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Prediction of soil organic matter in peak-cluster depression region using kriging and terrain indices

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ABSTRACT

In an ecosystem, soil organic matter (SOM) is an important indicator of soil fertility and soil quality. Accurate information about the spatial variation of SOM is critical for sustainable soil utilization and management in karst areas. This study was conducted to evaluate and compare spatial prediction of SOM by using multiple linear stepwise regressions (MLSR), ordinary kriging (OK) and regression kriging (RK) with terrain indices. Soil organic matter was estimated by using 149 observation data for Guohua Karst Ecological Experimental Area, a 10 km^2 study area in Guangxi Zhuang Autonomous Region, Southwest China. Correlation assessment between SOM and terrain indices showed that there was a significant correlation amongst 5 of the 8 pairs of indices. In the analysis of variance (ANOVA) applied in MLSR for SOM using terrain indices, two models of independant terrain indices were set to perform the models of MLSR. Relief degree of land surface (RDLS) entered into the regression equation for the first model (M1), whereas RDLS and distance to ridge of mountains (DRM) entered into the regression equation for the second model (M2). The assessment showed that the RK method combining with terrain indices obtained a lower mean predication error (ME) and root mean square prediction error (RMSE). Compared with OK, the application of RK_{M1} and RK_{M2} resulted in relative improvement (RI) of 13.87% and 15.61%, respectively. This study showed that including terrain indices in regression kriging might improve SOM prediction precision by up to 15% in the karst mountains.

1. Introduction

Soil organic matter (SOM) is the major determinant and indicator of soil fertility and quality, and is closely related to soil productivity (Susanne and Michelle, 1998; Al-Kaisi et al., 2005; Huang et al., 2007). From a global perspective, soils hold an important terrestrial stock of carbon, approximately twice as much as the atmosphere does, and triple as the terrestrial vegetation (Eswaran et al., 1993; Davidson et al., 2000) does. The carbon in the SOM of agricultural ecosystem is a dominant component of the terrestrial C stock (Janzen et al., 1997). Managing soil C can enhance productivity and environmental quality, and can reduce the severity and costs of natural disasters, such as drought, flood and disease (Chen and Aviad, 1990; Stevenson and He, 1990; Blanco-Canqui and Lal, 2004). The reduction of SOM will result in a decrease of soil nutrient supply, porosity and thus in soil productivity (Gray and Morant, 2003), while increasing SOM can reduce atmospheric CO_2 ratio, which contributes to climate change (Yadav and Malanson, 2007). So in order to utilize soils and protect environment in a sustainable way, it requires a better understanding of SOM content and its spatial variability.

In karst peak-cluster depression regions, there are positive and negative landforms, namely peak-cluster and depression, which make landforms in karst areas complex and changeful. In these areas, there is severe soil erosion such that bedrock is exposed and land productivity declines rapidly (Yuan, 1993; Cai, 1997; Huang and Cai 2006; Zhang et al., 2011). As a result of this rapid soil erosion, soils have become shallow and discontinuous, causing desertification of the karst area. This has caused barriers in the restoration of the karst. It is of important practical significance for the process to master the spatial distribution of SOM in karst areas. However, conventional soil survey methods for evaluating the SOM in karst mountainous areas require a lot of time, effort and hence relatively higher budget to perform.

Recently, studies on utilizing spatially correlated auxiliary information to improve the prediction accuracy of soil properties

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have received considerable attention in pedometrics (McBratney et al., 2003; Baxter and Oliver, 2005; Herbst et al., 2006; Takata et al., 2007; Zhu et al., 2010). Terrain variable is the most commonly used auxiliary information, which can enhance spatial prediction of soil properties and reduces the cost of sampling in three aspects (Pei et al., 2010). First, terrain variables are derived from a digital elevation model (DEM), and can be easily acquired at a low cost. Second, terrain variables are exhaustive and spatially extensive, and can potentially provide voluminous data sets, which provide relevant information on unsampled locations. The third and perhaps the most important aspect is the significant correlation between terrain variables and soil properties. Several previous studies have illustrated the potential of utilizing terrain indices (Mueller and Pierce, 2003; Simbahan et al., 2006; Pei et al., 2010; Zhang et al., 2012) to get more precise spatial estimations of SOM. However, few studies have been conducted in karst areas.

The objective of this paper was to select a suitable combination of terrain indices to improve the spatial prediction of SOM using regression kriging (RK). First, exploratory analyses were conducted to examine the correlations between SOM and terrain indices. Then, SOM was predicted spatially by ordinary kriging (OK), multiple linear stepwise regressions (MLSR) and RK. The RK model was based on the results of the exploratory analyses. By comparing the mean error (ME) and the root mean squared error (RMSE) with different spatial prediction methods, this paper explored whether the introduction of auxiliary indices with exploratory analyses can improve the prediction for a given prediction method.

