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Spatial Prediction of Soil Organic Matter Using Geostatistics and Topographic Unit Zoning Integrated in GIS: A Case Study

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Abstract: The spatial distribution of soil organic matter (SOM) has a close connection with topography. To understand the effects of topographic synergy effects in traditional geostatistic methods, the influence of topography is considered in SOM geostatistic studies by combining geographic unit zoning and spatial prediction. We explored the changes in the SOM distribution between that obtained using spatial interpolation integrated with 13 different classical topographic units and determined using global interpolation with 6485 random soil samples obtained from Zhongxiang City, Hubei Province, China. The steps are as follows. At first, the terrain factors were calculated from the digital elevation data (DEM) and the topographic units were precisely divided into 13 different classical types more subtly by integrating the terrain factors. The regions were divided, which was based on terrain classification rules formed by the distribution of terrain factors in different landforms. Secondly, soil samples were collected in different topographic types, and the distribution of SOM for each sample set in different topographic units was generated by ordinary Kriging. Then, the corresponding results of interpolation for each sample set were segmented based on topographic unit region, and combining the result in each region, the spatial distribution of SOM based on topographic unit was obtained. Finally, verification and comparison with the accuracy of each SOM distributions were performed, which were obtained by using topography based geostatistics and traditional global geostatistics, respectively. Our results indicated that more accurate SOM spatial distributions can be obtained using the proposed method, especially in regions with gentle topography, such as ridge, shoulder, summit, toe slope (north/northeast side), and low-lying terrain units.

Keywords: Soil Organic Matter, Geostatistics, Topographic Unit, Spatial Prediction

1. Introduction

Understanding the spatial variability of soil organic matter (SOM) is critical for studying soil composition and fertility characteristics. SOM has high spatial heterogeneity at both small and large scales and varies with time [1]. Determining the spatial variability of SOM can assist in exploring the role of SOM in soil quality [2], soil and water conservation [3], soil fertility [4] and the sustainable development of agroforestry [5]. Many authors have studied the spatial distribution of SOM [6-8]. Chen et al. [9] inverted the spatial distribution of SOM content based on ordinary Kriging with varying local means. Zhang et al. [10] predicted the spatial variability of SOM using terrain indices and categorical variables as auxiliary information. Dai et al. [11] predicted the spatial distribution of SOM on the Tibetan plateau based on a neural network model integrated with geostatistics. Guo et al. [12] predicted soil organic matter for rubber plantation at regional scale by using random forest plus residuals kriging approach. Mirzaee et al. [13] predicted SOM content by using remote sensing data as an auxiliary variable. All of the proposed methods have been shown to effectively improve the predictive accuracy SOM spatial distributions. Therefore, auxiliary information can be used to assist geostatistic theory, which may improve the predictions of SOM distributions.

When exploring SOM spatial distributions using traditional geostatistics, the synergy between terrain factors and the spatial redistribution of SOM are often ignored. Several previous studies have indicated that the spatial variability of SOM is dependent on terrain conditions, soil type, cultivation and management, and land use factors [14, 15]. Previously, research has been conducted to understand the effect of landforms on the spatial variability of soil properties [16]. Umali analyzed the effects of topography on the spatial variability of total organic carbon, electrical conductivity, pH and the coarse fraction in an apple orchard. In Umali's study, the terrain parameters had varying effects on the soil property distributions. The complex effects of topography on the spatial prediction of SOM must be simplified. A method for dividing the study area into topographic units was chosen. However, in traditional terrain classification methods, the division criteria for topographic units are not clearly specified; additionally, the scale of geomorphic types is too large because traditional terrain classification methods are based on a single index value, such as elevation. Accurate and reasonable topographic unit zoning can play an important role in studying the spatial distribution of soil properties [17]. Wei et al. [18] combined elevation grading and slope steepness grading to categorize geomorphic units, providing a basis for separating terrain units using a multidimensional quantitative index. Tian et al. [19] provided a digital elevation model (DEM)-based topographic unit diversity index by integrating several terrain parameters, including elevation, slope, slope position, slope aspect, flow accumulation and water information. This method has definite division criteria for topographic units and can categorize typical landform units in a more precise manner.

The impact of topographic synergy on the spatial redistribution of SOM requires additional examination. A new method is proposed in this paper based on topographic units to determine the spatial distribution of SOM based on data obtained from Zhongxiang City, China. Topographic effects on the spatial variability of SOM were considered, providing an example of how SOM distributions can be more precisely rendered using more accurate terrain partitioning, by separately analyzing the SOM distribution in each topographic unit, and by combining the readings. The proposed method is called geostatistics based on topographic units (GeoTU). The comparison method is called geostatistics based on global scale (GeoGS).

