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Mapping soil organic matter in the Baranja region (Croatia): Geological and anthropic forcing parameters

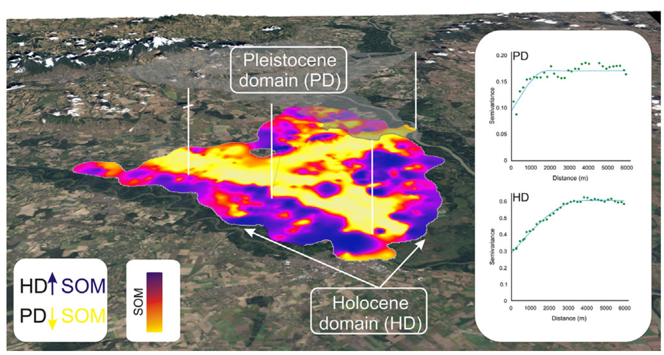
Igor Bogunovic [a], Sebastiano Trevisani [b,*], Paulo Pereira [c], Vesna Vukadinovic [d]

[a] University of Zagreb, Faculty of Agriculture, Department of General Agronomy, Svetosimunska 25, 10000 Zagreb, Croatia
[b] University IUAV of Venice, Department of Architecture, Construction and Conservation, Dorsoduro 2206, 30123 Venezia, Italy
[c] Environmental Management Center, Mykolas Romeris University, Ateities g. 20, LT-08303 Vilnius, Lithuania
[d] Josip Juraj Strossmayer University of Osijek, Faculty of Agriculture in Osijek, Kralja Petra Svačića 1d, 31000 Osijek, Croatia

HIGHLIGHTS

- SOM spatial distribution in a highly exploited agricultural area (1147 km^2)
- An extensive (4825 samples) and spatially dense data set is available.
- Geostatistical mapping: global interpolation versus stratified interpolation
- Insights on extrinsic and intrinsic influencing factors on SOM spatial distribution
- At regional scale the SOM spatial patterns follow the main geological domains.

GRAPHICAL ABSTRACT



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ABSTRACT

Spatial mapping of soil organic matter (SOM) and evaluation of the related natural and anthropic influencing factors are crucial to monitor the extent of degraded land and the evolution of soil functions. The objective of this work is to study the spatial distribution of SOM in a highly exploited agricultural area in the Baranja Region (Croatia). The spatially dense dataset available (4825 top-soil samples from 0 to 30 cm) allowed to produce reliable SOM maps using geostatistical interpolation kriging algorithms and to study the relationships with possible influencing factors. The interpolation has been conducted by means of two approaches. In one approach, the overall data set is considered for computing a global variogram and performing a direct interpolation of SOM values. In the second approach, the data are stratified according to two different geological and morphogenetic domains, Holocene Domain (HD) and Pleistocene Domain (PD), and a distinct geostatistical analysis is performed in each domain. The results showed that average SOM in the studied region was 2.29%, indicating a future need for adopting sustainable soil management practices in this region. SOM was significantly higher in HD (2.64%) than PD (1.97%) domain. SOM in PD generally had a much lower global variability. Global dataset analysis reveals that regional intrinsic factors prevail over local intrinsic and extrinsic factors in determining SOM spatial patterns. In contrast, the stratified approach can filter the effect of regional variability related to the main geological and geomorphological setting. The structural spatial correlation in PD is weaker than in HD, as manifested by spatial patches of low and high SOM content with smaller extension in PD with respect to HD. The strong relationships between SOM spatial patterns and geological/geomorphological factors suggest the possibility of adopting finer subdivision criteria in future research.

* Corresponding author.
E-mail address: strevisani@iuav.it (S. Trevisani).

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1. Introduction

Soils are the largest terrestrial carbon sink and play a key role in carbon sequestration (Lal, 2010; Pires et al., 2017). Soil organic matter (SOM) content plays a crucial role in improving aggregate stability, water infiltration and nutrient availability (Stockmann et al., 2013; Agegnehu et al., 2016). SOM tends to be high in areas with high mean annual precipitation, low mean annual temperature (Muñoz-Rojas et al., 2013; Olaya-Abril et al., 2017) and clay soils (Parras-Alcántara et al., 2015). SOM is a key factor in determining soil quality and productivity (de Paul Obade and Lal, 2016).

Soil management significantly affects SOM, especially in agricultural areas. Intensive grazing (Worrall and Clay, 2012), conventional tillage (Bogunovic et al., 2017a), poor crop rotation, intensive land use (Laudicina, 2015; Wang et al., 2017), and the intensive use of herbicides and pesticides (Sebiomo et al., 2011) all have a negative impact on SOM quantity and quality. Accordingly, sustainable practices are needed to decrease the risk of soil degradation of agricultural land. To adopt sustainable agricultural management practices, it is necessary to characterize SOM spatial distribution. The mapping and modelling of soil properties is crucial to understanding the processes and factors influencing soil characteristics and identifying patterns of soil degradation (Brevik et al., 2016; Pereira et al., 2017). Moreover, evaluating the impact of intensive agricultural practices on SOM spatial distribution, at both the local and regional scale, is important for determining the extent to which the anthropic signature superimposes the natural factors of soil formation.

