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Prediction of soil organic matter variability associated with different land use types in mountainous landscape in southwestern Yunnan province, China

Shiliang Liu *, Nannan An, Juejie Yang, Shikui Dong, Cong Wang, Yijie Yin

State Key Laboratory of Water Environment Simulation, School of Environment, Beijing Normal University, Beijing, 100875, PR China

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A B S T R A C T

SOM is a crucial factor that indicates soil fertility and vegetation status and, to a considerable extent, influences the CO_2 concentration in the atmosphere and even the global carbon cycle. We collected 294 SOM data from the secondary soil survey of Yunnan province in 1979 and investigated 210 soil sample sites (0–20 cm depth) in 2011 to enhance the understanding of the spatial variability of SOM between two phase data and its dominant influencing factors in the mountainous region in southwestern China. We examined whether land use types (farmland, grassland, forestland and scrubland), topographic conditions (elevation, slope and CTI) and vegetation coverage (NDVI) affect the spatial distribution and content of SOM in a mountainous region in southwestern China. The results indicated that, SOM content decreased among different land use types in the following order: forestland > scrubland > grassland > farmland. An accurate spatial prediction of SOM content has great significance in the estimation of the SOC pool. This study exhibited that the combined use of vegetation index and terrain attributes would result in a suitable method of predicting SOM distribution even in complex terrain. The prediction of spatial variability in SOM contents was achieved establishing IDW and UK. The root mean square error RMSE and ME methods were selected as comparison criteria to indicate prediction accuracy. Owing to the heterogeneous natural environment, the application of the UK and IDW methods is limited. And it is still challenging that further work was necessary to accurately predict spatial distribution of SOM by choosing appropriate methods in these mountain areas. This study laid a foundation to estimate and evaluate SOM sequestration for regional land use management.

1. Introduction

SOM content, which is typically measured in the form of soil organic carbon SOC content, is commonly regarded as a key indicator of soil quality and utilization. The presence of SOM has been proved to be beneficial for soil productivity, water holding capacity, and carbon sequestration (Prescott et al., 2000; Munson and Carey, 2004; Seely et al., 2010; Six and Paustian, 2014). Earlier studies showed that SOM is vulnerable to anthropogenic activities such as human trampling, farming practices, and other economic development activities (Huang et al., 2007; Kissling et al., 2009; Mao, et al., 2014). Knowledge about the land use practices affecting the SOM content has received considerable attention (King and Campbell, 1994; Zhu et al., 2014). SOM content commonly varied between different land use types (Riezebos and Loerts, 1998; Guimarães et al., 2013). Forest and grassland that have been converted into cultivated land are susceptible to decrease in SOM content and soil quality degradation (Celik, 2005). However, little is known about the SOM contents of various land use types in the mountainous region of southwestern China.

Utilizing spatially correlated auxiliary information to improve the prediction accuracy of soil properties has been widely recognized. The spatial variability in SOM content is generally controlled by environmental variables, such as elevation, terrain, and vegetation coverage (Zhang et al., 2013). Soil at higher elevation was found to contain a higher SOC concentration (David and Zhang, 2003; Tobiašová, 2011), and the elevation was shown to be significantly positively correlated with SOM content (Zhang et al., 2012). In addition to applications of DEM data, establishing a correlation between SOM content and spectral data would have interesting applications for remote sensing data. The NDVI is generally known as an indicator that reflects vegetation coverage and growth status. NDVI values have been correlated with a number of vegetation structures and functions such as biomass and soil-

Abbreviations: SOM, soil organic matter; SOC, soil organic carbon; NDVI, normalized difference vegetation index; RMSE, root mean square error; ME, mean error; MLR, multiple linear regression; DEM, digital elevation model; IDW, inverse distance weighting; UK, universal kriging; RK, regression kriging; OK, ordinary kriging; CTI, compound topographic index; TWI, topographic wetness index; SFD, single flow direction; MFD, multiple flow direction; DEMON, digital elevation model networks method; ERS, earth remote sensing; SPOT, Systeme Probatoire d'Observation de la Terre.

* Corresponding author at: School of Environment, Beijing Normal University, 19 Xinjiekouwai Street, Beijing 100875, PR China.
E-mail address: shiliangliu@bnu.edu.cn (S. Liu).

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dependent site qualities (Fu and Burgher, 2015). The distribution of SOC has been proven to be closely related to the NDVI (Sumfleth and Duttmann, 2008). Meanwhile, some findings have shown that the SOC content differed under different vegetation conditions (Neufeldt et al., 2002; Ding et al., 2012).

Geostatistics is a commonly-used statistical science based on the theoretical work of Matheron (1963). It is based on local variables and their variation, both stochastic and structural, which reflect the autocorrelation and dependence among spatial properties (Shi and Kriging, 2013). Surface interpolation techniques using GIS are very powerful tools for predicting surface values. The most commonly used interpolation techniques in these studies include IDW, kriging or Gaussian regression, MLR and cokriging interpolations. MLR is extensively applied, owing to its simplicity, efficiency, and straightforward interpretation. However, the relations between soil properties and environmental variables are almost no-linear in nature (McBratney et al., 2003). Kriging is one of the most commonly applied and is the best linear unbiased estimator in the sense that it minimizes the variance in the estimation error (Dai, et al., 2014). IDW takes into account the distance between the certain and uncertain samples. Furthermore, kriging regression includes not only the distance information but also the analysis of the structure and the variation associated with the spatial sites where the certain and uncertain samples are located. Hu et al. (2004) found that UK with a first-order trend performs the best, while IDW performs the worst for estimating soil mercury content. Gong et al. (2010) found that models with IDW are better than kriging models for predicting the groundwater arsenic concentrations in any area/aquifer. Bourennanea et al. (2014) showed that regardless of sample size, UK with external drift gave more accurate prediction on average than simple linear regression. Most topography-based predictions of soil properties were built to describe the relationships between soil properties and topographic attributes in a landscape. For example, McGrath and Zhang (2003) employed geostatistical methods to predict the spatial distribution and changes of SOC in Ireland. Some studies have demonstrated that the UK technique outperformed RK and linear regression in improving the SOM prediction (Li, 2010). However, in another study by Zhang et al. (2012) that the UK did not outperform both OK and cokriging.

