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Spatio-temporal topsoil organic carbon mapping of a semi-arid Mediterranean region: The role of land use, soil texture, topographic indices and the influence of remote sensing data to modelling

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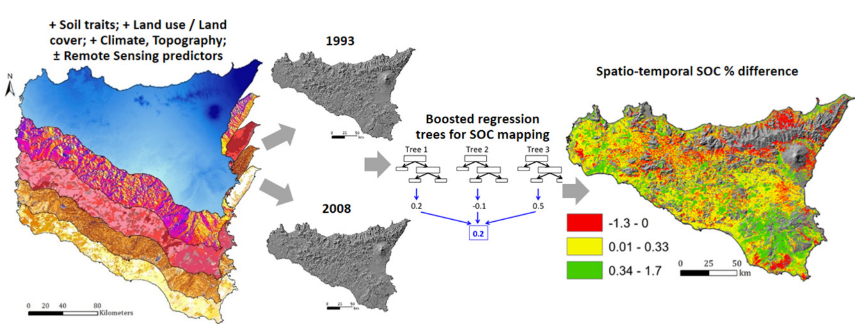
HIGHLIGHTS

- Modelling SOC in two samplings 15 year apart gave a view of SOC change.
- Texture and land use were main drivers of SOC concentration.
- Topographic indices were more important than climatic indices to estimate SOC concentration.
- SOC variation agreed with climatic trend and soil variability maps.
- Remote sensing covariates reduced the uncertainty of estimation.

GRAPHICAL ABSTRACT



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ABSTRACT

SOC is the most important indicator of soil fertility and monitoring its space-time changes is a prerequisite to establish strategies to reduce soil loss and preserve its quality. Here we modelled the topsoil (0–0.3 m) SOC concentration of the cultivated area of Sicily in 1993 and 2008. Sicily is an extremely variable region with a high number of ecosystems, soils, and microclimates. We studied the role of time and land use in the modelling of SOC, and assessed the role of remote sensing (RS) covariates in the boosted regression trees modelling. The models obtained showed a high pseudo-R^2 (0.63–0.69) and low uncertainty (s.d. < 0.76 g C kg^{-1} with RS, and <1.25 g C kg^{-1} without RS). These outputs allowed depicting a time variation of SOC at 1 arcsec. SOC estimation strongly depended on the soil texture, land use, rainfall and topographic indices related to erosion and deposition. RS indices captured one fifth of the total variance explained, slightly changed the ranking of variance explained by the non-RS predictors, and reduced the variability of the model replicates. During the study period, SOC decreased in the areas with relatively high initial SOC, and increased in the area with high temperature and low rainfall, dominated by arables. This was likely due to the compulsory application of some Good Agricultural and Environmental practices. These results confirm that the importance of texture and land use in short-term SOC variation is

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comparable to climate. The present results call for agronomic and policy intervention at the district level to maintain fertility and yield potential. In addition, the present results suggest that the application of RS covariates enhanced the modelling performance.

1. Introduction

Agricultural lands play a major role in the storage of soil organic carbon (SOC) and sequestration/release of atmospheric CO_2 (Bradford et al., 2016; Filippi et al., 2016; Post and Kwon, 2000). SOC is directly linked with a number of ecosystem services and agronomical benefits and is the main driver of soil fertility. However, agricultural soils have been depleted from their original SOC stock due to cultivation, which also negatively affected soil aggregation status, water infiltration rate, soil fertility and biota (Bruun et al., 2015; Parras-Alcántara et al., 2016; Saia et al., 2014). The preservation of soil quality is a priority to maintain agricultural productivity and environmental quality. In this framework, monitoring SOC concentration and stock changes through space and time is important to establish strategies to reduce soil loss and preserve its quality. SOC monitoring at regional scale relies on sparse sampling and application of an estimation process. Such a process should take into account the spatial interdependence of samples and abundance of predictors (Martin et al., 2014); and the distribution heterogeneity in space and among determinants (predictors) of SOC accumulation (Lacoste et al., 2014). With regards to the latter, the relationship in the domain of each predictor with SOC and the resolution of the predictors is particularly relevant for any spatial estimation (Miller et al., 2016; Miller et al., 2015a; Miller et al., 2015b). The spatial estimation of SOC concentration and stocks is commonly performed by statistical approaches (Meersmans et al., 2009; Orton et al., 2014) with different interpolation methods and machine learning predictive models (Henderson et al., 2005; Yang et al., 2015). The former is better suited to areas with dense SOC measurements, whereas the second is more appropriate for non-regularly sampled regions, since its outcome does not rely on the sample proximity to extract functional (ecological) relationships between dependent and independent variables.