SOM spatial distribution is the result of the interaction between multiple variables. Consequently, it can be highly variable in space, especially in agricultural areas, where anthropic disturbances can increase the complexity of SOM spatial distribution. Unfortunately, SOM mapping is generally not an easy task due to requiring very spatially dense data sets and the difficulty of modelling the relationships with influencing factors. Often, the spatial sampling density of SOM field measurements is not sufficient enough to permit reliable mapping of SOM for the studied area. To overcome these issues, SOM spatial mapping can, in some circumstances, be improved by using secondary variables as covariates by means of geostatistical and machine learning approaches (e.g., de Brogniez et al., 2015; Yigini and Panagos, 2016; Pereira et al., 2017). Unfortunately, very often the potential covariates to be used as auxiliary information, such as precipitation and temperature, have a coarser spatial resolution than available SOM data, or are not easily available (e.g. soil and vegetation characteristics). Other variables that can be extracted from a digital elevation model (DEM) can be weakly correlated with SOM. These limitations may reduce importantly the explanation capacity of the auxiliary variables. From this viewpoint, the efforts in mapping of SOC at the European scale using secondary variables, conducted by Yigini and Panagos (2016) and De Brogniez et al. (2015), are emblematic. In these studies the use of secondary variables permitted to obtain satisfactory results, considering the wide spatial coverage and the characteristics of available data; however, the resulting R^2 of the regression models were quite low, indicating, as stated by the authors, that a relevant portion of variance remains unexplained. Despite this, there are numerous studies involving different environments (e.g., forest, grasslands, etc.) and spatial scales (Guo et al., 2015; Were et al., 2015; Qiu et al., 2016). When secondary/auxiliary variables can be used as covariates, the accuracy of SOM predictions can be improved, as observed in several studies (Weismeier et al., 2011; Zhang et al., 2012; Bogunovic et al., 2017b). However, in others, the consideration of auxiliary variables did not improve spatial prediction (Song et al., 2016; Rosemary et al., 2017), as a consequence of the lack of correlation or due to spatial non-stationarity in the correlation between SOM and the secondary variables. This situation can occur in agricultural areas, where intensive soil management practices can greatly influence the spatial distribution of SOM, thereby increasing the complexity of the relationship between SOM and secondary variables.

In this context, the present research related to the spatial distribution of SOM in the agricultural landscape of Pannonia region (Croatia), an area under extreme ecological pressure due to intensive cropping practices, is particularly interesting. Firstly, at European scale there is a general lack of information on soil properties spatial distribution covering the Croatia (e.g., Yigini and Panagos, 2016). Then, for the studied area, with an extent of 1147 km^2, a very spatially dense dataset consisting of 4825 top-soil samples (0–30 cm) is available. This exceptionally dense dataset allows a reliable spatial analysis and mapping of SOM and to analyse the relationships of SOM with possible influencing factors. Finally, differently from the above cited studies, the spatial distribution and the spatial variability of SOM seems related more to the local geological and morphogenetic framework of the area (Buzjak et al., 2013; Velić and Vlahović, 2009) than to climatic or DEM derived secondary variables.

To map SOM and study its spatial variability, we followed a geostatistical approach (Cressie, 2015; Goovaerts, 2001; McBratney et al., 2003), testing two alternatives approaches based on an ordinary kriging interpolation algorithm. In one approach, we consider the overall data set for computing a global variogram and perform a direct interpolation of SOM values. In the second approach, we stratify the data according to two different geological and morphogenetic domains and perform a distinct geostatistical analysis in each domain. The pros and cons of the two approaches in terms of interpolation accuracy and interpretative potential are discussed. Finally, the SOM map produced is used to interpret the SOM distribution in the region, highlighting possible natural and anthropic forcing. The resulting map can also provide suggestions for soil quality recovery practices that should be adopted to improve agriculture sustainability.

2. Materials and methods

2.1. Study site

The study site is located in eastern Croatia in the Baranja region (18°20′–18°58′ E, 45°32′–45°55′ N) and covers an area of 1147 km^2 characterized by intensive agriculture (Fig. 1). The climate is classified as temperate continental and the mean annual temperature is 10.8 ± 0.61 °C, with average annual precipitation of 652 ± 193 mm (1961–1990, Osijek meteorological station). July is the warmest month (21 °C), while the coldest is January (−1.3 °C). The highest amount of precipitation occurs during June (88 mm), while the lowest occurs in February (40.3 mm).

The region is characterized by a gentle topography with elevations ranging from 62 m to 244 m (Fig. 1b). The DEM analysis (smoothed version of European Digital Elevation Model EU-DEM, version 1.1, 2016) highlights the existence of distinct morphological domains which are related to the main morphogenetic (Buzjak et al., 2013) and lithological units (Velić and Vlahović, 2009) of the region. The boundaries of the geological units are in general easily detectable given that they correspond to abrupt morphological transitions evident in the DEM (Fig. 1b).

The first domain, the HD, is represented by terrains in the low elevation plains (Fig. 1b, c). It is composed of Holocene sediments, representative of alluvial deposits of the Drava and Danube rivers and to a lesser extent, of lake deposits along the elongated depression near the Karašica stream. The terrains are the lowest elevations in the study area, corresponding to the fluvial plains of Drava and Danube rivers. In this area, a high degree of lithological heterogeneity should be expected given the presence of fluvial paleo-channels, leading to transitions from coarse sediments corresponding with paleo-channels, to finer sediments corresponding with distal deposits. The main soil types in this domain are Fluvisols and Gleysols.

The second domain, the PD, is represented by higher elevation terrains, corresponding to terraces and hills (Fig. 1b, c). It is composed of Pleistocene sediments representative of mainly loess deposits and, to a lesser extent, of terraced alluvial and colluvial deposits. These terrains