2. Materials and Methods

2.1. Description of the Study Area

The study area is located in Zhongxiang City, Hubei Province, China (30°42′–31°36′ N, 112°07′–113°00′ E). The area is located in the mid-latitudes, which is part of the northern subtropical monsoon climate region. For the past 10 years, the average annual temperature has been 15.9°C; the average annual rainfall has been 1496.8 mm. The region is hilly and located in central Hubei Province. The region is also located within the middle reach of the Hanjiang River. The river divides Zhongxiang City into two parts, i.e., eastern and western sides. The topography varies from plains in the central portion of the region to hilly mountains in the east and west, resulting in a saddle-shaped terrain. The soil parent material primarily consists of quaternary clay and alluvial deposits.

A total of 6485 random samples were collected from 2005 to 2006 (Figure 1). The sampling interval varied for different terrain conditions. Sampling was conducted for all topographic units and soil types except two portions: (a) a portion of the mountain area was not sampled due to accessibility issues and no global positioning system (GPS) signal and (b) no samples were collected to preserve the ecological environment in the eastern part of Zhongxiang City, which is where Dakou national forest is located. The resolution of the DEM was 30 m. The data set was provided by International Scientific and Technical Data Mirror Site, Computer Network Information Center, Chinese Academy of Sciences [20]. Additionally, the SOM content was determined from the samples using the potassium dichromate - sulfuric acid solution - bath oil method [21].

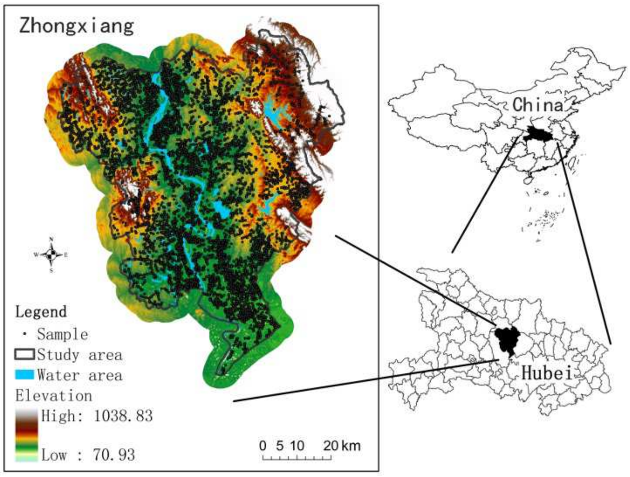


Figure 1. *Map of the study area.*

2.2. Topographic Unit Division and Sample Partitioning

Large study areas can be divided into subzones based on terrain units, although a specific range of precision is required. Then, each subzone can be analyzed according to the degree of complexity of the sampling strategy. A systematic evaluation of the soil nutrient spatial distributions in each subzone can be performed. In this study, the results were ultimately merged with a global map to ensure the precision of each region.

Terrain factors exhibit different spatial characteristics and environmental effects in the spatial distribution pattern of soil attributes. Therefore, these factors are often used as a comprehensive index to measure the effects of the soil environment [22, 23] In this study, the following four terrain factors were chosen: (a) slope (β), (b) aspect (α), (c) topographic wetness index (TWI), and (d) topographic position index (TPI); the results were analyzed using ArcGIS version 9.3 based on the aforementioned 30 m resolution DEM. The topographic position index depends on the size of the neighborhood analysis window [24], which was improved using the inverse distance weighted method for more reliable results [19]. The underlying principle of this method is expressed in the following equation:

$$TPI^{*} = \frac{1}{n}\sum_{i=1}^{n}\frac{TPI_i}{d_i} \tag{1}$$

Here, *TPI** is the improved TPI, n is the number of times used to choose a different annular sliding window size to calculate the TPI for the same unit, TPI_i represents the calculation of TPI at time i, and di is the average distance between every cell in the chosen annular sliding window and the target cell for calculating the TPI at time i.

