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Identifying scale-specific controls of soil organic matter distribution in mountain areas using anisotropy analysis and discrete wavelet transform

Yadong Guo[a,b], Ruiying Zhao[c], Yongnian Zeng[a,*], Zhou Shi[c], Qing Zhou[b]

[a] College of Geosciences and Information-Physics, Central South University, Changsha 410083, China
[b] College of Resources and Environment, Hunan Agricultural University, Changsha 410128, China
[c] Institute of Agricultural Remote Sensing and Information Technology Application, College of Environmental and Resource Sciences, Zhejiang University, Hangzhou 310058, China

A R T I C L E I N F O

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A B S T R A C T

Soil organic matter (SOM) is an important index to evaluate soil fertility. Knowing the spatial distribution of SOM and its controlling factors at different scales is basic to sustainable farmland management. The variability was explored mostly in plain farmlands or at small scales in previous studies. In the present study, combined with anisotropy analysis (AA) and discrete wavelet transform (DWT), we examined the spatial variability of SOM and its controlling factors at various scales in a mountainous area. Transect with dominant directions (major axis and minor axis) of SOM variability was extracted using AA and then the scale-specific variability was examined using DWT. Dominant factors of SOM variability at different scales were identified using correlation coefficients between SOM at different scales and various soil environmental factors. The results showed that the major axis along which SOM varied the most was 24° south by west, consistent with the strike of Wuling Mountains. The minor axis was perpendicular to the major axis direction. DWT separated the SOM variations into nine scale components (eight details, D1 through D8, and one approximation, A8) along the major axis and into eight scale components (seven details, D1 through D7, and one approximation, A7) along minor axis. The largest-scale component (A8 in major axis and A7 in minor axis) explained the most variance of SOM along both axes, accounting for half of the total variance. Compared with the original SOM before separation of scale components (undecomposed SOM), the scale components showed significant correlation with environmental factors. Both elevation and mean annual precipitation had positive correlation with SOM at large scales. However, there was a negative correlation between SOM and mean annual temperature. This indicates that the topography and local climate may have a stronger influence in controlling SOM spatial distribution in mountain regions. The relationship provides important information on environmental covariate selection in mapping soil resource. The combination of AA and DWT shows promise quantifying SOM spatial distribution and its control factors at different scales in mountainous areas.

1. Introduction

Soil organic matter (SOM) is a key indicator in the global carbon cycle (Marchant et al., 2015). Knowledge of SOM spatial variation is essential for soil landscape process modeling, soil quality assessment, precision agriculture and environmental management (Yong, 2010). However, spatial variability of SOM is controlled by various individual or combined soil-forming factors and processes, including natural factors and human activities with complex pedogenic processes, as they change across the landscape (Corstanje et al., 2007; Lal, 2009; Hartemink and Bockheim, 2013). Numerous studies have shown that the spatial distribution of SOM can be predicted by correlating ancillary environmental variables through the digital soil mapping (DSM) (Grimm et al., 2008). These environmental variables include structural such as topography, vegetation, climate and soil type, and random such as land use, management and production activities by human (Mcbratney et al., 2003; Franklin et al., 2003; Zhang et al., 2012; Hu et al., 2014). High-precision DSM depends on the selection of variables and understanding of their relationship with SOM. Though the high quality environmental variables are becoming more and more available, the interdependent nature makes it difficult to identify most dominant factors on SOM distribution and is a challenge of DSM framework (Poggio et al., 2013). Given that the factors and processes do not vary at a point rather over space, soil properties show different

* Corresponding author.
E-mail address: ynzeng@csu.edu.cn (Y. Zeng).

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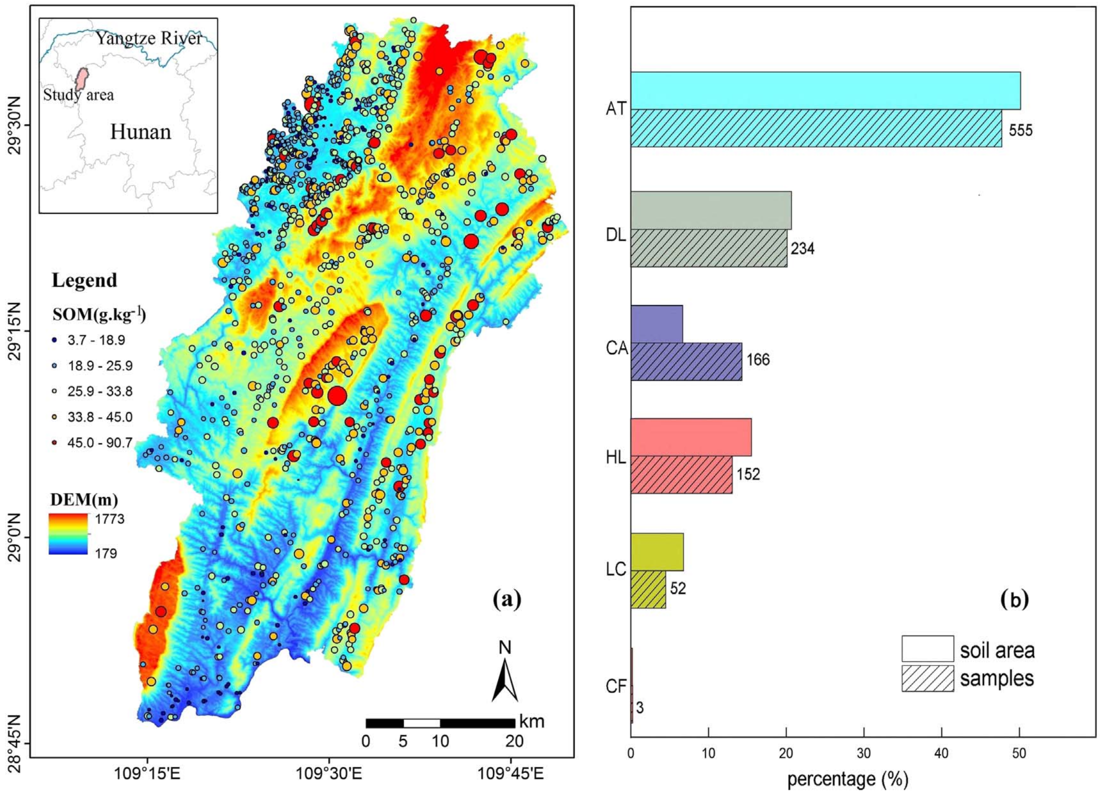

