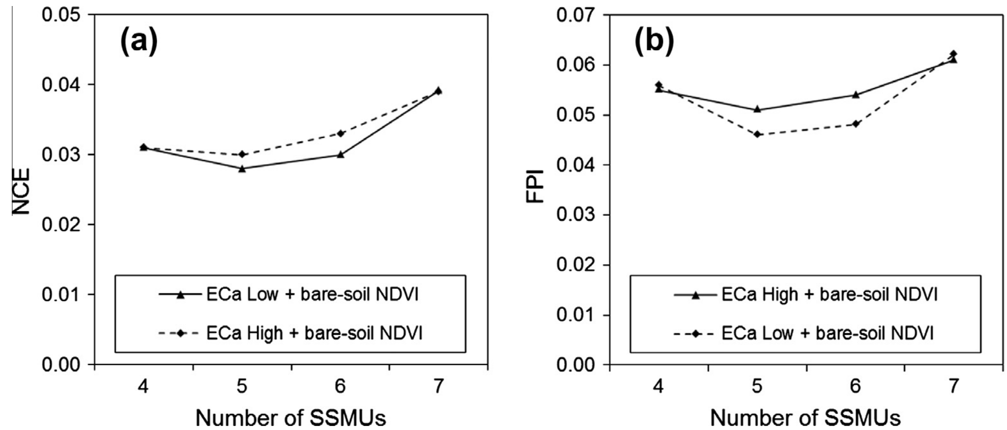

Fig. 7. (a) Normalized classification entropy (NCE) and (b) fuzziness performance index (FPI) as calculated for the study area when the delineation was carried out using *EC_a Low* with bare-soil NDVI and *EC_a High* with bare-soil NDVI. *SSMUs*, site-specific management units; EC_a, apparent soil electrical conductivity (dS m^{-1}); NDVI, normalized difference vegetation index.

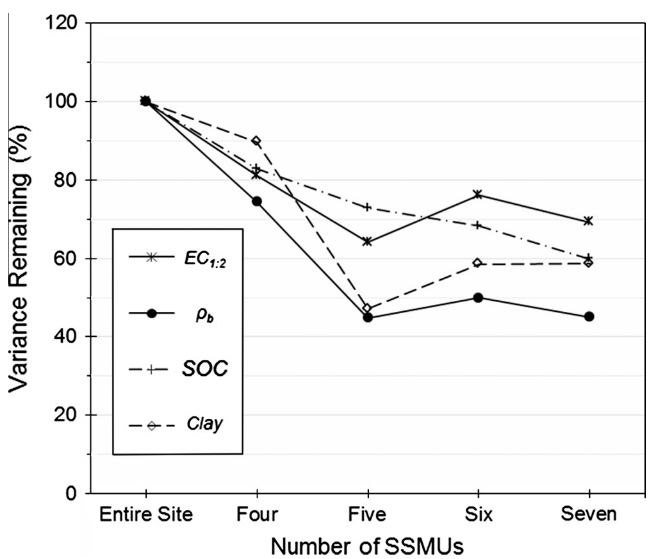

Fig. 8. Portion of within–unit variance remaining for soil salinity ($EC_{1:2}$), bulk density (ρ_b), and soil organic carbon (SOC) and clay contents after dividing the study site into site-specific management units (*SSMUs*).

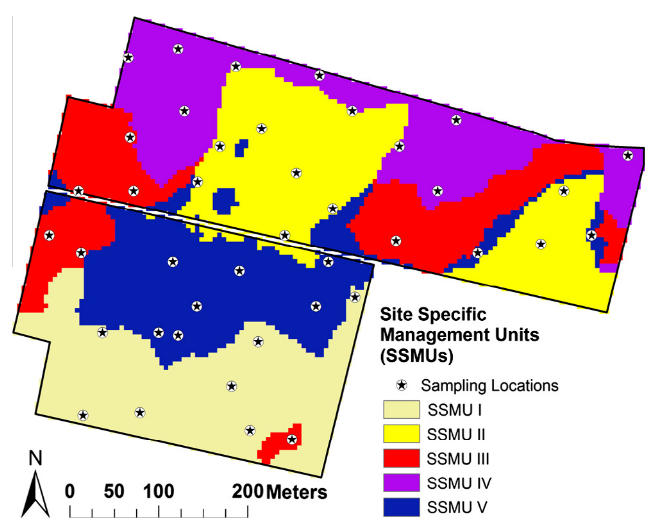

Fig. 9. Delineation of site-specific management units (*SSMUs*) using the fuzzy c-means unsupervised clustering algorithm on *EC_a Low* and NDVI; with sampling locations. EC_a, apparent soil electrical conductivity (dS m^{-1}); NDVI, normalized difference vegetation index.