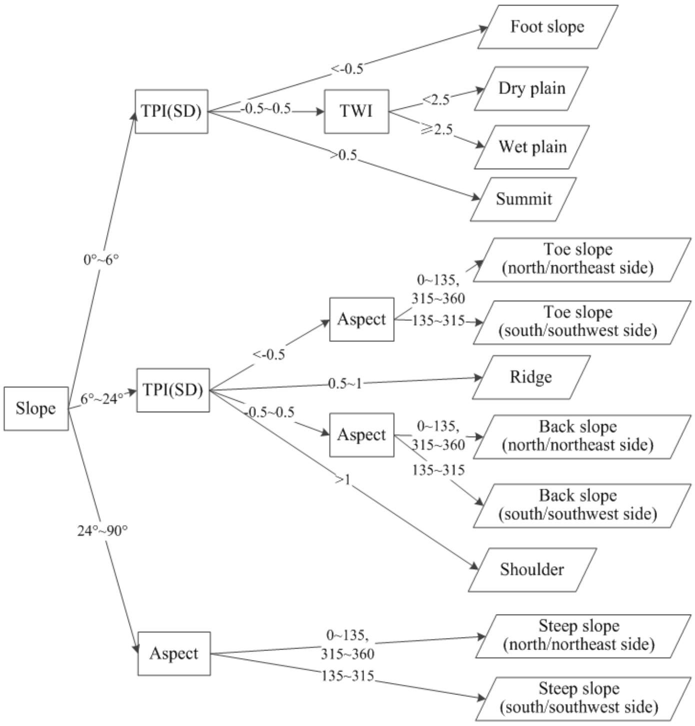


Figure 2. *Indicators of the topographic partitioning units.*

Terrain factors have specific distribution regularities in different topographic conditions. The study area can be divided into distinct topographic units based on the fact that the combination of terrain factors and the range of their value for each topographic unit are different. However, the types of natural topographic units are diverse and complex. 13 terrain types were selected to represent the conditions observed in the subject area based on representative, comprehensiveness and feasibility principles. Each terrain unit type was divided according to the classification rules shown in figure 2, which was performed using the raster calculator tool in ArcGIS. The classification criteria of slopes were based on the method presented in Anbalagan [25]. The aspect was divided into south / southwest and north / northeast, based on how the orientation of individual mountain ranges and the sunlight direction. The TPI values were determined based on the method proposed by Weiss [24]. According to the TWI algorithm [26], the grading standards of the Palmer drought severity index [27, 28] and the actual study area, the TPI values were divided by a boundary value of 2.5.

Zhongxiang City was divided into 13 terrain units according to the classification rules shown in figure 2. The results depicted in figure 3 show the 13 terrain unit zones. Areas not covered by the 13 zones, such as low-lying terrain units, were identified as Other Areas (see figure 3).

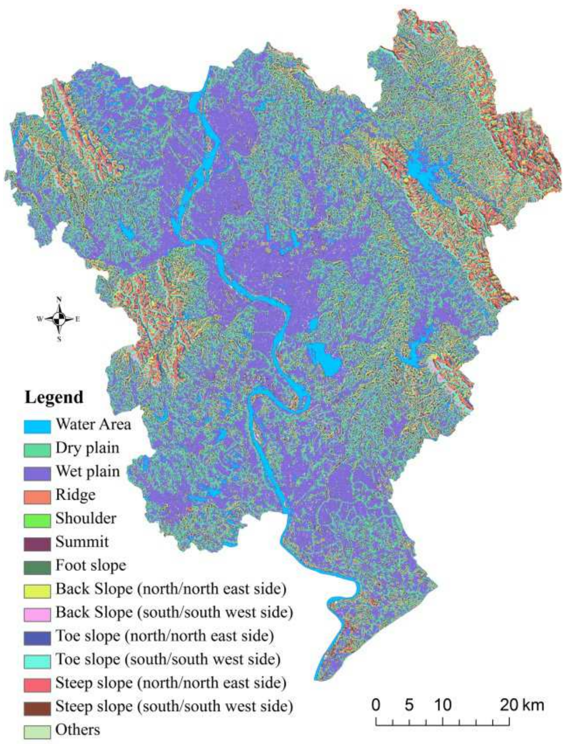


Figure 3. *Map of the topographic partitioning units.*

Sampling point sets were divided based on the corresponding terrain unit range. The statistical characteristics of the sample sets in each landform unit are shown in Table 1. The table shows that the wet plain zone represents the largest terrain unit in the study area; the dry plain unit has the second largest area. The smallest region is represented by the steep slope unit (south / southwest side). The ranges, means, and standard deviations (SDs) of the SOM contents in the different terrain units were similar. Subtle differences were found in the SOM distribution in each terrain unit according to the kurtosis and skewness statistics.

