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A geostatistical Vis-NIR spectroscopy index to assess the incipient soil salinization in the Neretva River valley, Croatia

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ABSTRACT

Soil spectroscopy can provide low-cost and high-density data for predicting various soil properties. However, a relatively weak correlation between the spectra and the measurements of salinized soil makes spectroscopy difficult to use in predicting areas at risk of salinization, especially for low and moderately saline soils. The main objective of the study was to propose an effective approach based on Vis-NIR spectroscopy and geostatistics for mapping soil salinity in the Neretva River valley (Croatia). A spectral index (SI), which synthesizes most of salt affected soil properties, was defined and used as covariate in ordinary cokriging (COK) for improving electrical conductivity (EC_e) prediction. The proposed approach was compared with a univariate predictor (ordinary kriging, OK), which uses only EC_e data and a multivariate predictor (ordinary cokriging, COK) using more covariates such as some chemical properties of primary importance in salt affected soils (Ca^{2+}, Mg^{2+}, Na^{+}, SO_4^{2-}, Cl^{-} concentrations and pH). The study was carried out in an agricultural area (5068 ha) located in the Neretva River valley (Croatia). Topsoil (0–30 cm) samples were collected at 246 locations with a grid (500 m × 500 m) sampling scheme and analyzed for some chemical and physical properties. Moreover, soil samples were used for visible and near infrared (Vis-NIR) spectra measurements with a range of wavelength between 350 and 2500 nm. The spectral data were pre-processed and EC_e was predicted with partial least squares regression (PLSR). The first significant latent variable, which accounted for 85% of the total variance, was selected and used as a SI to quantify and map spatial variation of soil salinity. The univariate and multivariate geostatistical approaches provided results and performances quite similar. Regarding the two multivariate approaches, the one using only the spectral index as covariate has provided better results in terms of unbiasedness and accuracy. Moreover, the spectral index SI is also very cost-effective and it could then be used in possible broad-scale surveys for preventing soil salinity at landscape scale.

1. Introduction

Extensive seawater intrusions in karst and alluvial coastal aquifers within the Mediterranean basin induce an increasing risk for soil salinization in coastal river valleys (Aureli et al., 2007; Castrignano et al., 2008). Soil salinization has an adverse impact on soil physical, chemical and biological processes: salt-affected soils cannot support vegetation owing to salt-induced water deficit, ion toxicity, nutrient imbalance, volatility and reduction of yield (Abrol et al., 1988; Amini et al., 2016; Karlen et al., 2008). In addition, and especially in clay soils, excess sodium can cause soil physical degradation phenomena, such as aggregate dispersion, permeability deterioration, surface crusting, compaction and erosion, which markedly affect local agriculture (Metternicht and Zinck, 2009). Moreover, it is expected that more frequent and severe droughts, irregular precipitations and changes in sea level will aggravate the salinization processes, which in turn might lead to desertification of many agricultural areas of the Mediterranean basin (Wöppelmann and Marcos, 2012). The problem of salt-affected soils is also present in the Mediterranean coastal region of Croatia, where seawater intrudes through porous media into calcareous aquifers and salinizes both ground and surface waters. This is especially evident in the karstic carbonate aquifer of the Neretva River. Salinization in the area occurs naturally by seawater intrusion into the mouth of the river and the coastal aquifer through the subsurface. In addition, the changes

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in hydrological conditions, due to the numerous water engineering systems and facilities within the Neretva River basin, contribute to intensified seawater intrusion, causing more severe groundwater salinization. This problem shows both temporal and spatial variability, being most pronounced in the summer time when seawater intrusion reaches maximum values (Romić et al., 2012). Most of the vegetable (watermelons, melons, early potatoes, cauliflowers) and fruit crops (mandarins), grown in the Neretva River valley, have low tolerance to salinity (Romić et al., 2008; Urlić et al., 2017). Mandarin (*Citrus reticulata* Blanco) crops are among the most sensitive to soil salinity: once soil salinity exceeds the threshold of 1.4 $dS\,m^{-1}$, the mandarin yield can decrease up to 13% per every $dS\,m^{-1}$ of electrical conductivity (EC_e) increase (Maas, 1993). Therefore, soil salinity management relies on the challenging task to identify appropriate techniques and methods for assessing and monitoring salt-affected soils. Traditional methods for soil salinity assessment, based on soil EC_e, provide precise information about soil salinity but, on the other hand, are very time consuming and generally expensive, therefore unsuited for mapping the wide variability at the landscape scale (Corwin and Lesch, 2003). In addition, because of strongly skewed EC_e data distributions and the ever always-persistent problem of undersampling at landscape level, univariate spatial estimates of EC_e are generally of limited accuracy (Douaoui et al., 2006). The use of different remote sensing data for salinity assessment has proved promising, but only in an advanced stage of salinization process and especially in semiarid and arid agro-ecological zones (Volkan Bilgili et al., 2010), where vegetation does not completely cover the soil. Laboratory spectroscopy in the visible (Vis = 400–780 nm) and near infrared (780–2500 nm) region of the electromagnetic spectrum, combined with chemometrics treatments, has been suggested as a cost- and time-saving procedure to characterize soil chemical properties (Conforti et al., 2015, 2018; Shepherd and Walsh, 2002; Stenberg et al., 2010a; Summers et al., 2011; Udelhoven et al., 2003). Partial least square regression (PLSR) is a common chemometrics method used for estimating regression models from spectral information and reference analytical data (Casa and Castrignanò, 2008; Haaland and Thomas, 1988; Lucà et al., 2017; Martens and Næs, 1989). Different soil chemical and physical properties have been successfully predicted by PLSR modelling of spectroscopic data (Conforti et al., 2018; Cozzolino and Morón, 2003; Viscarra Rossel et al., 2006). EC_e is generally poorly predicted by both mid- and near-infrared spectroscopy (Soriano-Disla et al., 2014) and the same occurred with Vis-NIR spectroscopy (Kodaira and Shibusawa, 2013). One of the main reasons for fairly poor spectroscopic prediction of EC_e values is that soil salinity, due to the large spatial and temporal variability, does not produce well defined Vis-NIR spectra (Wang et al., 2012). Recently, several studies indicated that pure sodium chloride spectrum is hardly distinguishable in Vis-NIR region (Liu et al., 2015; Zhang et al., 2011). Landscape and climatic factors jointly with soil properties (soil moisture) exert an important impact on soil salinity as well as on EC_e spatial distribution. The success of spectroscopy to describe EC_e depends on its relationships with soil properties that have a clear response in NIR-SWIR region of the spectra (Minasny et al., 2009; Soriano-Disla et al., 2014). Therefore, the ability of spectroscopy and chemometrics to predict EC_e values is commonly specific to particular environments and soil types (Minasny et al., 2009; Zornoza et al., 2008).

