Ecological Indicators 10 (2010) 610–619

Contents lists available at ScienceDirect

Ecological Indicators

journal homepage: www.elsevier.com/locate/ecolind

Mapping soil organic matter using the topographic wetness index: A comparative study based on different flow-direction algorithms and kriging methods

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ARTICLE INFO

Article history:
Received 1 January 2009
Received in revised form 22 August 2009
Accepted 13 October 2009

Keywords:
Collocated cokriging
Single-flow-direction (SFD)
Multiple-flow-direction (MFD)
Auto-correlation
Cross-correlation
Terrain variable
Digital soil mapping

ABSTRACT

Terrain attributes derived from digital elevation models have been used widely for mapping soil organic matter (SOM). Among these attributes, the topographic wetness index (TWI), an index for quantitatively indicating the balance between water accumulation and drainage conditions at the local scale, has been shown to correlate with SOM. However, TWIs used in most studies are calculated using a single-flow-direction (SFD) algorithm, which assumes that all water from a grid cell flows into only one neighboring cell. This assumption is not always valid, especially in areas with low relief where movement of water may be divergent. To overcome this SFD limitation, a multiple-flow-direction (MFD) algorithm has been developed, which distributes flow from a grid cell to several downslope neighbors. In this study we compared the effect of TWI calculations based on SFD and MFD in predictive mapping of SOM by incorporating them into different kriging methods over a 51.76 km^2 area in Nenjiang County of northeastern China. We found that the MFD-based TWI was better correlated with SOM than was the SFD-based index. We then compared the accuracies of SOM maps which were derived from MFD-based TWI and SFD-based TWI incorporated by ordinary kriging (OK), simple kriging with varying local means (SKlm), kriging with external drift (KED) and collocated cokriging (CC). The MFD-based TWI, used as a secondary variable in SKlm and CC, outperforms the SFD-based TWI. For the different kriging methods, CC (incorporating either MFD-based TWI or SFD-based TWI) showed the best performance, and OK generated a better result than SKlm and KED. Both the MFD-based TWI and SFD-based TWI proved to be incompatible with KED and SKlm due to their numerical instability caused by the rough TWI surfaces. Among all predictive methods, CC incorporating the MFD-based TWI produced the best results. This is because: (1) the MFD-based TWI is best able to indicate quantitatively soil moisture and therefore has the strongest correlation with SOM; (2) CC is capable of utilizing effectively the spatial auto-correlation of SOM and the cross-correlation between SOM and the MFD-based TWI.

1. Introduction

Terrain variables have been used widely in soil organic matter (SOM) content mapping as they can be incorporated into geostatistical methods and used as secondary variables (Bell et al., 2000; Mueller and Pierce, 2003). Terrain variables enhance SOM map quality and reduce the cost of sampling in three ways. First, terrain variables that are derived from a digital elevation model (DEM) can be acquired at a low cost. Second, terrain variables are exhaustive and spatially extensive, and provide potentially voluminous data sets, which provide relevant information at unsampled locations. The third and perhaps most important aspect is the significant correlation between terrain variables and SOM. Studies have revealed that soils with high moisture content increase SOM due to the promotion of plant growth and the slowdown of organic matter decomposition (Starr et al., 2000; Janzen et al., 2002). Since soil moisture can be modeled quantitatively by terrain indices, SOM might also exhibit significant correlation with terrain variables (Jenny, 1941; Moore et al., 1993; Janzen et al., 2002; Mueller and Pierce, 2003). The better soil moisture is quantified by a terrain variable, the stronger

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doi:10.1016/j.ecolind.2009.10.005

the relation between SOM and the variable. Consequently, the higher the efficiency of the variable for the SOM mapping will be. Thus it is important to utilize improved terrain variables that may better describe soil moisture and enhance mapping quality.

Among the many terrain variables developed, the topographic wetness index (TWI) is considered a good indicator of soil moisture distribution at different landscape positions where overland flow dominates water transport processes, and may therefore show a significant relationship with SOM distribution (Beven and Kirkby, 1979). Moore et al. (1993) found significant correlations between terrain variables calculated from a DEM and measured soil attributes, and showed that slope gradient and TWI accounted for more than half of the variability of the A-horizon thickness and SOM. Bell et al. (1995) identified TWI and the depression proximity index as the most suitable predictors of the A-horizon and carbonate depth. Western et al. (1999) found that during wet periods TWI and contributing area explain up to 61% of the spatial variation in soil moisture (compared with several other terrain variables). Luca et al. (2007) proposed that terrain variables such as contributing area and TWI that incorporate upslope length could further improve SOM estimation, as these variables better reflect water redistribution. Sumfleth and Duttmann (2008) also showed that the distribution of soil carbon corresponds significantly to the TWI.

