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Mapping soil organic matter in low-relief areas based on land surface diurnal temperature difference and a vegetation index

Ming-Song Zhao[a,b,c], David G. Rossiter[a,d], De-Cheng Li[a], Yu-Guo Zhao[a], Feng Liu[a], Gan-Lin Zhang[a,b,*]

[a] State Key Laboratory of Soil and Sustainable Agriculture, Institute of Soil Science, Chinese Academy of Sciences, No. 71 East Beijing Road, Nanjing 210008, Jiangsu Province, China
[b] University of Chinese Academy of Sciences, No. 19A Yuquan Road, Beijing 100049, China
[c] Institute of Geodesy and Geomatics, Anhui University of Science and Technology, No. 168 Xueyuan Road, Huainan 232001, Anhui Province, China
[d] Faculty of Geo-information Science and Earth Observation ITC, University of Twente, PO Box 217, 7500 AE Enschede, The Netherlands

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ABSTRACT

Accurate estimates of the spatial variability of soil organic matter (SOM) are necessary to properly evaluate soil fertility and soil carbon sequestration potential. In plains and gently undulating terrains, soil spatial variability is not closely related to relief, and thus digital soil mapping (DSM) methods based on soil–landscape relationships often fail in these areas. Therefore, different predictors are needed for DSM in the plains. Time-series remotely sensed data, including thermal imagery and vegetation indices provide possibilities for mapping SOM in such areas. Two low-relief agricultural areas (Peixian County, 28 km × 28 km and Jiangyan County, 38 km × 50 km) in northwest and middle Jiangsu Province, east China, were chosen as case study areas. Land surface diurnal temperature difference (DTD) extracted from moderate resolution imaging spectroradiometer (MODIS) land surface temperature (LST), and soil-adjusted vegetation index (SAVI) at the peak of growing season calculated from Landsat ETM+ image were used as predictors. Regression kriging (RK) with a mixed linear model fitted by residual maximum likelihood (REML) and residuals interpolated by simple kriging (SK) were used to model and map SOM spatial distribution; ordinary kriging (OK) was used as a baseline comparison. The root mean squared error, mean error and mean absolute error calculated from leave-one-out cross-validation were used to assess prediction accuracy. Results showed that the proposed covariates provided added value to the observations. SAVI aggregated to MODIS resolution was able to identify local highs and lows not apparent from the DTD imagery alone. Despite the apparent similarity of the two areas, the spatial structure of residuals from the linear mixed models were quite different; ranges on the order of 3 km in Jiangyan but 16 km in Peixian, and accuracy of best models differed by a factor of two (3.3 g/kg and 6.3 g/kg SOM, respectively). This suggests that time-series remotely sensed data can provide useful auxiliary variable for mapping SOM in low-relief agricultural areas, with three important cautions: (1) image dates must be carefully chosen; (2) vegetation indices should supplement diurnal temperature differences, (3) model structure must be calibrated for each area.

1. Introduction

Soil organic matter (SOM) is a crucial soil constituent related to soil physical, chemical, and biological processes, soil fertility and agricultural productivity. SOM is also a major component of the global carbon pool (Yadav and Malanson, 2007). Current digital soil mapping (DSM) methods to map SOM are mostly based on quantitative soil–landscape relationship models using easily-obtained regional environmental factors (McBratney et al., 2003, 2000; Qi et al., 2006; Thompson et al., 2006), especially geomorphometry, vegetation, land cover and parent material. However, models based on geomorphometry perform poorly in low relief areas such as alluvial and coastal plains (Pei et al., 2010; Santos et al., 1997; Stoorvogel et al., 2009; Zhu et al., 2010). Moreover, in old agricultural areas such as east China long-term cultivation has weakened the relationship between soil properties and land cover (Ding et al., 1989; Zhu et al., 2010), and therefore DSM methods based on soil–landscape relationships using geomorphometry and land cover as predictors are often ineffective in these areas.

Recently, some attempts have been made to map SOM in plains using DSM techniques and other predictors, such as using multi- and hyper-spectral remote sensing (RS) (Chen et al., 2008;

* Corresponding author at: State Key Laboratory of Soil and Sustainable Agriculture, Institute of Soil Science, Chinese Academy of Sciences, No. 71 East Beijing Road, Nanjing 210008, China. Tel.: +86 25 86881279; fax: +86 25 86881000.
E-mail address: glzhang@issas.ac.cn (G.-L. Zhang).

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Stevens et al., 2010) and the soil line Euclidean distance calculated from near-infrared remotely sensed data (Fox and Sabbagh, 2002). Bartholomeus et al. (2011) used imaging spectroscopy and spectral unmixing to map soil organic carbon of partially vegetated agricultural fields. Direct sensing of the soil has three disadvantages (1) the soil surface is often obscured by vegetation; (2) the land surface may be obscured by clouds; and (3) only the surface few millimeters are sensed.

With the development of multi- and hyper-temporal RS, attempts have been made to use time-series analysis to model spatial variability of soil properties. Chang et al. (2003) used the brightness temperature of multi-temporal RS to identify soil texture in the southern Great Plains of North America based on an artificial neural network applied to multiple drying cycles. Zhu et al. (2010) developed a method called land surface dynamic feedbacks (LSDF) based on Moderate Resolution Imaging Spectroradiometer (MODIS) imagery to differentiate the spatial variability of soil type after a major rainfall event in low-relief areas with partial vegetation cover in Heilongjiang and Xinjiang, China. Liu et al. (2012) mapped soil texture (sand, silt, and clay concentration) using LSDF derived from MODIS after a major rain event in south-central Manitoba, Canada. Wang et al. (2012) predicted soil texture in Jiangyan (one of our study areas, see below) using the changing pattern of land surface diurnal temperature difference (DTD) derived from MODIS land surface temperature (LST), based on fuzzy-c-means clustering method. These researches suggested that soil properties that affect water content can be related to LST, DTD and their change pattern.