Fig. 1. Geographic location of the study area and the distribution of sampling points with topographic variations (a), the proportion of area and sample numbers in each soil type (b) Note: AT: Anthrosols; DL: Dystric Luvisols; CA: Chromic Acrisols; HL: Haplic Luvisols; LC: Leptic Cambisols; CF: Calcaric-Fluvisols.

spatial variations and response relationships with the controlling factors at different scales (Vanwalleghem et al., 2013; Huang et al., 2015; Zhou et al., 2016).

Numerous methods, such as classical statistics, geostatistics, fractal theory and spectral analysis, have been developed and used to quantify the spatial variability of soil properties at different scales (Webster and Oliver, 2001; Zhang et al., 2014; Reza et al., 2015). Classical statistics describe this variability using the coefficient of variation, and are suitable for a situation without spatial structure (Lacasse et al., 2007). Geostatistics methods have been widely applied in soil science. The semivariogram, the central tool of geostatistics, can quantify the scale and intensity of spatial variation of properties under consideration. It can also be used in an exploratory manner to discover underlying causes of the variation (Oliver, 2010). However, the method must be in accord with intrinsic hypotheses and the fitting curve is greatly influenced by subjective randomness (Goovaerts, 1998; Mabit et al., 2008). Fractal theory is introduced into the soil spatial variability in the 1980s. It reflects the complexity of the variable space distribution structure, but it is useless for which soil properties do not have self-similarity characteristics (Zeleke and Si, 2006). Spectral analysis reveals the scale effect of the data sequence by converting scale to a frequency range by Fourier transform. For example, it has been used to extract periodic patterns in gilgai soils in Australia (Webster and Oliver, 2001). However, spectral analysis must meet stationarity conditions in the spatial sequence, and spectrum coherence cannot evaluate the relevance of the scale of two sequences with different frequency distributions. Besides the spatial similarity and periodicity, non-stationarity is one of the characteristics of property spatial of soil properties but has not been considered widely.

The wavelet transform (WT) is an advanced mathematical method that provides scale and location information for spatial variation (Si and Zeleke, 2005; Zeleke and Si, 2006; Lark, 2016), and is suitable for the study of multiscale stationary/nonstationary soil processes occurring over a finite spatial domain (Graps, 2010). It has been used to examine scale-dependent spatial heterogeneity of soil properties (Biswas et al., 2013). The WT can be divided into continuous wavelet transform (CWT) and discrete wavelet transform (DWT), each with its own advantages and disadvantages (Shu et al., 2008). Multi-resolution analysis using DWT can visualize soil variations orthogonally at different spatial scales (Lark and Webster, 1999). The Pearson correlation coefficient is a common measure of linear correlation between two variables at measurement scale. Some researchers have successfully used DWT and Pearson correlation to separate SOM variations at different scales and identify the dominant controls on SOM at those scales (Lark and Webster, 2005; Lark, 2005; Zhou et al., 2016).

The anisotropy is often unavoidable because the variations in SOM may dominate in some specific directions. The variogram shows different length scales in different directions by fitting a model to the spatial correlation or continuity. The major direction or minor direction along the variogram ranges are expected to be the longest or the smallest among all directions. It can be examined using a directional variogram, which is useful in assessing anisotropy degree (Biswas et al., 2014). Some various anisotropic analyses (AA) methods were used to identify representative transacts. Simon (1997) calculated spatial dependence along different directions in polar coordinates allowing exact significance testing. Another way is by calculating the semivariogram of target properties at different directions and by fitting the ranges using an ellipse. The direction of the major and the minor range of the ellipse represent the longest and the shortest distance of auto-correlation, respectively. Although the dominant directions of variation can be determined by the above methods, it is still difficult to select representative transect because of countless parallels along a specific direction (Huang et al., 2015).

The objectives of the present study were to examine the scale-specific spatial variability of SOM and its dominant controls at leading directions in mountainous areas by combining AA and DWT. SOM data were collected from Wuling mountain areas of central-south China. The relationships between SOM and environmental factors were examined