2. Materials and methods

2.1. Study area

Guohua Karst Ecological Experimental Area (40°14′–40°48′N, 116°41′–117°30′E) is located in Pingguo County in Southwest China, covering a total area of 10 km^2 (Fig. 1). In the past, karst rocky desertification seriously impacted the area. To protect the fragile karst environment, the 'Green for Grain' program was initiated in Southwest China, and Guohua Karst Ecological Experimental Area was founded in 2001. Forests in hilly areas have been effectively managed and protected, and illegal wood cutting has been restrained. The vegetation has been partly restored and karst rocky desertification has been relieved. Topography in this area is characterized with typical karst peak-cluster depression landscape (a combination of clustered peaks with a common base) with the altitude ranging from 120 to 560 m above mean sea level. Climate is a subtropical monsoon humid one with a mean annual temperature of 13–14 °C and abundant but seasonally uneven rainfall. The annual mean precipitation for the period from 1958 to 1992 was 1347 mm, but over 86% of this amount fell during the rainy season (April–October) (Yang et al., 2013). Various types of natural vegetation occur in the study area, dominated by evergreen broad-leaved forest and deciduous broad-leaved forest. The generally thin karst soil is unevenly distributed because soil formation occurs slowly and varies widely across the terrain. Soil types include mainly calcareous, yellow and red soils, with calcareous soil covering 87.3% of the study area. Five land use categories occur in the study area: forest land, grassland, cultivated land, water bodies and urbanized areas (towns, roads and other urbanized areas). Cultivated land includes dry and paddy land.

2.2. Soil sampling and soil analysis

The study area was 3.7 km wide from east to west and 2.9 km long from north to south. Soil samples were obtained from the study area in August 2012 following a method on a regular 140 m × 140 m grid. Because of the complex topology in the study area, it is too difficult to reach some sample sites such as the summit and steep slope. When some sample sites distribute in the summits, steep slopes, water bodies or in urbanized areas, the soil samples cannot be obtained. Therefore, a total of 149 soil samples were obtained. The actual locations of the sampling sites were recorded using a global positioning system (GPS) receiver (Juno ST). Three to five soil sub-samples were collected at a depth of 0–20 cm within a circle of radius 2 m surrounding the specified sampling location and mixed thoroughly to make a composite sample. Then, 1.0 kg of this composite soil sample was obtained and used for soil testing. The samples were air-dried and ground to pass a 2-mm sieve. The content of soil organic carbon (SOC) was determined by using the potassium dichromate-wet combustion procedure, and SOM was obtained by multiplying SOC by a conversion factor (NSS, 1995).

All data were subject to exploratory analyses by producing boxplots and Paūta Criterion to remove outliers (Zhang and Yuan, 1997). In this study, there were no outliers being removed through the exploratory analyses. The soil sample data were divided into two groups, i.e., training (interpolation) data, which were used for the computation of spatial models, and test (validation) data, which were used for validating the spatial models; the latter representing about 20% of the whole sample data. The training data and the test data were automatically generated in ArcGIS software, using the Geostatistical Analyst extension (Fig. 2).

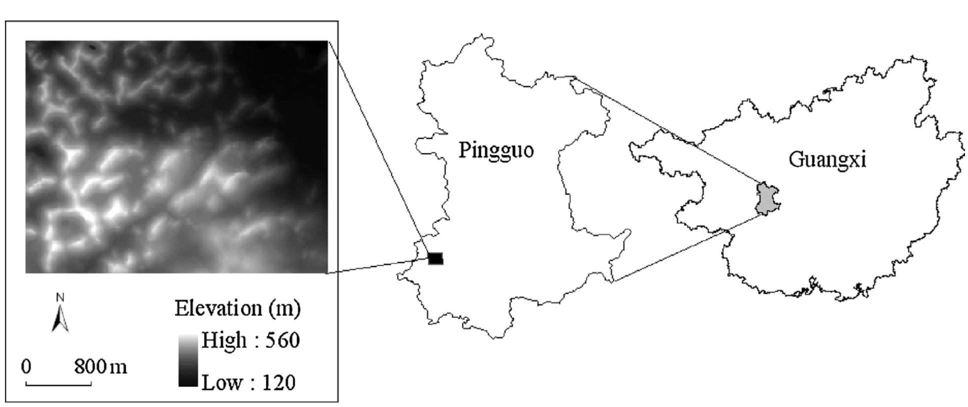

Fig. 1. Location of Guohua Karst Ecological Experimental Area in Pingguo County of Guangxi Zhuang Autonomous Region, Southwest China.