The relevance of TWI for SOM mapping can be explained by considering its definition (Eq. (1)):

$$\mathrm{TWI} = \ln\left(\frac{a}{\tan\beta}\right) \quad (1)$$

where α is the specific catchment area (SCA), and $\tan\beta$ is the local slope gradient. SCA indicates the potential flow accumulation to a specific location, and $\tan\beta$ reflects the local drainage potential (Beven and Kirkby, 1979; Quinn et al., 1995). The combination of SCA and local slope gradient represents the balance between water accumulation and drainage conditions at the local scale, which reflects soil moisture and SOM distribution.

The TWI can be computed using different algorithms. There are two significant approaches to determine SCA: the single-flow-direction (SFD) algorithm and the multiple-flow-direction (MFD) algorithm. SFD assumes that all water from a grid cell flows into only one neighboring cell (that with the lowest relative elevation), and MFD assumes that flow from the current position drains into more than one downslope neighboring cell (Wolock and McCabe, 1995). Previous studies have shown that MFD performs significantly better than SFD in constructing the spatial distribution of SCA or TWI (Quinn et al., 1991; Freeman, 1991; Fairfield and Leymarie, 1991; Bertolo, 2000). Although the significant differences between SCAs and TWIs resulting from different computation approaches have been investigated, few studies have characterized explicitly the effects of different TWI algorithms on SOM mapping.

To compare the effect of different TWI algorithms on SOM mapping, we incorporated TWIs based on these algorithms into different kriging methods. Geostatistical methods are some of the most widely used tools in estimating soil properties because they utilize the auto-correlation of the primary variable and the cross-correlation between the primary variable and secondary variables. There are two ways to combine the secondary variables into a kriging system. The first is to treat the primary variable as the summation of the local mean and the residual value. The local mean can be modeled with a regression function between the primary and the secondary variable, and the residual value, acquired by subtracting the local mean from the original data, can be kriged by simple kriging (Raspa et al., 1997; Hengl et al., 2007). The second approach is to use the cokriging method in which the secondary variable(s) is (are) embedded directly into the cokriging system (Journel and Huijbregts, 1978; Vauclin et al., 1983). Comparisons between these two methods have been made (Knotters et al., 1995; Goovaerts, 2000), showing that quality of estimation is dependant on not only the kriging strategy but also the performances of the variables, that is, the auto-correlation of primary variable and the cross-correlation between variables. In this regard, we think it is necessary to use different kriging methods to determine which combination (between different kriging methods and secondary variables) is the most efficient for SOM mapping.

In this paper, we compare of impact of MFD-based TWI and SFD-based TWI on SOM mapping by implementing different kriging methods in which the TWIs are employed as secondary variables. We first compute correlation coefficients between SOM and eight secondary terrain variables and identify that both SFD- and MFD-based TWI are correlated significantly with SOM. We then map SOM by incorporating both TWIs into different kriging methods: ordinary kriging (OK), simple kriging with varying local means (SKlm), kriging with an external drift (KED) and collocated cokriging (CC). Finally we evaluate the results generated by various combinations of selected secondary variables and kriging methods by means of cross-validation.

The remainder of the paper is arranged in five sections. Section 2 describes the research area and the data set. Section 3 presents the descriptions of correlation coefficients, all kriging methods and the evaluation criteria. In Section 4, the correlations between the derived secondary variables and SOM are compared and mapping results using different kriging strategies are presented. The impact of the MFD-based TWI on SOM mapping is analyzed through the comparison between various combinations in Section 5. Concluding remarks are presented in Section 6.

2. Study area and data

2.1. Study area

The study area is located in Heshan County, Heilongjiang Province, Northeastern China (48°53′24″–48°59′24″N, 125°8′24″–125°16′12″E) (Fig. 1a). It is situated in the Laolaihe watershed, which has a total area 51.76 km^2. Mollisols are the dominant soil class in this area (Zhang et al., 2007; Yang, 2007). Clay content ranges from 5% to 20%, and the texture is loam to clay loam. The area has low relief, with elevation ranging from 278 m to 362 m above sea level and a slope gradient below 5%. The average annual temperature at the site is 12.2 °C, and the average annual precipitation is between 400 and 600 mm. Overland flow dominates soil water redistribution in spring and summer. This is due to frozen subsoil does not thawing until late April preventing significant infiltration of spring precipitation and there being abundant rainfall in summer, both of which lead to overland flow (Zhang et al., 2007; Yang, 2007). The area is managed under conventional agricultural production and the predominant crops are soybean and spring wheat.

A 10 m-resolution DEM was derived from a 1:10,000 scale topographic map (published by Chinese Bureau of Surveying and Mapping, 1987) using ArcGIS 8.3. We collected 54 soil samples at different topographic locations in July 2005 (Fig. 1b). We dug 1.2 m-depth profiles at each location, and collected SOM samples from the A-horizon. The locations of the samples were determined by GPS handset, with a positional error <10 m. Soil thickness in the area varies from 0.30 m to 1.25 m. The samples were analyzed for SOM, N, P, K and particle size distribution.

2.2. Computation of TWIs and other related terrain variables

We derived eight terrain variables from the DEM: (1) profile curvature (P_cuv), (2) plan curvature (F_cuv), (3) horizontal