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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

Elia Scudiero [a,*], Pietro Teatini [b], Dennis L. Corwin [c], Rita Deiana [d], Antonio Berti [a], Francesco Morari [a]

[a] Department of Agronomy, Food, Natural resources, Animals, and Environment (DAFNAE), University of Padua, Viale dell'Università 16, Legnaro 35020, Italy
[b] Department of Civil, Environmental, and Architectural Engineering (ICEA), University of Padua, Via Trieste 63, Padua 35121, Italy
[c] USDA-ARS, United States Salinity Laboratory, 450 West Big Springs Rd., Riverside, CA 92507-4617, USA
[d] Department of Cultural Heritage: Archaeology, History of Art, Cinema, and Music, University of Padua, Piazza Capitaniato 7, Padua 35139, Italy

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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.

* Corresponding author. Tel.: +39 049 827 2886.
E-mail address: scudiero@dmsa.unipd.it (E. Scudiero).

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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