Large-Scale Modeling of Solum Thickness Based on the Local Topographic Attributes of Ground and Bedrock Surfaces

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Large-scale modeling of solum thickness based on the local topographic attributes of ground and bedrock surfaces

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ABSTRACT

This study was aimed to address the importance of neighborhood scale and using bedrock topography in the soil-landscape modeling in a low-relief large region. For this study, local topographic attributes (slopes and curvatures) of the ground surface (DTM) and bedrock surface (DBM) were derived at five different neighborhood sizes (3×3, 9×9, 15×15, 21×21, and 27×27). Afterward, the topographic attributes were used for multivariate adaptive regression splines (MARS) modeling of solum thickness. The results demonstrate that there are statistical differences among DTM and DBM morphometric variables and their correlation to solum thickness. The MARS analyses revealed that the neighborhood scale could remarkably affect the soil-landscape modeling. We developed a powerful MARS model for predicting soil thickness relying on the multi-scale geomorphometric analysis ($R^2 = 83\%$; RMSE = 12.70 cm). The MARS fitted model based on DBM topographic attributes calculated at a neighborhood scale of 9×9 has the highest accuracy in the prediction of solum thickness compared to other DBM models ($R^2 = 61\%$; RMSE = 19cm). This study suggests that bedrock topography can be potentially utilized in soil-related research, but this idea still needs further investigations.

Keywords: Bedrock topography, Geomorphometry, MARS, Neighborhood Scale, Soil depth

INTRODUCTION

Soil-landscape modeling is an essential component of sustainable land management (SLM) (Khanifar et al., 2020). The topography is the primary pedogenic factor that affects the pattern of soil properties variability across the landscape by controlling hydro-geomorphic processes (Khanifar and Khademalrasoul, 2021). This relationship allows us to utilizing the topographic attributes to model soil properties. Geomorphometry is the knowledge that deals with quantitative analysis of the topographic surface, and in general mode focuses on the derivation of topographic attributes from the Digital Elevation Models (DEMs) (Pike et al., 2009). Various topographic attributes of DEM (or morphometric variables) were employed to model soil thickness (e.g. Thompson et al., 2006; Mehnatkesh et al., 2013), which is a fundamental variable in the soil quality assessment.

One idea is to utilize the topographic attributes of the bedrock surface in the soil properties prediction. The bedrock is defined as the integrated solid rock that lies under un-consolidated surface materials, like soil and gravel. The bedrock appears in some zones at the ground's surface, but in regions can be located at a depth of one thousand meters below the earth's surface (Shangguan et al., 2017). Predicting depth to bedrock is a critical research field in geophysical studies. Depth to bedrock data has special applications in various fields of geoscience. Depth to bedrock influences energy and hydrology cycles and has the potential to be applied as an input variable for mapping natural hazards like earthquake and landslide (Yan et al., 2020).

An important setting in soil-landscape modeling is the operational scale, which is less considered. Operational scale refers to the size of the space in which processes associated with a particular phenomenon operate (Bian, 1997); it is defined in the form of a locally moving neighborhood window in geomorphometry. Most geomorphometric analyzes are based on the

neighborhood size of 3×3 , but this scale cannot be ideal for all soil–landscape modeling because of the diversity of pedogenic processes (Wang et al., 2010; Khanifar and Khademalrasoul, 2021). Compliance the operational scale of pedogenic processes with the neighborhood size that is applied for mathematical calculations of topographic attributes can be an influential factor in the model performance. This study was conducted in a multi-scale framework to demonstrate the importance of operational scale and evaluate the idea of utilizing bedrock topography in the modeling of solum thickness using MARS.

MATERIALS AND METHODS

Study Area and Data Collection

The study site with an area of 129560 km² is located in a region in eastern China (114° 05' to 118° 16' E and 32° 50' to 35° 54' N; Figure. 1). The land use of the major part of study site based on MODIS images (MCD12Q1; land cover product) is agricultural. The bedrock elevation map (DBM) of the study site represented in Figure (1) has a grid spacing of 90m. It is produced from the difference between the STRM DEM and depth to bedrock data that are having the same grid spacing. The data of Depths to bedrock were derived from www.globalchange.bnu.edu.cn, and more information about this dataset are discussed in (Yan et al., 2020). The lowest and highest bedrock elevation values are 307.80 and 1029.45m, which are nearby of these two locations the highest and lowest depth to bedrock, respectively (Figure. 1).

