Science of the Total Environment 643 (2018) 548–558

Contents lists available at ScienceDirect

Science of the Total Environment

journal homepage: www.elsevier.com/locate/scitotenv

Identifying localized and scale-specific multivariate controls of soil organic matter variations using multiple wavelet coherence

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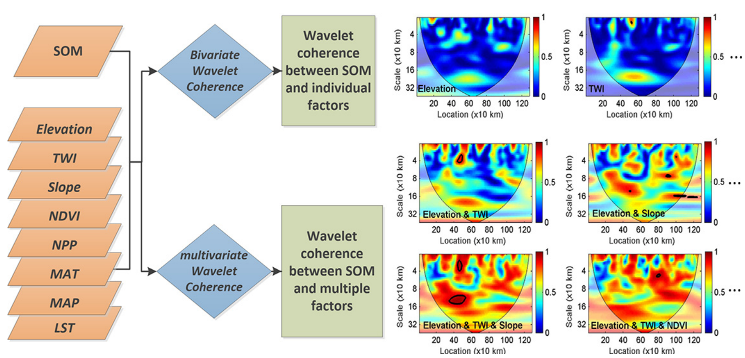
HIGHLIGHTS

- Multiple wavelet coherence identified localized and scale-dependent controls of SOM.
- Climate & terrain dominated at large scales, vegetation dominated at small scales.
- Three-factor combination was acceptable to explain variability at large scales.

GRAPHICAL ABSTRACT



ARTICLE INFO

Article history:
Received 16 April 2018
Received in revised form 16 June 2018
Accepted 17 June 2018
Available online xxxx

Editor: Jay Gan

Keywords:
Scale-location variability
Controlling factors
Multiple wavelet coherence
Multivariate relationship
China

ABSTRACT

Environmental factors have shown localized and scale-dependent controls over soil organic matter (SOM) distribution in the landscape. Previous studies have explored the relationships between SOM and individual controlling factors; however, few studies have indicated the combined control from multiple environmental factors. In this study, we compared the localized and scale-dependent univariate and multivariate controls of SOM along two long transects (northeast, NE transect and north, N transect) from China. Bivariate wavelet coherence (BWC) between SOM and individual factors and multiple wavelet coherence (MWC) between SOM and factor combinations were calculated. Average wavelet coherence (AWC) and percent area of significant coherence (PASC) were used to assess the relative dominance of individual and a combination of factors to explain SOM variations at different scales and locations. The results showed that (in BWC analysis) mean annual temperature (MAT) with the largest AWC (0.39) and PASC (16.23%) was the dominant factor in explaining SOM variations along the NE transect. The topographic wetness index (TWI) was the dominant factor (AWC = 0.39 and PASC = 20.80%) along the N transect. MWC identified the combination of Slope, net primary production (NPP) and mean annual precipitation (MAP) as the most important combination in explaining SOM variations along the

Abbreviations: AWC, average wavelet coherence; BWC, bivariate wavelet coherency; DEM, digital elevation model; DSM, digital soil mapping; Elev, elevation; EMD, empirical mode decomposition; FT, Fourier transform; LST, land surface temperature; MAT, mean annual temperature; MAP, mean annual precipitation; MCC, multiple correlation coefficient; MEMD, multivariate empirical mode decomposition; MODIS, Moderate Resolution Imaging Spectroradiometer; MRA, multi-resolution analysis; MSC, multiple spectral coherence; MWC, multiple wavelet coherence; N, north; NDVI, normalized difference vegetation index; NE, northeast; NPP, net primary productivity; PASC, percent area of significant coherence; SOM, soil organic matter; TRMM, Tropical Rainfall Measuring Mission; TWC, trivariate wavelet coherence; TWI, topographic wetness index; WT, wavelet transform.

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https://doi.org/10.1016/j.scitotenv.2018.06.210

NE transect with a significant increase in AWC and PASC at different scales and locations (e.g. AWC = 0.91 and PASC = 58.03% at all scales). The combination of TWI, NPP and normalized difference vegetation index (NDVI) was the most influential along the N transect (AWC = 0.83 and PASC = 32.68% at all scales). The results indicated that the combined controls of environmental factors on SOM variations at different scales and locations in a large area can be identified by MWC. This is promising for a better understanding of the multivariate controls in SOM variations at larger spatial scales and may improve the capability of digital soil mapping.

1. Introduction

Soil organic matter (SOM), as a major sink and source of soil carbon, plays an important role in terrestrial carbon dynamics and has strong potential for mitigating climate change (Arthur et al., 1990; Davidson and Janssens, 2006; Marchant et al., 2015). It is also a key indicator for soil fertility and soil quality. Thus, an adequate understanding of SOM spatial variations is essential for reducing uncertainty in assessing terrestrial carbon cycles, evaluating soil quality and developing sustainable agriculture (Corwin et al., 2006; Rumpel and Kögel-Knabner, 2011; Stockmann et al., 2015; Xu et al., 2018).