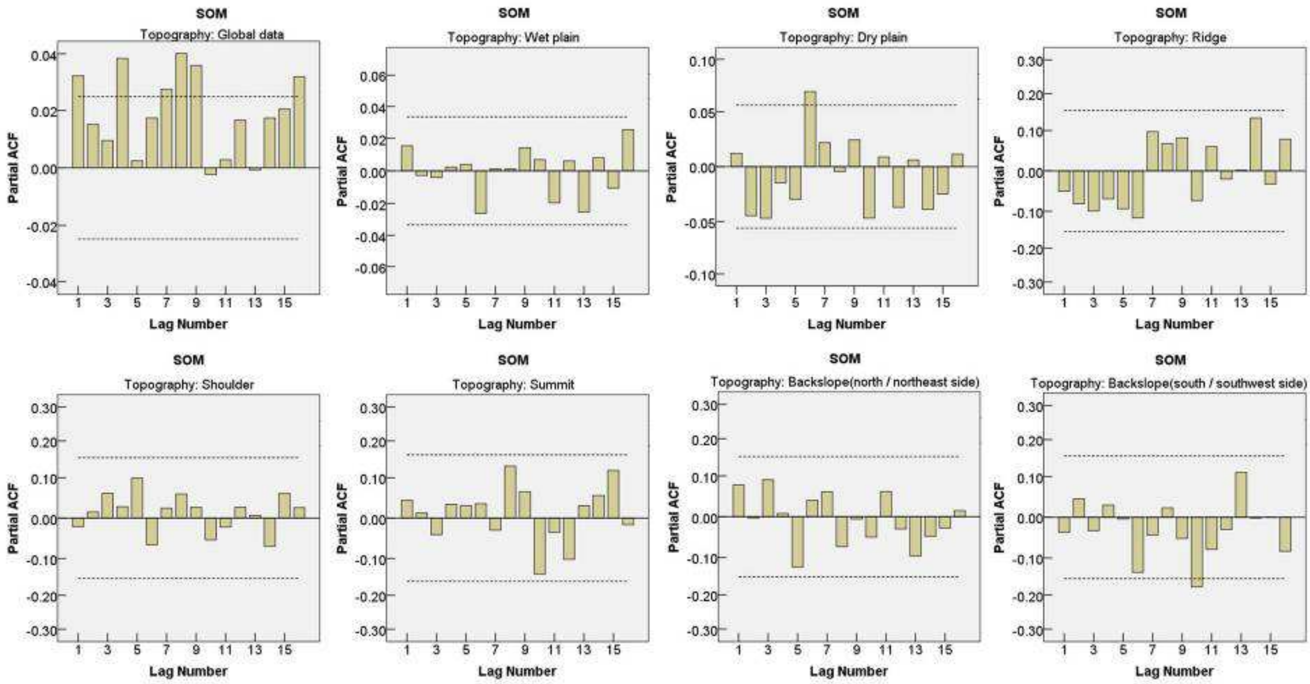
Table 1. *Descriptive statistics of the SOM contents in each topographic partitioning unit.*

Topographic partitioning unit	Area ratio	Sample number	Kurtosis	Skewness	SOM content (g * kg-1)				
					Minimum	Maximum	Range	Average	SD
Dry plain	22.69%	1268	-0.31	0.37	5.00	60.00	55.00	26.42	10.10
Wet plain	39.62%	3590	-0.12	0.48	5.00	60.00	55.00	24.54	9.61
Ridge	4.53%	169	-0.51	0.43	6.42	51.50	45.08	24.91	9.93
Shoulder	2.45%	170	0.27	0.74	6.70	60.00	53.30	25.72	11.06
Summit	5.23%	154	1.11	0.63	5.00	60.00	55.00	24.53	9.72
Back slope[a]	5.20%	176	-0.42	0.36	5.00	60.00	55.00	27.39	11.76
Back slope[b]	3.99%	167	-0.01	0.47	5.00	58.90	53.90	26.28	10.14
Toe slope[a]	2.74%	127	-0.01	0.67	7.96	60.00	52.04	27.97	11.95
Toe slope[b]	3.58%	93	-0.62	0.22	5.00	54.40	49.40	27.34	11.68
Steep slope[a]	1.22%	73	-0.41	0.48	7.30	60.00	52.70	26.44	12.07
Steep slope[b]	0.68%	99	0.40	0.56	5.00	60.00	55.00	28.43	11.98
Foot slope	6.74%	302	-0.30	0.29	6.19	60.00	53.81	31.49	11.23
Low-lying	1.32%	97	0.99	0.78	5.60	59.20	53.60	24.40	9.80
Entire region	100.00%	6485	-0.04	0.51	5.00	60.00	55.00	25.58	10.20

Note: The area ratio is the ratio of the landform unit area to the total study area; SD represents the standard deviation. a) North / northeast side of a terrain unit. b) South / southwest side of a terrain unit.

