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Revealing the scale-specific controls of soil organic matter at large scale in Northeast and North China Plain

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ABSTRACT

Soil organic matter (SOM) plays an important role in terrestrial ecosystem functioning and is closely related to soil fertility and soil health. Better understanding on the spatial distribution of SOM is vital to agriculture and C-cycle management. With the advancement of digital soil mapping framework and data mining technology, selection of environmental covariates become critical to identify the controls of SOM spatial distribution at different scales and were rarely discussed in previous studies. The objectives of this study were to separate the scale-specific variations in SOM and their dominant controls at those scales along two transects from Northeast and North China Plain. Spatial distribution of SOM was separated into seven scale components (six details, D1 through D6 and one approximation, A6) along each transect using the discrete wavelet transform. The largest variations in SOM were separated in A6 (>1280 km) along the northeast transect (91.2% of the total) and D5 (320–640 km) along the north transect (40.6% of the total). Unlike the northeast transect, considerable amount of variations was also separated in other scale components of the north transect. There were no significant correlations between the scale-components of SOM and terrain factors along both the transects. While a relatively stronger correlation was observed between SOM and climatic and vegetation factors along the northeast transect, no significant correlation was observed along the north transect at large scales. This may be due to the long-term cultivation in the Northern China Plain. Principal components 1 and 3 identified from the proximally sensed visible and near infrared (vis–NIR) spectra had strong correlation with SOM along the north transect while the principle component 2 was highly correlated with SOM along the northeast transect. The scale-specific controlling factors at different locations may help in selecting environmental factors in digital soil mapping at different scales for improving mapping accuracy.

1. Introduction

Soil organic matter (SOM) is one of the key variables for agronomic and environmental management. It controls soil fertility and has a significant impact on atmospheric CO_2 concentration thus the global carbon cycle (Smith et al., 1997). Therefore, detailed understanding of the spatial distribution of SOM is necessary for better fertility management and comprehension of the process of terrestrial carbon cycle.

Spatial distribution of SOM is controlled by a suite of environmental factors including geomorphology, predominant vegetation type and intensity, climate, land use and others (McBratney et al., 2003; Scull et al., 2003) as they change across the landscape (Corstanje et al., 2007). Following Jenny's (1941) soil formation theory, therefore, a functional relationship can be developed between SOM and environmental factors. For example, a functional predictive relationship can be developed between the SOM and the controlling factors at observed locations using some mathematical and statistical theory. Once developed, the relationship can be extended to locations with unobserved SOM but known controlling factors to prepare a high resolution map. This concept is known as the digital soil mapping (DSM, McBratney et al., 2003) and has received an extreme attention of soil scientists in the recent past. This became more attractive with the development of powerful computers and availability of high-resolution information on large numbers of controlling factors or predictor variables (Poggio et al., 2013; Mansuy et al., 2014; Viscarra Rossel et al., 2014). However, the success of DSM depends on the selection of predictor variables, calibration of the model or predictive relationship, and the validation of the model. Nevertheless, current DSM research often emphasizes the latter two, leaving the predictor variable selection process to the researcher's expert knowledge (Miller et al., 2015). It is still a challenge to embody the factors to the variables we observe and identify from mass data catalog. Additionally, the variability within the environmental

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covariates makes this more challenging. Often the environmental factors operate in different intensities and at different scales therefore exhibiting scale-dependent relationship with SOM. This scale-dependent variability makes the predictive relationship development yet more challenging. Therefore, it is necessary to understand the variability of SOM at different scales and the dominant controlling factors at those scales which may help in selecting the appropriate environmental covariates.

Though the Pearson correlation analysis is the most commonly used method in identifying the dominant controlling factors, it explains the linear association globally without taking into account the scale effect. Soil properties may vary over space with either linear or nonlinear trends as affected by diverse environmental conditions and cannot be examined using Pearson correlation analysis (Biswas and Si, 2011). Wavelet transform, an advanced mathematical method, has been applied to spatial data series of soil variables whose variance, at multiple scales, cannot plausibly be treated as uniform in space (Lark and Webster, 1999; Milne et al., 2014). Wavelet transform has been used to examine the scale-dependent spatial heterogeneity of soil properties (Lark and Webster, 1999; Biswas et al., 2013) and shows promise in these studies to examine the scale-dependent variability of SOM and its controlling factors at different scales. Therefore the objectives of this study were to examine the spatial scale characters of SOM distribution along two transects from Northeast and North China Plain and identify the dominant controls of SOM at those scales. We have used discrete wavelet transform to separate the variations in SOM at different scales and their contribution towards the overall variability. Then we have correlated each scale component of SOM with environmental factors to identify the scale-specific dominant controls.

2. Materials and methods

2.1. Data

2.1.1. Soil sampling and measurement

The study area is located in the Northeast and Northern Plains, China, covering approximately 642,000 km^2. A total of 1078 sampling locations were selected using an approximately 30-km grid across the agricultural production areas in 2003 and 2004 (Fig. 1). Soil samples were collected from the 20-cm surface layer, air-dried and sieved to less than 2 mm and analyzed in a laboratory for SOM colorimetrically after H_2SO_4-dichromate oxidation at 150 °C. The SOM of 1078 locations were interpolated over the whole study area using inverse distance weighting in ArcGIS 10.0. The cross validation of the interpolation showed a determination coefficient of 0.70.