The soil property utilized in MARS modeling is solum thickness. Solum is defined as the upper section of the soil profile where pedogenesis are active. Solum in the soil consists of the sum A, E, and B horizons. The most activities of soil fauna and flora are bounded to the solum section (Patel et al., 2008). Solum thickness data have been derived from ISRIC's global database (Batjes et al., 2019).

Geomorphometry analysis

In this study, the local topographic attributes were only used in MARS modeling. The definition and formulas of local topographic attributes are given in Table (1). The topographic attributes of ground surface (DTM raster) and bedrock surface (DBM raster) were calculated based on Wood (1996) approach at five different neighborhood sizes (3×3, 9×9, 15×15, 21×21, 27×27). The Wood method is a generalized of the Evans algorithm (Evans, 1979) for larger operational scales.

Evans algorithm is approximates the partial derivatives by finite differences using only the 3×3 square-gridded moving neighborhood window. In this study, a Low Pass filter was used to eliminate local noises in the DEM and DBM. The effect of applying this filter on DEM is evident in the histograms presented in Figure (1). After geomorphometry analysis, the values of DTM and DBM morphometric variables were extracted for the sampling points' position.

Statistical analysis

Descriptive statistics of solum thickness and topographic attribute was performed in Statistica V.12 software. To assessing the statistical differences of topographic attributes across the groups of DTM and DBM, the Kruskal-Wallis test followed by a post hoc test (multiple comparisons of mean ranks) was used. The MARS algorithm was used to model the relationship between DTM and DBM topographic attributes and solum thickness at different neighborhood scales. Multivariate Adaptive Regression Splines (MARS) is a non-linear and non-parametric regression method that models the relationships between explanatory and response variables based on a set of spline functions called the basis function (BF) (Friedman, 1991). The forms of BFs are as follows:

$$\max(0, x - t) \text{ or } \max(0, t - x); \quad (1)$$

Where t is called a knot and is one of the observed values of the explanatory variable (x). The MARS algorithm splits the range of predictor variables by knots into smaller regions and fits a BF at each region. The general form of the MARS model is as follows:

$$y = f(x) = \beta_0 + \sum_{m=1}^M \beta_m h_m(x); \quad (2)$$

Where y is the response variable predicted by the function $f(x)$, M is the number of terms, β_0 is a constant, β_m is the m th BF's coefficient, and $h_m(x)$ is individual BF or a product of two or more BFs. The MARS model is generated in two stages. In the first step, all possible BFs are

consecutively added to the model, leading to a complex and over-fits model. In the second stage, the BFs with the least contribution are pruned. Finally, the optimal model is selected based on the generalized cross-validation (GCV), a measure of the goodness of fit. The prediction accuracy of the fitted models was evaluated using the coefficient of determination (R^2) and the mean square error (RMSE) (30% of dataset was selected for validation, $N = 22$). MARS analyses were performed using the Salford Predictive Modeler (SPM) software.

RESULTS AND DISCUSSION

The results of statistical analysis of the solum thickness are shown in in Table 2. The solum thickness of the studied soil profiles varies from 12 to 150 cm, with an average of 37.80. The Shapiro–Wilk test confirms that solum thickness does not have a normal distribution like topographic attributes. The solum thickness has high variability ($CV = 80.80\%$) in the region. The study area is the large extent, and most of it has low relief, but land use under the influence of topography is one of the main reasons for the increase in the CV. Mehnatkesh et al. (2013) obtained the CV value for a soil depth of 78% in a rainfed hilly region. In Kuriakose et al. (2009), the CV values of soil thickness vary from 45.93 to 80.82 at a landscape with different land uses. In an agricultural landscape, the contribution of topography to soil diversity depends on time because management activities such as tillage over time can reduce topographic control over soil properties. The topography can lead to spatial differentiation of solum thickness through its control the water of the soil system. If the depth to the bedrock is shallow, the relationship between the bedrock topography and the soil solum was physically justifiable, but in the region, the average depth to the bedrock is about 150 m (S.D. = 94 m). The results presented in Table (3) demonstrate that in the neighborhood scale of 27×27 , there is a positive and significant correlation between all DTM and DBM topographic attributes, but at the scale of 3×3 , all correlations are very weak. This could be a reason for using bedrock topography as a predictor as it confirms that it has a significant relationship with the landform characteristics of the earth's surface.