The SOM spatial distributions in different terrain units were analyzed using the global autocorrelation method. Because the size of each landform unit and the number of samples were different in each unit, the instability of the intrinsic variance contained in the SOM contents may not be consistent with the stability or intrinsic hypotheses indicated in spatial autocorrelation analysis, which can induce errors, as predicted by Moran's I. Therefore, the SOM distribution may deviate from the real situation due to the sampling design or the combined solution. These influences can be eliminated by standardizing the SOM distributions using global autocorrelation analysis [29].

The partial autocorrelation plots for the global data and the individual units are shown in Figure 4. Autocorrelations should be near zero for randomness, which is the case in this study (Figure 4). Therefore, the randomness assumption is acceptable. The partial autocorrelation plots reveal some autocorrelation at lag 1, lag 5, lag 8, lag 9, and lag 16 for the global data, although there was at most one autocorrelation for each individual unit. Therefore, all observations were retained for the subsequent analysis.



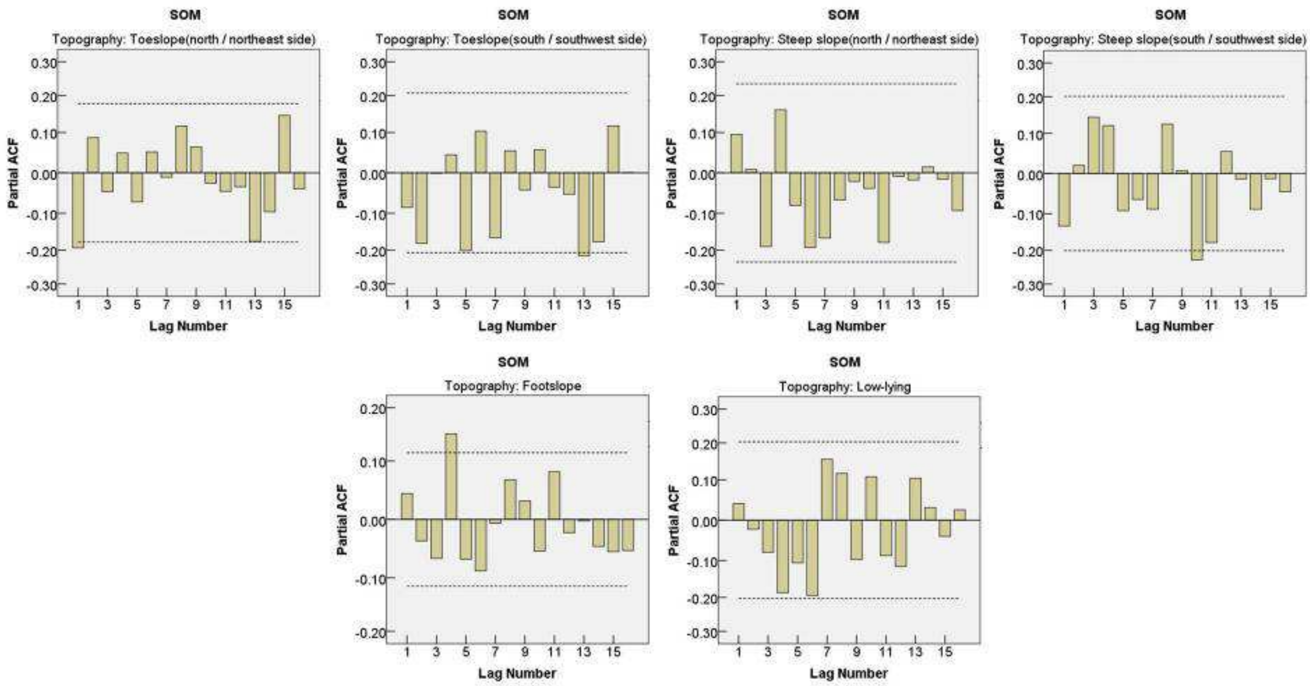


Figure 4. Autocorrelation plots for the global data and individual units.

2.3. SOM Prediction Based on Landform Units

It is well known that the similarity of soil information is related to the similarity of the spatial attributions of individual characteristics (and vice versa). More specifically, the terrain conditions within similar terrain units are comparable; the spatially differences in similar terrain units are also smaller. The terrain effects on SOM spatial distributions are consistent. However, if the terrain conditions are different in different terrain units, the spatial differences in terrain factors are larger. The terrain effects on SOM spatial distributions are distinct [30]. Therefore, it is inappropriate to interpolate soil landscape relationships on a global scale. The area can be classified into different landform units based on terrain conditions. Then, soil landscape relationships and the spatial distribution of soil nutrients within each topographic unit can be separately analyzed.