$$ln(EC_a\ High) = 0.29 + 0.18 \times EC_{1:2} - 0.74 \times \rho_b + \varepsilon \quad (6)$$

with R^2 = 0.438 (adjusted R^2 = 0.408) and RMSE = 0.34 dS m^{-1}. The intercept term was non-significant, whereas $EC_{1:2}$ and ρ_b were both significant to the <0.01. An adjustment for the spatial autocorrelated error structure was employed to obtain optimal regressions for both Eqs. (5) and (6).

According to Eqs. (5) and (6), high soil salinity and low bulk density led to high EC_a. It is well known that bulk density is correlated with EC_a (Rhoades et al., 1999; Corwin, 2008). As already observed for the Ca' Bianca soils by Scudiero et al. (2012), low ρ_b values were observed in areas rich in peat and/or clay, which are known to facilitate the conduction of electricity in the soil (Anderson-Cook et al., 2002; Corwin and Lesch, 2005a).

Conversely, the backward stepwise *OLS MLR* for bare-soil NDVI was significantly described by the spatial variability of SOC and clay:

$$\mathrm{NDVI} = 0.251 + 0.003 \times SOC - 0.003 \times clay + \varepsilon \quad (7)$$

with R^2 = 0.511 (adjusted R^2 = 0.485) and RMSE = 0.049. The intercept, SOC, and clay terms were significant to the <0.001, <0.01, and <0.001, respectively. High SOC and low clay increased bare-soil NDVI. An adjustment for the spatial autocorrelated error structure was used in Eq. (7).

3.4. Site-specific management units delineation and validation

Soil apparent electrical conductivity and reflectance are known to provide good ancillary information for *SSMU* delineation (Ortiz et al., 2007; Ortiz et al., 2010; Roberts et al., 2012). Indeed, in our experiment the complementary use of EC_a and bare-soil NDVI was the only feasible option to delineate *SSMUs* according to the spatial variability of the investigated soil properties. In particular, two couples of ancillary data were tested for the *SSMU* delineation: *EC_a Low* with NDVI and *EC_a High* with NDVI. The use of *EC_a Low* with NDVI provided better NCE and FPI values than *EC_a High* with NDVI (Fig. 7a and b). According to both indices, the goodness of the fuzzy c-means clustering was maximized with the study site divided into five management units. The concordance of the two indices is an indication of the goodness of the classification (Fridgen et al., 2004; Morari et al., 2009). The NCE and FPI were in the same range of other published data (Li et al., 2007) and remarkably lower than those provided by Brock et al. (2005) and Morari et al.

Table 5
Number of soil-sampling locations and yield data points included within each site-specific management unit (*SSMU*).

SSMU	Number of Soil Samples	Number of yield data points in 2010	Number of yield data points in 2011
I	7	555	595
II	9	659	690
III	7	510	506
IV	9	588	564
V	9	584	618

(2009). These very small values suggested that the clustering identified areas characterized by contrasting properties.

The analysis of within-unit soil variance confirmed that the best *SSMU* delineation was obtained with five units (Fig. 8). Using the variance of the entire site (i.e., one management unit) as reference (i.e. 100% level) (Fraisse et al., 2001), within-unit variance of $EC_{1:2}$ (−35.8%), ρ_b (−55.2%), and clay content (−52.8%) showed the maximum reduction when five units were delineated, whereas the lowest SOC within-unit variance (−40.2%) was observed with seven *SSMUs*.

On the basis of these outcomes, the EC_a *Low* and bare-soil NDVI maps where used to delineate five *SSMUs*, hereafter named I, II, III, IV, and V (Fig. 9). Each management unit included from 7 to 9 soil-sampling locations (Table 5).