Managing of areas with salt affected soils requires quantifying and mapping spatial distribution of soil salinity. Geostatistics (Matheron, 1971) has been widely applied for mapping soil salinity and assessing salinity risk (Bourgault et al., 1996; Castrignanò et al., 2008; Hosseini et al., 1994; Huang et al., 2015; Li et al., 2014; Odeh et al., 1998; Oliver and Webster, 1990; Scudiero et al., 2016; Sylla et al., 1995; Walter et al., 2001).

Spectral data, besides being directly used for statistically predicting soil properties, can be integrated in a geostatistical analysis (Cobo et al., 2010) and used as an auxiliary (covariate) measure of soil quality, to describe soil variation within the landscape (Vågen et al., 2006). Information extracted from spectral data can be incorporated as secondary information in spatial prediction of soil salinity through multivariate geostatistical methods (Castrignanò et al., 2008).

There are many examples of mapping soil salinity by using different types of soil covariates as auxiliary information to improve the prediction of soil salinity (Triki Fourati et al., 2017; Vermeulen and Van Niekerk, 2017), whereas the combination of Vis-NIR salinity data and geostatistical methods has not yet been proposed.

The main aim of the study was to propose an effective approach based on Vis-NIR spectroscopy and geostatistics for mapping soil salinity in the Neretva River valley (Croatia). More specific objectives included: 1) to develop a spectral index (SI) as a cost-effective substitute of soil properties and to identify the areas with increasing soil salinity, and 2) to use the SI as an auxiliary variable to improve EC_e prediction in a geostatistical framework. In addition, the proposed approach was compared with a univariate predictor (ordinary kriging, OK), which uses only EC_e data, and a multivariate predictor (ordinary cokriging, OCK) using as covariates some soil chemical properties, in order to prove the actual advantages stemming from the use of a cheaper spectral index (SI), much less demanding in terms of labor-time than a set of laboratory soil measurements.

2. Materials and methods

2.1. Study area and soil sampling

The study area is located in floodplain of the Neretva River valley in the Mediterranean part of (Fig. 1). The Neretva River valley (12,067 ha) is an exceptional natural and geographical environment, cut in a karstic limestone and dolomite bedrock in the south-eastern part of Croatia (Fig. 1a, b). Presently, the main river-bed in the downstream part of the system is under the strong influence of the Adriatic Sea and is subject to tidal fluctuations that extend from the river mouth to about 25 km inland. In the 20th century, the most part of this large delta on the eastern Adriatic coast has been converted to agricultural land use (5216 ha) by extensive reclamation projects. A pumping system protects the region by flooding.

Climatically, the Neretva basin marks a transition from continental to Mediterranean climate with semi-arid hot dry summers and wet winters. Most rainfall occurs from October to April, with annual average of 1203 mm (Romić et al., 2012). Agriculture is the main activity in the area of the Neretva River valley, primarily dominated by vegetable production and citrus growing applying irrigation. The soils within the Neretva River valley are hydromorphic, being characterized by excessive water presence due primarily to shallow groundwater. They are classified as Fluvisols Eutric Calcaric, Mollic Fluvisols Calcaric, Mollic Gleysols, and Histic Gleysols (Romić et al., 2012). More details in geomorphology, soil characteristics and reclamation in the study area can be found in Romić et al. (2012).

Soil sampling was carried out at the end of the dry season (August 2010), when the accumulation of salts at the soil surface horizon occurs. Soil survey was conducted at 1:25000 map scale and 246 sampling locations were selected using a systematic sampling scheme on a regular 500 × 500-m-grid (Fig. 1c). Soil samples were collected up to 25 cm-depth and were georeferenced using a global position system (GPS) with a metric accuracy.

2.2. Soil laboratory analysis and geochemical speciation of ion species

Soil samples were first air-dried, ground and sieved (< 2 mm); then they were analyzed in laboratory for: 1) particle size distribution with the pipette method; 2) amount of calcium carbonate ($CaCO_3$) with volumetric calcimeter method after HCl attack; and 3) effective cation exchange capacity (CEC) using $BaCl_2$ solution. EC_e was predicted using the standard saturated paste extract procedure proposed by Rhoades (1996). Ion concentration in saturation extracts were measured as