The SOM distribution in each terrain unit was individually predicted using ordinary kriging with only the samples in the unit. Then, the predictions for the sampling points were clipped according to the corresponding landform unit region. The highest predictive accuracy around a sample in the same terrain unit was retained. After repeating the same procedure in each terrain unit, the spatial distribution plots for each terrain unit were stitched into a global map.

Differences between the measured values and the predicted values in each terrain unit were evaluated using the root-mean-square error (RMSE) and correlation coefficient values. The validation samples in each terrain unit constituted 5% of the samples in the corresponding terrain unit. The RMSE of each method was calculated using the predicted value and the measured value at the validation sample's site.

3 Results and Discussion

3.1. Spatial Autocorrelation Analysis of SOM

The spatial autocorrelations of the SOM contents in the 13 terrain units and the entire region were calculated using the spatial statistics module in the ArcGIS 9.3. The significance tests for global Moran's I of the SOM content in each topographic partition unit are summarized in Table 2.

Table 2. *Significance tests for global Moran's I of the SOM content in each topographic partition unit.*

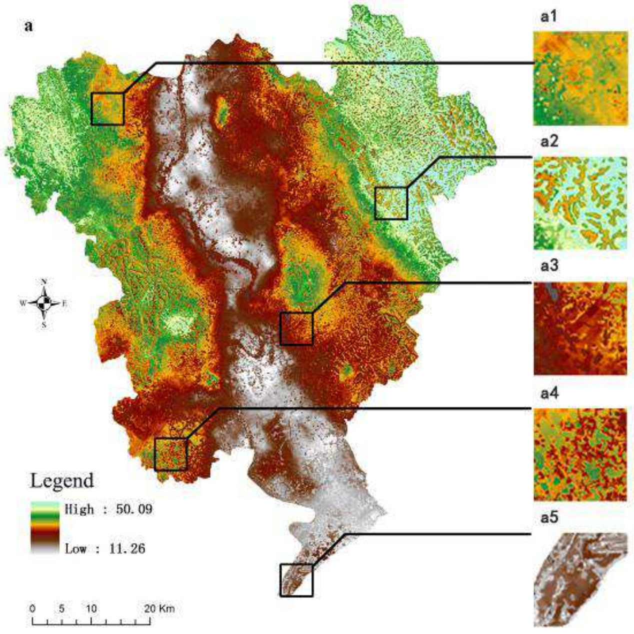
Topographic partitioning unit	Moran's I	Z score	P value
Dry plain	0.28	33.79	<0.001
Wet plain	0.24	73.80	<0.001
Ridge	0.28	8.04	<0.001
Shoulder	0.32	9.53	<0.001
Summit	0.17	4.64	<0.001
Back slope[a]	0.30	8.46	<0.001
Back slope[b]	0.21	5.99	<0.001
Toe slope[a]	0.33	7.00	<0.001
Toe slope[b]	0.29	4.66	<0.001
Steep slope[a]	0.28	3.80	<0.001
Steep slope[b]	0.20	3.54	<0.001
Foot slope	0.36	13.06	<0.001
Low-lying	0.25	4.30	<0.001
Entire region	0.34	131.21	<0.001

Note: The Z score is a multiple of the standard deviation. The P value represents the probability. Z is associated with P; when $|Z| > 1.96$, $P<0.05$, i.e., the confidence level exceeds 95%.

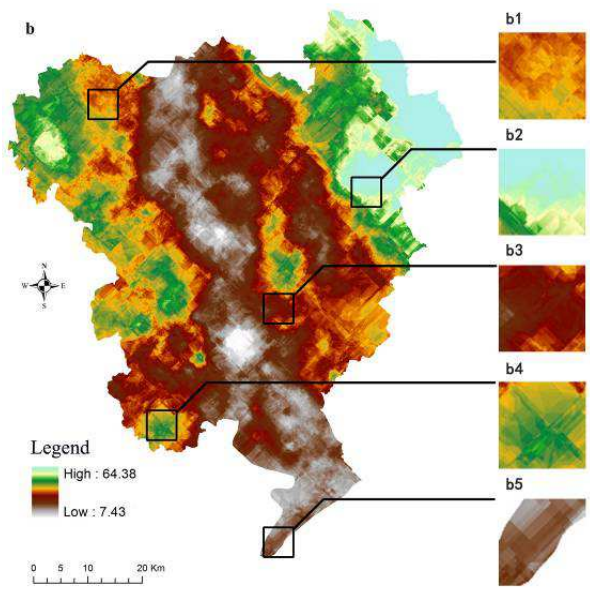
The global Moran's I values of the SOM content in each landform unit are positive, and the P values are less than 0.001. Therefore, the county-scale SOM distribution in each landform unit is not random. Instead, the distributions exhibit significant spatial aggregation. The aggregation effects of the SOM contents are different in different landform unit regions. A significant positive correlation was found between the SOM spatial distribution and the landform unit type, which is indicated by both the Moran's I and P values (see Table 2). The highest spatial aggregation of the SOM contents was found in the foot slope area, while the lowest aggregation was found in the steep slope area. These results provide further evidence that the study area can be divided into multiple subzones according to each terrain unit, which can increase the precision of the county-scale SOM spatial distributions. Moreover, the aforementioned findings suggest that the study are can be used to explore SOM distributions under different terrain conditions.