SSMU I was characterized by fairly small EC_a *Low* (<0.6 dS m^{-1}) and high NDVI (>0.30). The highest EC_a *Low* (>0.8 dS m^{-1}) characterized *SSMU* II. *SSMU* III identified most part of the well-preserved paleochannels, where clay content was very low, with soil showing very small EC_a *Low* (<0.4 dS m^{-1}) and NDVI in the 0.19–0.26 range. *SSMU* IV was representative of areas with low NDVI (<0.1.9) and EC_a *Low* (<0.6 dS m^{-1}). Finally, fairly high EC_a *Low* (>0.6) and NDVI (>0.24) values were typically found in *SSMU* V.

According to the analysis of variance, all soil properties showed significant differences within the five management units (Fig. 10). In particular, the proposed methodology for *SSMU* delineation helped to identify a very saline area (*SSMU* II), where the average $EC_{1:2}$ = 1.90 dS m^{-1} was almost twice as high as the average salinity observed in the other units (1.05, 0.64, 0.99, and 0.98 dS m^{-1} in *SSMUs* I, III, IV, and V, respectively). *SSMU* III was characterized by the highest ρ_b values (average = 1.22 Mg m^{-3}), the lowest clay content (average = 8.86%), and low to mid-low soil salinity. *SSMU* IV was characterized by low average salinity and the lowest SOC (5.80%) and highest clay (22.53%) average contents. It is worth noting that the northern part of the eastern paleochannel, where texture was finer, was mainly confined within *SSMU* IV. *SSMUs* I, II, and V were the units with the highest SOC average contents (~12%), with very high maximum SOC (SOC > 20%) in *SSMUs* I and V, and were associated with the lowest observed pH values (Table 2).

The yield data in 2010 and 2011 were classified according to the five management units (Table 5). In the year 2010, *SSMUs* III and IV were identified as the most productive zones, suggesting that the low salinity and SOC contents observed in the paleochannels were favorable for maize (Fig. 10e). *SSMUs* I, II, and V were characterized by a lower average yield. The medium–high average salinity and SOC, which are associated with pH values generally in the 4.5–5.5 range in the southern portion of the study site, were most likely responsible for the yield reduction. In 2011 the yield in *SSMU* III was significantly smaller than in *SSMU* IV (Fig. 10f), suggesting that the low rainfall occurring in that year significantly reduced the yield in the paleochannels with low clay and high ρ_b. The effect of high salinity (*SSMU* II) seemed to be confirmed in 2011. Moreover, *SSMU* II showed an average yield as low as that observed in units I and V, which were confirmed as the areas with the lowest maize production also in 2011.