The theory behind these results is as follows. Water has a much higher thermal capacity than mineral or organic matter in soils, so that wetter soils have higher thermal capacity, given a constant composition (Verstraeten et al., 2006). Thus intra-day changes of LST are reduced because of the increased thermal inertia; this is reflected in lower DTD, which effect is most visible when the soil is drying after a heavy rain (Huang, 2000). Wet soils also have slower decomposition of organic matter. Thus the hypothesis is that in the long term, soils showing low DTD have high SOM concentration, and vice versa. Further, clay has a higher thermal inertia than sand; this fact implies a positive feedback to the moisture effect just noted: finer-textured soils retain more moisture and hold it more tightly due to their finer pore-size distribution. Further, clay provides both physical and chemical mechanisms protecting SOM from microbial breakdown, while soils high in sand generally have higher mineralization rates and thus lower SOM concentration (Hook and Burke, 2000; Konen et al., 2003; Oades, 1988). The question remains to what degree these theoretical differences can be seen by remote sensing.

Numerous spectral indices have been developed to characterize land and vegetation cover, such as ratio vegetation indices, the normalized difference vegetation index (NDVI) and the perpendicular vegetation index (PVI) (Huete, 1988). As is well-known, SOM is a key contributor of soil fertility. Thus it is expected that soil high in SOM will be more fertile, promoting vegetative growth, resulting in high values of these spectral indices. The soil-adjusted vegetation index (SAVI) developed by Huete (1988) has the advantage of removing the soil background and thus being a better measure of vegetation vigor, and we hypothesize, thus a partial surrogate measure of SOM.

A spatially distributed variable (in this case, SOM) can be accounted for by sum of deterministic and stochastic components, which may be termed a universal model of soil variation (Hengl, 2009):

$$Z(s) = Z^{*}(s) + \varepsilon + \varepsilon(s) + \varepsilon'(s) \qquad (1)$$

where $Z(s)$ is the true (unknown value) of property Z at location s, $Z^{*}(s)$ is a predicted value based on some deterministic model from covariates (for example, RS products or geomorphometry), $\varepsilon(s)$ is a spatially-correlated random field of the residuals from the deterministic component, and $\varepsilon'(s)$ is pure noise. The deterministic component is most conveniently formulated as a multivariate linear model of the covariates, for example indices derived from remote sensing products. The spatially-correlated component may be fitted by variogram modeling and predicted with simple kriging (SK); the sum of the two components has been termed regression kriging (RK) (Hengl et al., 2007).

The linear models of deterministic components have often been fitted by ordinary least squares (OLS), however, this does not take into account the assumed spatial correlation of the model residuals $\varepsilon(s)$. If observations are design-based the fitted model is unbiased (Brus and De Gruijter, 1993); however if observations are collected by systematic sampling on transects, or grids, or without any probability design (purposive sampling), OLS methods are not appropriate. This is explained by Lark and Cullis (2004) and Lark et al. (2006), who present a method to model and predict using an "empirical best linear unbiased predictor" (EBLUP) with residual (sometimes called "restricted") maximum likelihood (REML). This statistical technique has been used in a few soil studies. The previously mentioned two studies used soil water content as the target variable and spatial trend as the co-variable. Chai et al. (2008) found that REML-BLUP provided better-structured residual variograms and more accurate prediction of SOM than RK with the external drift by computed by OLS; this study used geomorphometric co-variables. Santra et al. (2012) obtained similar results for soil hydraulic properties, also using geomorphometric co-variables.

Based on the direct, indirect and interactive relationships between SOM, soil moisture, soil texture and the change of surface soil temperature, our hypothesis is that DTD could reflect the spatial variability of SOM when the soil is drying after an adequate rain event following a prolonged dry period. The objectives of this study were (1) to examine this hypothesis and how much information of SOM can be explained by appropriately-chosen DTD in low-relief agricultural areas, (2) to examine the sensitivity of models to the lag between a rain event and DTD, and (3) to predict SOM concentration by RK, with the deterministic model fitted by generalized least squares (GLS) using REML, and determine the relative contributions of DTD, SAVI and soil type to model success. We also wanted to see how well the method performs in general, so we selected two apparently similar areas in the same province and to see if the method would give similar results in both.

2. Materials and methods

2.1. Description of the study area and soil

Both study areas are in Jiangsu Province, East China, in the lower Yangtze River delta and East Sea coastal plain. The first area is Peixian County, 28 km × 28 km, 116°44′48″–117°3′8″ E, 34°30′16″–34°45′28″ N, in northwest Jiangsu (Fig. 1a). Elevation ranges from 30 to 50 m decreasing from southwest to northeast. The climate is warm temperate and semi-humid monsoon, mean annual temperature 14.2 °C, precipitation 820 mm, and sunshine duration 2308 h. Soil parent materials are carbonate-rich paleo-alluvium in the southwest and lacustrine sediments in the northeast. According to Chinese Soil Taxonomy (CST) (Gong et al., 2003) the soils are Calcaric and Parasalic Ochri-Aquic Cambosols mapped as four soil series (Fig. 1a) (CRGCST, 2001). The textures vary considerably, with the finer textures from lacustrine parent materials in the northeast and coarser textures from the paleo-alluvium the southwest (OSSPC, 1984). The dominant land uses are dryland and paddy field, accounting for 49% and 31% of the total study area (Fig. 2a); these largely follow the distribution of