3.2. Analysis of the SOM Predictions

The ordinary kriging prediction method was used to predict the SOM spatial distributions in each terrain unit. The SOM spatial distribution within each topographic unit was then stitched into a global map. The results are shown in Figure 5a. The results shown in Figure 5b were obtained using GeoGS. Five subzones were chosen as examples to present a close-up version of the maps in the transition zones; the zones were separately marked. Additionally, these maps clearly depict the differences in the SOM distributions predicted using the GeoTU method compared to the GeoGS method.



(a)



(b)

Figure 5. *SOM spatial distribution based on individual topographic partitioning units (a) and the entire region (b).*

Figure 5 shows that the predictions produced by both methods exhibit similar spatial variations, although differences between the two methods exist at the county scale. The depth of detail is consistent with the distribution rule for the terrain units. The boundaries in the GeoTU method were smooth and changed gradually. The boundaries in the global-scale prediction results were coarse and changed abruptly; areas with the same SOM content were very large. The SOM contents predicted using the GeoTU method were 11.26 g•kg^{-1}–50.09 g•kg^{-1}; the range was found to be 7.43 g•kg^{-1}– 64.39 g•kg^{-1} for the GeoGS method. To compare the differences between the two methods, a statistical analysis was conducted; the results are explained in the following section.

3.3. Comparison and Verification of the SOM Spatial Prediction Accuracy

A statistical analysis was conducted to determine the root-mean-square error (RMSE) of the measured versus predicted values; the results for the two methods are shown in Table 3. The deviations between the predicted (using the two methods) and measured values were evident in the RMSEs. However, the degree of similarity was very high, and the correlation coefficient of the GeoTU method was smaller than that of the GeoGS method by an average of 0.15. The correlation between two methods was 0.75. This result shows that the predicted and measured values were not exactly the same, although they were very similar.

Table 3. *Accuracy tests for the SOM spatial distributions based on the GeoTU and GeoGS predictions.*

Topographic partitioning unit	Sampling Density	$RMSE_{GeoTU}$	$RMSE_{GeoGS}$	R_{GeoTU}	R_{GeoGS}
Dry plain	1.27	8.81	8.04	0.61**	0.67**
Wet plain	2.05	7.46	7.06	0.56**	0.61**
Ridge	0.85	5.79	6.81	0.92**	0.86**
Shoulder	1.57	8.66	10.29	0.90**	0.85**
Summit	0.67	6.55	7.08	0.80*	0.76*

Topographic partitioning unit	Sampling Density	$RMSE_{GeoTU}$	$RMSE_{GeoGS}$	R_{GeoTU}	R_{GeoGS}
Back slope a	0.77	11.04	10.45	-0.12	0.08
Back slope b	0.95	10.81	9.04	-0.16	0.46
Toe slope	1.05	6.85	7.31	0.86*	0.85*
Toe slopeb	0.59	9.30	8.09	0.56	0.69
Steep slopea	1.35	22.27	17.93	-0.02	0.05
Steep slopeb	3.32	9.08	6.94	0.87	0.88
Foot slope	1.02	10.57	8.78	0.51*	0.68**
Low-lying	1.67	5.02	8.01	0.58	-0.01
Entire region	1.47	8.20	7.65	0.58**	0.65**

Note: The sampling density is the average number of sampling points per square kilometer; * represents significant correlations at the 0.05 level; ** represents significant positive correlations at the 0.01 level.

In high rugged terrain units, the predicted SOM spatial distributions based on the individual terrain units do not exhibit large differences compared with the global predictions for the same terrain units. The results in ridge, shoulder, summit, toe slope (north/northeast side), and low-lying areas exhibited better results using the GeoTU method than the GeoGS method, with a 16.39% lower RMSE on average. This improvement was found in regions in which the local topography was relatively flat, such as near the tops of mountains and near valleys. The corresponding SOM content was either relatively high or low compared to common values; therefore, the prediction accuracy for the range in SOM contents in the edge was relatively high. In the remaining units, the RMSE was approximately 1.51 higher for the GeoTU method than the GeoGS method. Although the RMSE was slightly higher, a strong degree of similarity was observed between the two methods in these terrain units; the correlation between the predictions was 0.93. The SOM prediction accuracy based on the GeoTU method was similar to the accuracy of the GeoGS method because the corresponding terrain region was in the transitional zone, where the corresponding SOM content was near the middle of its range and the pattern variations were not clear. However, these aspects rendered the prediction prone to errors. Regardless of the prediction method used, some inherent errors existed in the spatial predictions due to interpolation effects.