Mapping soil properties variability at the field, regional, national, and global scale has improved in the past two decades (Chaplot et al., 2000, 2010; Guo et al., 2013;Viscarra Rossel et al., 2014; Mansuy et al., 2014; Zhang et al., 2017; Chen et al., 2018), especially after digital soil mapping (DSM) was put forward. DSM describes a soil-landscape model based on the spatial prediction function between soil properties and a series of environmental factors, such as terrain, climate, organic and relief factors (McBratney et al., 2003; Scull et al., 2003). High-precision DSM requires the selection of the most valuable factors for developing a high performing and meaningful relationship between soil properties and environmental factors, which are selected according to data availability or the researcher's expertise (Miller et al., 2015). However, the factors under different environmental conditions often present variable privileges and different interactive relationships (Poggio et al., 2013; Minasny et al., 2013). Additionally, SOM variability was the consequence of the combined effects of soil physical, chemical, and biological processes that operate at different intensities and on a wide range of spatial and temporal scales (Goovaerts, 1998; Biswas and Si, 2011). Some of these processes with high frequency varying in space are called as small-scale processes, while other processes with low frequency are known as large-scale processed (Si, 2008). Therefore, the relationship between SOM and environmental factors was scale- and location-dependent (Lark et al., 2004; Hu and Si, 2013). Exploring multivariate interactive and localized and scale-dependent relationships in controlling SOM variability make it possible to select the optimal and potentially useful factors from a massive data catalog, leading to the development of a more accurate spatial distribution model of SOM.

Quantitative methods have been widely employed to characterize scale-/location-specific relationships between soil properties and controlling factors individually including Fourier transform (FT) (Webster, 1977; McBratney and Webster, 1981), multi-resolution analysis (MRA) (McBratney, 1998; Biswas et al., 2013a), empirical mode decomposition (EMD) (Biswas et al., 2013b; Huang et al., 2015, 2017) and wavelet transforms (WT) (Zhou et al., 2016; Guo et al., 2018; Huang et al., 2018). However, the processes in geoscience are usually complex and may be affected by multiple variables, concurrently. SOM variance may not be well explained by single factor (Dai and Huang, 2006). During the past few decades, several methods have been explored for analyzing multivariate relationships at different scales and locations. For example, multiple spectral coherence (MSC) was used to reveal the relationships between soil-saturated hydraulic conductivity and multiple soil properties at different scales (Si, 2008). However, MSC underestimated the multivariate relationships and was able to build on the assumption of stationary examples from the spatial series. Multivariate empirical mode decomposition (MEMD) can separate each variable into a finite number of intrinsic mode functions (IMFs) according to dominant scales (Rehman and Mandic, 2010). Since it works well for non-linear and non-stationary data, the combination of MEMD and squared multiple correlation coefficient (MCC) has advantages in exploring the multivariate relationships (Hu and Si, 2013; She et al., 2015). However, the correlation between SOM and environmental factors changes with scales and locations. The neutralization effect of MCC and the insufficiency of MEMD in capturing all the variances may fall short in explaining SOM variations at multiple scales and locations (Hu et al., 2017). Moreover, the above mentioned multivariate methods are not suitable to identify localized multivariate relationships.

Multivariate wavelet coherency (MWC), developed from bivariate wavelet coherence (BWC) and trivariate wavelet coherence (TWC), is relatively a new method (Hu and Si, 2016). Owing to its capacity to deal with cross-correlated variables, MWC is much more robust than BWC and TWC. MWC has been compared with common multivariate methods and it demonstrated superior performance in untangling scale-specific and localized multivariate relationships in the geosciences (Agarwal et al., 2017; Karatas et al., 2017). Therefore, it can be useful for selecting factors for developing scale- and location- dependent SOM spatial prediction models. However, currently, MWC has only been employed for certain properties, such as evaporation from water surfaces and soil water content (Hu and Si, 2016; Hu et al., 2017) at the field-scale. There is no information on the localized multiple controlling factors of SOM variability at multiscale and different environment conditions. Therefore, the objectives of the study were 1) to characterize scale- and location-dependent univariate and multivariate controlling relationships between environmental factors and SOM along two transects from the Northeast and North China Plain using BWC and MWC and 2) to compare the factors performance and identify dominant combinations of factors explaining the SOM variability at different scales and locations in different landscapes.

2. Materials and methods

2.1. Study area and soil sampling

The study area and SOM dataset presented in this paper have been previously reported by Zhou et al. (2016). In brief, the study area is located in the Northeast and North China Plains, China (111°27′80″E–135°7′39″E, and 32°18′46″N–48°21′20″N) covering an area of approximately 642,000 km^2 (Fig. 1). A total of 1078 soil samples were collected from the 20-cm surface layer in 2003 and 2004. After being air-dried and sieved, the SOM content was determined calorimetrically after H_2SO_4-dichromate oxidation at 150 °C for 30 min. SOM sample points were interpolated over the whole study area using inverse distance weighting and the cross validation of the interpolation showed a determination of coefficient of 0.70.

Two transects were identified in considering the climatic zone within the study area: mid-temperate zone of Northeast (NE) and warm temperature zone of North (N) China Plain. Both transects were 1280 km long with 128 sample points at 10 km sampling intervals.