Two transects were constructed considering the climate zone of China. One transect was constructed in the mid-temperate zone, which was from the northeast corner to about the center of the study area that lay within the Northeastern Plain of China (Fig. 2). The second transect was constructed in the warm temperate zone, which was from the central part to the southwest corner of the study area that lay within the North China Plain (Fig. 2). Both transects were 1280 km long with 128 sample points each (10 km sampling interval) and extracted SOM value from the interpolation of SOM map (Fig. 3).

2.1.2. Collection of environmental covariates

A number of environmental covariates were used in this study including remote sensing data, digital elevation model and proximal sensing data (Table 1). Two types of remote sensing data were obtained and used in this study. The first one is Moderate Resolution Imaging Spectroradiometer (MODIS). It has shown advantages in land surface research (Justice et al., 1998) and provides users information with a combination of basic surface variables, such as spectral reflectance, albedo, land surface temperature, vegetation index, leaf area index, active fires, burned area, snow and ice cover and net primary production. Products of MOD11A2 (land surface temperature of daytime, LST_D and land surface temperature of night, LST_N), MOD13A1 (normalized difference vegetation index, NDVI), MOD16A3 (evapotranspiration, ET) and MOD17A3 (net primary productivity, NPP) were used in this study. Intra-annual variance of the NDVI (VNDVI) was computed from the NDVI. NDVI and NPP are factors used to indicate vegetation information. Vegetation is the key source of the SOM, thus NDVI and NPP have been successfully used to predict soil organic carbon/matter (Bou Kheir et al., 2010). However, human activities sometimes may weaken the relationship between vegetation and SOM distribution (Kunkel

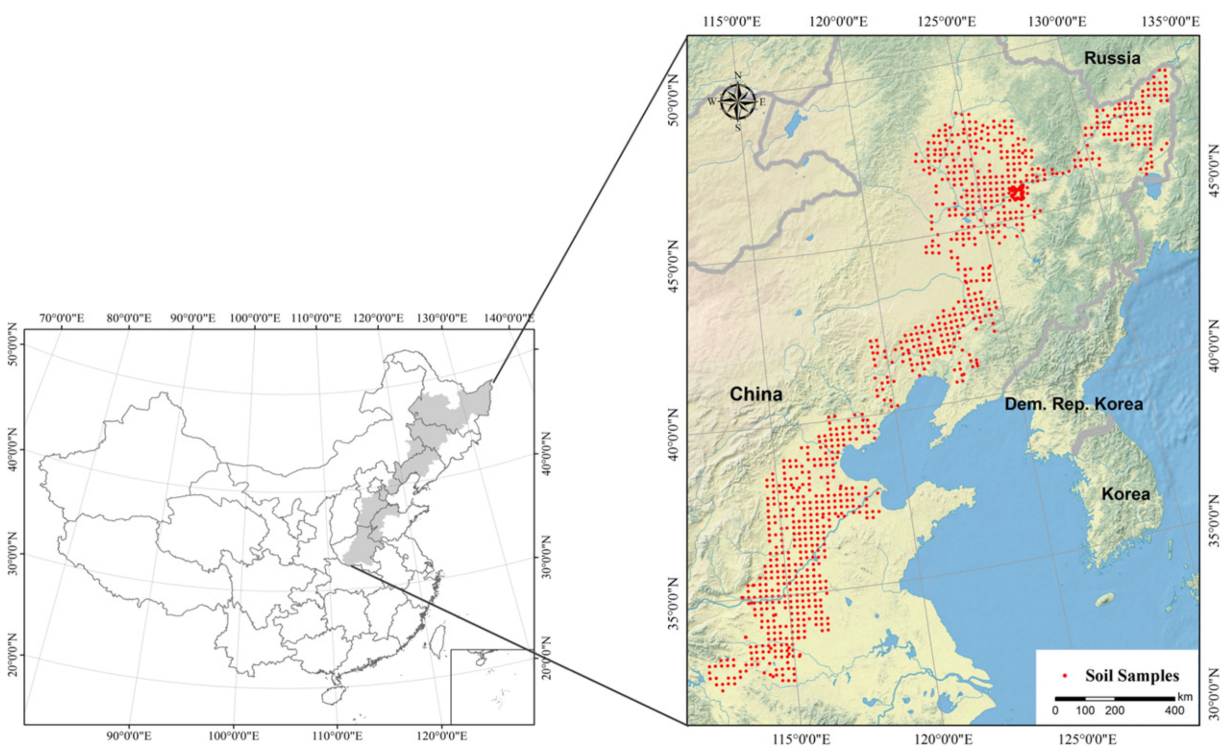

Fig. 1. Soil sample locations across the Northeast and North China Plain.