The results of solum thickness modeling based on topographic attributes extracted from DTM and DBM at different neighborhood scales using MARS are presented in Table (4). The difference between the highest and the lowest coefficient of determination (R^2) values for DTM

and DBM models is 0.59 and 0.39, respectively. This difference reflects the importance of operational scale in the soil-landscape analysis. Khanifar and Khadmalrasoul (2021) reported that the neighborhood scale was the remarkable factor in the setting a calculation operation, which has the greatest impact on the topographic attributes and, as a result, of the soil-landscape modeling. For this reason, in this study, we focused only on the neighborhood scale. The results of model validation show that between DTM and DBM models, DTM-27×27 and DBM-9×9 models have more robust and accurate performance than other models (Table 4). In the best prediction made by the DTM-27×27 model, the current topographic attributes could explain 84% of soil variability for solum thickness. The DTM-27 × 27 model is as follows:

$$\text{BF1} = \max(0, \text{ProfileCurvature} - 1.05337e - 006); \quad (3)$$

$$\text{BF2} = \max(0, 1.05337e - 006 - \text{ProfileCurvature}); \quad (4)$$

$$\text{BF6} = \max(0, \text{ProfileCurvature} + 1.94602e - 006); \quad (5)$$

$$\text{BF9} = \max(0, \text{SlopeAspect} - 5.96046e - 008); \quad (6)$$

$$\text{BF11} = \max(0, -1.47133e - 007 - \text{ProfileCurvature}) \times \text{BF9}; \quad (7)$$

$$\text{BF12} = \max(0, \text{MaximalCurvature} - 8.06982e - 008) \times \text{BF9}; \quad (8)$$

$$\text{BF14} = \max(0, \text{MaximalCurvature} - 1.07411e - 006) \times \text{BF2}; \quad (9)$$

$$\text{BF15} = \max(0, 1.07411e - 006 - \text{MaximalCurvature}) \times \text{BF2}; \quad (10)$$

$$\text{BF17} = \max(0, 1.23589e - 007 - \text{MaximalCurvature}); \quad (11)$$

$$\text{BF18} = \max(0, \text{ProfileCurvature} + 1.75449e - 006) \times \text{BF9}; \quad (12)$$

$$\text{BF20} = \max(0, \text{SlopeAspect} - 0.910438); \quad (13)$$

$$\begin{aligned} \text{Solum Thickness (cm)} = & -116.105 - 2.73256e + 007 \times \text{BF1} + \\ & 3.46253e + 007 \times \text{BF2} + 4.72116e + 007 \times \text{BF6} + 81.6832 \times \\ & \text{BF9} - 3.92932e + 007 \times \text{BF11} + 2.18822e + 007 \times \text{BF12} - \\ & 9.36235e + 011 \times \text{BF14} + 1.27891e + 013 \times \text{BF15} - \\ & 5.41049e + 007 \times \text{BF17} - 3.62842e + 007 \times \text{BF18} - \\ & 191.228 \times \text{BF20}; \end{aligned} \quad (14)$$

The MARS algorithm has maintained eleven BFs based on slope aspect, profile curvature, and maximum curvature in the final model from the set of all fitted BFs in the backward phase. According to the above BFs, when profile curvature is greater than 1.05337e-006, solum thickness will decrease by 2.73256e+007 times the amount in excess of the threshold value (BF1). Also, when profile curvature is less than the threshold, soil thickness will be 3.46253e+007 times the profile curvature in excess of 1.05337e-006 1/m (BF2). Some of BFs are

produced by multiplying two BFs. BF12 indicates that the impact of maximal curvature has emerged through the interaction with the slope Aspect. The contribution of all BFs to the solum thickness values is shown in the 3-D plots presented in Figure 2b. Mehnatkesh et al. (2013) showed that the model based on slope gradient (local MV), catchment area (regional MV), wetness index, and sediment transport index (secondary MVs) could explain 76% of soil depth variability within a hilly area. In this study, the LMVs only have been utilized, but in many studies such as Gessler et al. (2000) and Thompson et al. (2006), it is observed that some MVs of other classes are also included in the soil depth models.

