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The impact of rainfall magnitude on the performance of digital soil mapping over low-relief areas using a land surface dynamic feedback method

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ABSTRACT

Previous studies have demonstrated that the pattern of land surface dynamic feedbacks (LSDF) based on remote sensing images after a rainfall event can be used to derive environmental covariates to assist in predicting soil texture variation over low-relief areas. However, the impact of the rainfall magnitude on the performance of these covariates has not been thoroughly investigated. The objective of this study was to investigate this impact during ten observation periods following rainfall events of different magnitudes (0–40 mm). An individual predictive soil mapping method (iPSM) was used to predict soil texture over space based on the environmental covariates derived from land surface dynamic feedbacks. The prediction error showed strong negative correlation with rainfall magnitude (*Pearson's r* between root-mean squared error of prediction and rainfall magnitude = −0.943 for percentage of sand and −0.883 for percentage of clay). When the rainfall reaches a certain magnitude, the prediction error becomes stable. The recommended rain magnitude (threshold) using LSDF method in this study area is larger than 20 mm for both sand and clay percentage. The predictive maps based on different observed periods with similar rainfall magnitudes show only slight differences. Rainfall magnitude can thus be said to have a significant impact on the prediction accuracy of soil texture mapping. Greater rainfall magnitude will improve the prediction accuracy when using the LSDF. And high wind speed, high evaporation and low relative humidity during the observed periods also improved the prediction accuracy, all by stimulating differential soil drying.

1. Introduction

Low relief areas generally are agricultural areas, it is necessary to understand their soil spatial distribution. Local interpolation methods such as kriging are usually adopted in such areas, but these have strict requirements on the number and distribution of samples (Goovaerts, 1999; Li, 2010; Zhang et al., 2013; Mueller et al., 2004; Bragato, 2004). The soil-landscape models, such as multiple linear regression, regression-kriging, artificial neural networks, random forest, and similarity-based method, are most widely used in digital soil mapping (Kumar et al., 2012; Qiu et al., 2003; Song et al., 2016; Wiesmeier et al., 2011; Zhu, 1997, 2000; Zhu et al., 2015). These models use easy-to-measure, soil-forming factors which mainly include landform, vegetation, climate, parent material, and etc. to predict the spatial variation of soil. However, in low relief areas, the spatial variation of landform is too gentle to indicate soil spatial variation (Liu et al., 2012; Zhu et al., 2010; Pei et al., 2010; Santos et al., 1997). Moreover, long-term cultivation and interference by human activities have weakened the relationship between

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soil properties and vegetation (Zhao et al., 2014; Zhu et al., 2010; Ogle et al., 2005; Angers and Caron, 1998). New environmental covariates have thus been sought that can be used to predict soil spatial variation over low-relief areas (Guo et al., 2015, 2016; Zhu et al., 2010; Liu et al., 2012; Chang et al., 2003; Jackson et al., 1999).

The rapid development of remote sensing technology provides the potential to extract soil information at scales from regional to global (Croft et al., 2012; Montzka et al., 2011; Dent et al., 2013; Rouze et al., 2015; Dobos et al., 2000). Single multispectral or hyperspectral sensors have frequently been used to predict the spatial variation of soil attributes (Ahmed and Iqbal, 2014; Krishnan et al., 1981; Shepherd and Walsh, 2002; Stoorvogel et al., 2009). Ahmed and Iqbal (2014) explored the potential of spectral data from a Landsat TM5 satellite for evaluating the spatial variability of surface soil texture and organic matter and obtained good results. Dobos et al. (2000) tested the effect of the Advanced Very High Resolution Radiometer (AVHRR) data on the soil classification in a floodplain area of northern Hungary using NDVI and five AVHRR channels. But single AVHRR images failed to capture information for distinguishing soil conditions. The single multispectral image generally cannot provide comprehensive information about overall changes in soil reflectance, because they are by definition static, i.e., representing only one moment in time. And due to the variety of land cover, cultivation management, sensor noise, and atmospheric conditions, the relationships between a single spectral band and soil properties are often weak (Stoorvogel et al., 2009; Anderson and Croft, 2009; Mulder et al., 2011).