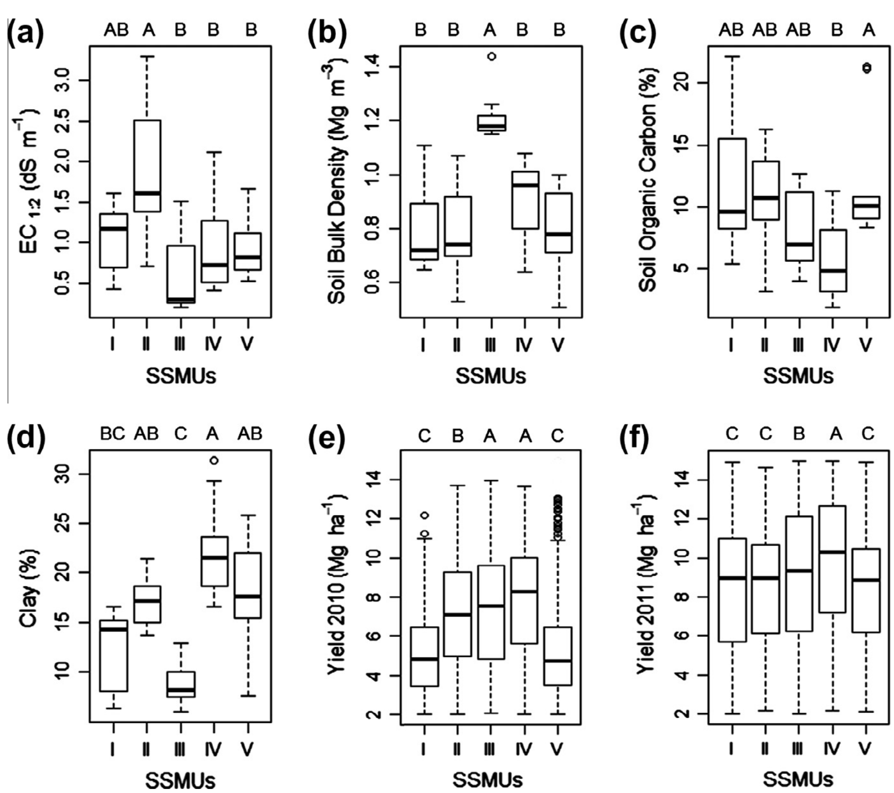

Fig. 10. Boxplots for (a) $EC_{1:2}$, electrical conductivity of a soil extract with a soil to water ratio of 1:2, (b) soil bulk density, (c) soil organic carbon content, (d) clay content, and the yield data of (e) 2010 and (f) 2011. The bold line crossing the rectangles represents the median value; circles represent outliers. Within plots, boxes topped with the same capital letter are not significantly different (P<0.05).

4. Summary and conclusions

Yield is affected by the combined influence of a range of factors including edaphic, meteorological, biological, topographic, and anthropogenic factors. Unfortunately, many of these factors are impractical to control and mitigate. As edaphic factors are generally consistent in time, long-term site-specific soil management can be a reliable solution in areas characterized by high soil spatial variability. Understanding which soil properties play a major role influencing within-field spatial variability of crop yield is the first step in *SSMU* delineation (Corwin et al., 2003; Corwin and Lesch, 2005b; Corwin and Lesch, 2010).

Once a group of relevant soil properties is identified, soil proximal- and remote-sensing can be used to describe their distribution over a large area from a limited number of ground-truth soil samples. Often, a single class of proximal-sensing data is insufficient to characterize the variability of all the soil properties influencing yield. In agreement with Corwin and Lesch (2010), this paper suggests that multiple sensors should be selected to provide complementary information to represent the spatial variability of all the properties of interest. Multiple sensors can be used regardless of the fact that their readings correlate with crop yield or not. As a matter of fact, proximal-sensing data, such as soil apparent electrical conductivity (EC_a), have often been misinterpreted as a tool to understand yield spatial variability. Often times EC_a correlates inconsistently with crop yield. In those cases where EC_a does not correlate with yield then it is known that either EC_a is not measuring a soil property that is affecting crop yield (Corwin et al., 2003) or that the combined influence of soil properties affecting yield, but that are not measured by EC_a, are diminishing EC_a's statistical correlation with yield.

In this paper soil salinity ($EC_{1:2}$), bulk density (ρ_b), and organic carbon (SOC) and clay contents were identified as the soil properties significantly influencing the spatial variability of maize yield in a farmland affected by saltwater intrusion at the southern edge of the Venice Lagoon, Italy. Apparent electrical conductivity and bare-soil NDVI in combination were shown to describe the spatial variability of these soil properties. Due to the soil nature in the area, EC_a was used to represent the spatial distribution of $EC_{1:2}$ and ρ_b only. On the other hand, bare-soil NDVI was significantly related to SOC and clay contents. The combined use of both proximal-sensing spatial datasets culminated in the delineation of *SSMUs*, whereas individually the two proximal sensors were of limited success. A fuzzy c-means clustering of the EC_a and bare-soil reflectance data proved to be a useful statistical tool for *SSMU* delineation, identifying: one homogeneous unit with optimal maize yield, one unit affected by very high soil salinity, one unit characterized by very coarse texture (i.e. sandy paleochannels), and two units with both medium–high soil salinity and high organic carbon content.

From a practical point of view, this research strongly supports the potentiality of using multiple-sensor platforms to delineate *SSMUs*. The use of multiple sensors indeed increases the likelihood of capturing the spatial variation of all soil properties influencing the within-field variation of crop yield. Once the proximal-sensing data is appropriately selected, the *SSMU* delineation can be carried out with a good probability that each selected management unit would differ from the others in terms of the soil properties influencing yield. The approach proposed could be easily adopted by agriculture consultants who can now rely on cheap proximal sensors, easily accessible satellite data, and user friendly software suites.

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