The DBM-9×9 model was able to explain 62% of the solum thickness variability in the region.

This MARS model is as follows:

$$\text{BF1} = \max(0, \text{MinimalCurvature} + 6.62094e - 005); \quad (15)$$

$$\text{BF2} = \max(0, -6.62094e - 005 - \text{MinimalCurvature}); \quad (16)$$

$$\text{BF3} = \max(0, \text{MinimalCurvature} + 9.6802e - 005); \quad (17)$$

$$\text{BF5} = \max(0, \text{MinimalCurvature} + 4.29591e - 005); \quad (18)$$

$$\text{BF6} = \max(0, -4.29591e - 005 - \text{MinimalCurvature}); \quad (19)$$

$$\text{BF7} = \max(0, \text{PlanCurvature} + 0.000354182) \times \text{BF5}; \quad (20)$$

$$\text{BF10} = \max(0, \text{SlopeGradient} - 0.094707) \times \text{BF6}; \quad (21)$$

$$\text{BF11} = \max(0, \text{SlopeGradient} - 0.094707) \times \text{BF2}; \quad (22)$$

$$\text{BF12} = \max(0, \text{ProfileCurvature} + 0.000105308) \times \text{BF2}; \quad (23)$$

$$\text{BF13} = \max(0, \text{MinimalCurvature} + 2.26205e - 005); \quad (24)$$

$$\text{BF15} = \max(0, \text{MinimalCurvature} + 1.56615e - 005); \quad (25)$$

$$\text{BF17} = \max(0, \text{MinimalCurvature} + 3.21959e - 005); \quad (26)$$

$$\begin{aligned} \text{Solum Thickness (cm)} = & -82.4783 - 2.26636e + 006 \times \text{BF1} + \\ & 2.46035e + 006 \times \text{BF2} + 2.8291e + 006 \times \text{BF3} + 3.47893e + \\ & 008 \times \text{BF7} + 3.44934e + 006 \times \text{BF10} - 5.43481e + 006 \times \\ & \text{BF11} + 2.4645e + 009 \times \text{BF12} - 1.00828e + 007 \times \text{BF13} + \\ & 5.92644e + 006 \times \text{BF15} + 3.76481e + 006 \times \text{BF17}; \end{aligned} \quad (27)$$

The DBM-9×9 is generated based on twelve BFs. The contribution of the BFs to the values of solum thickness is shown in Figure 2a. Apart from the maximum curvature and slope aspect, other topographic attributes have been identified by MARS as the influential variables for predicting soil thickness. The MARS algorithm takes into account the non-linear relationships between variables that are expected in a natural system. Assessing the accuracy of the DTM-

27×27 and DBM-9×9 models showed that their RMSE values are equal to 12.70 and 19 cm, respectively. In this regard, A-Xing et al. (2008) reported that the accuracy of digital soil mapping is considerably influenced by the neighborhood scale used for calculating morphometric variables. The appropriate neighborhood scale depends on the landscape and the operational scale of the studied phenomenon (Khanifar and Khadmalrasoul, 2021).

The statistical analysis of topographic attributes calculated at neighborhood scales of 9×9 and 27×27 are presented in Figure 3. The curvatures when are extracted from the topographic surface of the bedrock, a relatively broad range of positive and negative values can be observed, which representing high variability in bedrock surface bending between sampling positions. However, in the most DTM morphometric variables, the values range and the bending variability are remarkably lower. Up-scaling has also led to a dramatic decrease in the curvatures and slope gradient value range due to smoothing of the surface roughness, which results from the dilution of their potential information with other data on the large neighborhood size. The Kruskal-Wallis test followed by multiple comparisons post hoc test confirmed that the difference between some groups of slope gradient, maximum curvature, and minimum curvature was significant (at the 1 % level).

CONCLUSIONS

In this research, if the local topographic attributes were derived only at the basic neighborhood scale (3×3), which is used in most studies, just DTM and DBM models with lower performance would be generated. Increasing the neighborhood scale to an appropriate extent, in addition to reducing noise in the elevation data, can lead to improved modeling of soil properties. Since no procedure has been provided to find the optimal range of neighborhood size in each landscape, the use of multi-scale geomorphometric algorithms is appropriate. The modeling results confirm the idea of applying bedrock geometry in the soil-landscape modeling. It is recommended that a fine scale research be conducted to survey more the correlation between bedrock topography and soil properties in various landform units.