SOC dynamics under different land uses are still poorly understood (Francaviglia et al., 2017; Meersmans et al., 2008; Purton et al., 2015), especially when deriving data from wide areas and with different climates. In Mediterranean environment, lack of knowledge on SOC dynamic is further due to variable climatic and erratic meteorological conditions. It has been shown that cultivation exerts a negative role on SOC accumulation in various environments (Francaviglia et al., 2017; Kämpf et al., 2016; Novara et al., 2013) and this likely depends on both soil tillage and reduction of biomass return to the soil. In particular, a reduction of the tillage intensity can favor SOC accumulation irrespective of aridity (from semi-arid to humid) and can be up to 1 t SOC ha^{-1} yr^{-1} (Conant et al., 2001; Kämpf et al., 2016; Kurganova et al., 2014; Post and Kwon, 2000). The SOC dynamic also depends on other factors such as soil genesis and type, land use history and management and useful information could be gained from SOC spatial models (Badagliacca et al., 2017; Martin et al., 2014; Schillaci et al., 2017; Schillaci et al., 2015; Vereecken et al., 2016).

In the last two decades the integration of physical, chemical, and biological information derived from different covariates in the models has boosted the studies on soil properties (Bui et al., 2009; Henderson et al., 2005) and also for SOC mapping from global or continental (Hengl et al., 2014; Lugato et al., 2014) to regional and plot scales (Akpa et al., 2016; de Gruijter et al., 2016; Martin et al., 2014; Schillaci et al., 2017). SOC mapping attempts at giving an image of the spatial distribution despite it is costly (Minasny et al., 2013 and reference therein).

The most recent developments in the digital soil mapping include machine learning (Forkuor et al., 2017; Gasch et al., 2015; Hengl et al., 2017) to study space-time variation of soil properties and use of remote sensing (RS) covariates (Castaldi et al., 2016a). Thanks to their high accessibility, resolution and availability for wide areas, RS data gained importance for spatial prediction of the topsoil organic C (Bou Kheir et al., 2010; Poggio et al., 2013). For example, Bou Kheir et al. (2010) found that SOC maps built with a classification-tree analysis of the sole RS parameters gave the same accuracy of a model built with sole digital elevation model (DEM) parameters, and both of them had sole ca. 10% less accuracy that a full RS + DEM + soil parameters model built. Poggio et al. (2013) found that integration of RS with terrain attribute data increased the predictive ability comparing to the model built with only terrain parameters. However, some of the SOC estimates lack uncertainty analysis and this compromises the reliability of predictions for decision making (Maia et al., 2010; Minasny et al., 2013; Ogle et al., 2010). In addition, Conant et al. (2011) highlighted the limitation to document time changes in SOC because of the spatial variability in the factors that influence SOC distribution.

In a regularly-spaced data collection, SOC samples are taken from representative or random sampling sites in a given study area. Legacy data comes from a mixture of sampling campaigns resulting in data collected for different aims (Chartin et al., 2017), which frequently allow to make predictions for areas with sampling limitations (Rial et al., 2017). Depending on the scope of each survey (e.g. regional soil characterization or precision agriculture) sample density can change abruptly. This can consist in drawbacks including their non-regular distribution in space, which call for the use of particular modelling method and predictors. Due to these difficulties, only few examples on mapping at regional extent with legacy data are available. For example, Ross et al. (2013) and Grinand et al. (2017) carried out a space-time assessment of SOC in subtropical regions of south-eastern United States and Madagascar, respectively.

Little information is available on SOC dynamics in semi-arid Mediterranean areas due to the unavailability of consistent databases. Nonetheless, time dynamic of SOC storage in the soil is highly dependent to the climatic zone of the area under study (Doetterl et al., 2015). In addition, spatial and time change of SOC can respond to different determinants at varying the climate of area under study.

The present work fits within the big picture of spatial SOC mapping and time change. This was made by means of a legacy dataset and use of remotely sensed data. In particular, we used legacy data of two sampling campaigns 15 years apart (1993–2008), coupled with climate (from Worldclim data Bio1,12), and land use information (from CORINE 1990 to 2006) to map the topsoil SOC variation across time in the agricultural area of a semi-arid Mediterranean region (Fig. 1). Such aim was achieved by applying a machine learning method, namely boosted regression trees (BRT), to each sampling campaign dataset using land use, soil texture, topographic and remote sensing predictors. We also tested the role of remote sensing covariates in the spatial SOC prediction and predictors' importance by running each model either with or without the implementation of the RS covariates. In the area under study, i.e. cropped fields in which plants (mostly field crops) have limited or no growth during summer and early fall, the inclusion of remote sensed variables could capture part of the SOC variation due to biomass return to the soil.

2. Material and methods

2.1. Study area

The study area, Sicily (Italy), is a semiarid region located in middle of the Mediterranean Sea (Fig. 1). Its area is about 25,286 km^2, 60% of