In summary, the GeoTU method, dividing large study areas into subzones based on 13 terrain units by using specific indicators of topographic partition units, was put forward for the first time. It is feasible to use this method when specific ranges of precision are required. Each subzone can be subsequently examined according to the degree of complexity of the sampling strategy. Moreover, a systematic examination of the spatial distribution of soil nutrients in each subzone can be performed. Eventually, the results can be merged into a global map to ensure the precision in each region. For terrain units in which the local topography is flat, the prediction accuracy of the SOM spatial distribution can be improved after using the GeoTU method. In addition, the SOM predictions obtained using the terrain unit-based method were found to be similar to the global prediction results in some regions, although the former approach provides additional spatial details. Wen et al. [31] compared four interpolations or predictive methods including ordinary kriging, regression kriging, ordinary kriging integrated with land-use type and a soil land inference model (SoLIM) to predict soil organic carbon (SOC) of Loess Plateau, which only considered that the global relationships. GeoTU might be a new method to predict soil organic matter in such areas with complex hilly-gully terrain and various land-use types.

The purpose of this paper is to improve the prediction accuracy of SOM spatial distributions. In addition, the sampling density, considered as an impact factor, was discussed below. When the sample points were divided into subsets according to the terrain units, the sampling point spacing within a unit area changed. The negative correlation between the sampling density and the RMSE exhibited a very weak significance level. The correlation values for the predictions based on individual terrain units and the global predictions were -0.03 and -0.11, respectively. The positive correlation between the sampling density and the correlation coefficients exhibited a very weak significance level. The correlation values for the predictions based on individual terrain units and the global predictions were 0.28 and 0.12, respectively. The positive and negative correlations corresponded well with the actual relationships. If the sampling number per unit area were to be increased, the predicted spatial distributions of the soil properties in the region would better reflect the actual distributions. Furthermore, the correlation between the sampling density and the prediction accuracy of the two methods is very small, although some differences are evident. The impact of the sampling density on the prediction accuracy based on individual terrain units is considerable. The prediction accuracy for the global predictions is small. Changes in accuracy for the two prediction methods are partially related to the sampling density, although the sampling density is not the dominant factor affecting changes in accuracy. Determining the specific factors is a topic for future research. Furthermore, the prediction accuracy at junctions between terrain units and improving the division of terrain units requires additional attention.

4. Conclusions

In this paper, a method called GeoTU is proposed that incorporates the effects of the terrain factors in SOM distribution predictions. The method was used to divide the study area into 13 different topographic units according to the specific indicators of classification; the spatial distribution of each unit was separately analyzed. Each SOM distribution obtained using the two methods for each terrain unit resulted in different accuracies throughout the 13 studied terrain units. The average of the precision in the ridge, shoulder, summit, toe slope (north/northeast side), and low-lying terrain units was 16.39% higher than that of other method.

However, the prediction accuracy for other terrain types was comparable to the global prediction method. The mean Pearson correlation coefficient was 0.75.

The results presented herein demonstrate that predictions with the GeoTU method are more accurate than spatial interpolation at a global scale. When interpolations are performed on a global scale, complex soil landscape relationships are not accurately captured, although the GeoTU method can resolve these deficiencies. Lydia et al. [32] discussed the application of ordinary kriging in mapping Soil Organic Carbon (SOC) in Zambia. The area of Lusaka Province belongs to Agroecological Zone II of Zambia, where the terrain is flat. Their results could be better convinced if they considered this situation. Bameri et al. [33] presented the relationships between the spatial variability of SOC and the topographic features by using geostatistical methods. Their result showed that the Mean Error and RMSE of cokriging are relatively lower than those kriging and IDW methods. We could probably attempt more different interpolation approaches based on topographic units to improve prediction accuracy of SOM and produce higher-quality soil information products.

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Author Contributions：ZHOU Ziyan and HUANG Wei designed the study; HAN Zongwei collected the data; Fu Peihong analyzed the results; and ZHOU Ziyan wrote the main manuscript text. All authors reviewed the manuscript.

Conflicts of Interest

The authors declare no conflict of interests.

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