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FIGURE CAPTIONS

Figure 1. The location of the study area. **(a)** Histogram of DEM raster before applying the Low pass filter. **(b)** Histogram of DEM raster after applying the Low pass filter.

Figure 2. Statistical analysis of DTM and DBM topographic attributes calculated at neighborhood sizes of 9×9 and 27×27 . Different letters indicate statistically significant differences between groups.

Figure 3. The contribution of DBM **(a)** and DTM **(b)** topographic attributes to the solum thickness in the MARS models.

Table 1. Topographic attributes used in this study (adapted from Schmidt et al., 2003)

Attributes	Symbol (Unit)	Meaning	Formula
Slope	G (°)	slope gradient	$\arctan \sqrt{p^2 + q^2}$
Aspect	A (°)	slope azimuth	$\arctan \left(\frac{q}{p} \right)$
<i>Curvature measures dependent of slope (gravity)</i>			
Plan	$C_p (m^{-1})$	contour direction	$-\frac{q^2 r - 2 p q s + p^2 t}{\sqrt{(p^2 + q^2)^3}}$
Profile	$C_v (m^{-1})$	gradient direction	$-\frac{p^2 r + 2 p q s + q^2 t}{(p^2 + q^2) \sqrt{(1 + p^2 + q^2)^3}}$
<i>Curvature measures independent of slope (gravity)</i>			
Minimal	$C_{min} (m^{-1})$	minimum	$-r - t - \sqrt{(r - t)^2 + s^2}$
Maximal	$C_{max} (m^{-1})$	maximum	$-r - t + \sqrt{(r - t)^2 + s^2}$
<p><i>Note1.</i> p, q, r, s and t are partial derivatives of the function $z = f(x, y)$:</p> $p = \frac{\partial z}{\partial x}, \quad q = \frac{\partial z}{\partial y}, \quad r = \frac{\partial^2 z}{\partial x^2}, \quad t = \frac{\partial^2 z}{\partial y^2}, \quad s = \frac{\partial^2 z}{\partial x \partial y}$			
<p><i>Note2.</i> Circular aspect was converted to continuous variable using the Topographic Radiation Aspect Index (<i>TRASP</i>) metric (Ironsides et al., 2018):</p> $TRASP = \frac{1 - \cos \left(\left(\frac{\pi}{180} \right) (A^\circ - 30) \right)}{2}$			

Table 2. Descriptive statistics of solum thickness (cm) (n = 74).

Soil Property	Minimum	Maximum	Mean	S.D.	C.V. (%)	Shapiro-Wilk p-Value
Solum thickness	12.00	150.00	37.80	30.55	80.80	0.00
<i>S.D.</i> : Standard Deviation.		<i>C.V.</i> : Coefficient of Variation				

Table 3. Spearman correlation coefficients among topographic attributes of DBM and DTM that calculated at different neighborhood scales.

Topographic Attributes	3 × 3	9 × 9	15 × 15	21 × 21	27 × 27
Slope Gradient	-0.06	0.04	0.11	0.22	0.27*
Slope Aspect	0.14	0.23*	0.17	0.24*	0.28*
Plan Curvature	-0.05	-0.09	0.15	0.29*	0.32**
Profile Curvature	0.04	0.04	0.19	0.34**	0.31**
Maximum Curvature	-0.02	0.04	0.22	0.30**	0.31**
Minimum Curvature	-0.07	0.12	0.30**	0.31**	0.28*
*significant at $P<0.05$, **significant at $P<0.01$.					

Table 4. Comparison of performances of the MARS models at different neighborhood scales (Evaluation criterion = R^2).

Model		3×3	9×9	15×15	21×21	27×27
DBM	Learn	0.31	0.62	0.46	0.23	0.34
	Test	0.32	0.61	0.44	0.22	0.31
DEM	Learn	0.25	0.66	0.58	0.76	0.84
	Test	0.20	0.65	0.58	0.74	0.83

Figure 1

Figure 2

Figure 3