In order to overcome these limitations, Zhu et al. (2010) and Liu et al. (2012) proposed a method called "land surface dynamic feedback" (LSDF) to distinguish soil conditions in low-relief areas where common covariates such as topography and vegetation indices are ineffective at revealing soil spatial variation. They hypothesized that differences in soils would be indicated by differences in land surface feedback patterns captured by high temporal resolution remote sensing observations during a short drying period after a major rain event. The studies considered rainfall an input to land surface. Changes in soil reflectance that occurred in the process of drying after a rain event were considered dynamic feedback in response to the rainfall event (Zhu et al., 2010). The method was tested in several areas with good results (Guo et al., 2015; Liu et al., 2012; Zhao et al., 2014; Zhu et al., 2010; Guo et al., 2016). Liu et al. (2012) applied the approach to map soil texture in a low-relief area in south-central Manitoba, Canada. Guo et al. (2015) proposed an approach to fill the data gaps caused by cloud cover and reduce the data collection requirement for LSDF methods. In addition, Zhao et al. (2014) evaluated the method for mapping SOM content in two counties of Jiangsu Province.

In order to capture the changes in soil reflectance from wet to dry, a key step is the selection of a period for land surface response of remote sensing feedback. Zhu et al. (2010) suggested three requirements for the selection. First, the area of interest should have a long period with little or no rain so that the area is very dry. Second, the magnitude of rainfall should be great enough to force the land surface to produce a clear response. Third, there should be no precipitation over the area in the days after the rainfall event. The impact of rainfall magnitude of the selected event on mapping accuracy was not investigated, however. It is also important to know how consistent the prediction results are when different observation periods are selected after a similar rain event. This is because cloudy conditions can prevent acquiring all post-event imagery for all of the required days.

Thus this study has two main objectives. The first is to determine how rainfall amount affects the prediction accuracy of digital soil mapping using the LSDF method. We use soil texture over areas with low relief as an example and an individual predictive soil mapping method (iPSM) proposed by Zhu et al. (2015) to conduct the digital soil mapping of texture based on the covariates derived from land surface dynamic feedbacks. The second objective is to examine the consistency of the results when different periods are selected after similar rain events. We chose soil texture in this study, especially for the second objective, because it hardly varies over years or even decades, unlike organic matter or chemical properties.

2. Materials and methods

2.1. Study area and data sets

The study area is located in the north of XuanCheng city in Anhui Province of China (Fig. 1). It covers approximately 2357 km^2 (31°00′N–31°18′N and 118°36′W–119°18′W). The land is mainly farmland including paddy fields and dry land on a low-relief landscape. The area has experienced intensive human activity in recent decades and its soil types are primarily Anthrosols in both the Chinese Soil Taxonomy system (Chinese Soil Taxonomy Research Group, 2001) and the World Reference Base for Soil Resources (FAO, 2014). The climate is warm and humid in summer and relatively cool and dry in winter. According to the climate data set (V3.0) of the international exchange station of China, the average temperature in the study area is approximately 14–16 °C and annual average precipitation is about 1300–1400 mm, most of which occurs between May and October. The soil parent materials are Quaternary vermicule boulder and gravel clay, Quaternary siltstone, gravel and sandy clay, conglomerate, limestone, granite and granodiorite. The area was chosen mostly for its gentle terrain.

Sixty-nine topsoil samples (0–20 cm) (Fig. 1) were collected from a campaign in 2011 for other purposes in previous studies (Zhang et al., 2016; Yang et al., 2016). Several sampling strategies were adopted in the campaign. Extensive discussion on those sampling strategies is not necessary here because the mapping method used in this study has no requirement on the distribution or number of soil samples. Interested readers are referred to the above references for details. The sampling density in our study area is one sample every 34 km^2. Percentage of soil sand (0.05–2 mm size fraction, % by weight) and percentage of soil clay (< 0.002 mm size fraction, % by weight) were used as the target variables. These were analyzed by a laser diffraction technique using a Mastersizer 2000 laser particle size analyzer (Wang et al., 2013). The frequency percentage histograms of soil sand and soil clay percentage are shown in Fig. 2. The variation for soil sand percentage is much greater than for soil clay.

The environmental covariates extracted from the LSDF method mentioned in Section 2.2.2 were used to predict soil texture. Parent material as the original source of soil particles, elevation even in low relief areas as a factor in topsoil redistribution and vegetation as it affects transpiration also affect LSDF. Thus, parent material, elevation and enhanced vegetation index (EVI) were also acquired and resampled as necessary to the coarsest resolution, i.e., 250 m of MODIS. The parent material was derived from a lithology map generated from the 1: 500 000 geological map of China, and rasterized to a 250 m grid. The Digital Elevation Model (DEM) was obtained from the Shuttle Radar Topographic Mission (SRTM) (http://srtm.csi.cgiar.org/SELECTION/inputCoord.asp). The EVI data were obtained from the MODIS Vegetation Indices product (MOD13Q1) over the observation period (http://ladsweb.nascom.nasa.gov/data/search.html).

2.2. Methodology

The study used the environmental covariates derived from LSDF after different rainfall events to make a predictive map of soil texture and analyze the impact of rainfall magnitude on mapping