To quantify the spatial distribution of SOM content, multiple regression analysis has also been widely applied. Cheng et al. (2004) established a multiple regression equation between SOM content and soil parent material and topographic factors (e.g., elevation, slope) in subtropical China. Meersmans et al. (2008) concluded that the application of a multiple regression model resulted in remarkably low standard errors in the SOC values for various land use types.

In southwestern Yunnan province, there are large areas of mountainous ecosystems, and the SOM content along the Lancang River is vulnerable to runoff due to the complex environmental conditions. In mountainous ecosystems, the high vegetation coverage can improve soil nutrient sequestration and water–soil conservation, while the presence of degraded vegetation might lead to degradations in soil quality (Aranda and Oyonarte, 2005; Merilä, et al., 2010). Owing to frequent anthropogenic activities such as human trampling, deforestation, and construction activities, the SOM content might change in this study area near Lancang River.

However, to the best of our knowledge, only little is known about the relationships underlying the spatial distribution of SOM and simultaneously using different methods to predict SOM content in the mountainous region of southwestern Yunnan province. The objectives of this paper mainly are: 1) to explore the spatial variability in SOM under different land use types in the mountainous region of southwestern Yunnan province, 2) to confirm the relationship between SOM content and auxiliary variables (e.g., topographic factors and vegetation indices), and 3) to compare the spatial distribution of SOM content determined employing two prediction techniques (IDW and UK).

2. Study site

The Mekong River is the largest international river in Asia. The Mekong River originates in the eastern Qinghai province in China and enters the South China Sea in Vietnam. The upper Mekong River in China is called the Lancang River. The study area, where is located in the mountainous landscape in the middle reaches of the Lancang River (Fig. 1), is characterized by a subtropical low-latitude mountain climate with a clear dry–wet season. The average temperature ranges from 18 °C to 20 °C, and annual mean precipitation ranges from 1000 to 1150 mm (Zhao et al., 2014; Liu et al., 2013; Zhao et al., 2013). According to investigations of vegetation type in the study area, the main land use types are scrubland and forestland, and there are small areas of farmland and villages. In the broad-leaved forest, *Alnus nepalensis* and *Quercus acutissima* are the dominant species of vegetation; they are joined by *Pinus massoniana* Lamb and *Platycladus* to form the theropencedrymion. *Pinus yunnanensis* are the dominant species in the coniferous forest, while *Pinus khasys*, *Juglans sigillata* and *Blue eucalyptus* are the dominant species in the planted forest. *Woodfordia fruticosa*, *Glochidion daltoni*, *Crofton weed*, and *Melastoma normale* are the dominant species in the scrubland, and the farmland mainly consists of corn and sugarcane. The soil types and soil texture in the study area include red and sandy soil (Liu et al., 2014).

3. Materials and methods

3.1. Field investigation and soil sampling

We collected the SOC data from the second soil census data in Yunnan province investigated by the China government in 1979. In light of the equation: SOM $(g \cdot kg^{-1}) = SOC(g \cdot kg^{-1}) * 1.724$, the SOM content in 1979 was achieved. In soil survey of Yunnan province, a total of 294 topsoil sampling sites were located in Yun County, Fengqing County, Nanjing County, and Jingdong County (Fig. 1). Although the precise location was not obtained for soil sampling in 1979, the 294 sampling sites are also located in the Lancang River watershed including most typical land use types, which is consistent with those of 2011. It is assumed that the soil types under different land use types are considered similar, to vast extent. There were 35 sampling sites in broad-leaved forest, 31 in coniferous forest, 49 in theropencedrymion, 44 in planted forest, 38 in scrubland, 22 in grassland, and 75 in farmland, respectively. In June 2011, soil samplings were collected from five quadrats in each of seven land use types: (1) broad-leaved forest, (2) coniferous forest, (3) theropencedrymion, (4) planted forestland, (5) scrubland, (6) grassland, and (7) farmland. For each quadrat in different land use types, six 1.0 m × 1.0 m grids were randomly taken for each of the depth ranges of 0–20 cm. There are 30 soil samplings in each land use type and 210 soil samplings for all land use types totally investigated in this study. In addition, the sampling design in 2011 is same as that in 1979. The longitude and latitude of each sampling site in 2011 were recorded with a GPS. Soil samples in the cutting ring were fully taken out three times, and the fallen leaves and stones on the surface of the soil samples sites were fully removed. All of the samples were placed in polyethylene plastic bags and kept at 4 °C until laboratory analysis. After transportation to the laboratory, the samples were kept frozen until analysis. The soil samples were then air-dried and sieved through a 2-mm nylon mesh (Metson, 1956). In the laboratory, SOM contents were measured by the H_2SO_4–$K_2Cr_2O_7$ method (McGill et al., 1986).

3.2. Environmental variables

3.2.1. Terrain variables

In the study region, a DEM with a spatial resolution of 25 m was obtained. Low-elevation areas were located along the Lancang River, whereas high-elevation areas were mainly located in the margin of the study area.