



Article

Digital Mapping of Soil Particle Size Fractions in the Loess Plateau, China, Using Environmental Variables and Multivariate Random Forest

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Abstract: Soil particle size fractions (PSFs) are important properties for understanding the physical and chemical processes in soil systems. Knowledge about the distribution of soil PSFs is critical for sustainable soil management. Although log-ratio transformations have been widely applied to soil PSFs prediction, the statistical distribution of original data and the transformed data given by log-ratio transformations is different, resulting in biased estimates of soil PSFs. Therefore, multivariate random forest (MRF) was utilized for the simultaneous prediction of soil PSFs, as it is able to capture dependencies and internal relations among the three components. Specifically, 243 soil samples collected across the Loess Plateau were used. Meanwhile, Landsat data, terrain attributes, and climatic variables were employed as environmental variables for spatial prediction of soil PSFs. The results depicted that MRF gave satisfactory soil PSF prediction performance, where the R^2 values were 0.62, 0.53, and 0.73 for sand, silt, and clay, respectively. Among the environmental variables, nighttime land surface temperature (LST_N) presented the highest importance in predicting soil PSFs in the Loess Plateau, China. Maps of soil PSFs and texture were generated at a 30 m resolution, which can be utilized as alternative data for soil erosion management and ecosystem conservation.

Keywords: digital soil mapping; spatial prediction; soil management; soil texture; machine learning



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1. Introduction

Soil texture, measured by particle size fractions (PSFs), partly determines the state and quality of soil, which plays a crucial role in modeling hydrological, ecological, and environmental processes [1,2]. High-resolution maps of soil PSFs are essential for sustainable agriculture and soil erosion management. Notably, a sampling survey is a widely accepted approach to obtain soil properties at a regional scale [3,4]. Soil samples are collected in accordance with planned sampling profiles and then carried to the laboratory for the soil PSF analysis. However, for a large-scale investigation of soil properties, it is labor-intensive and time-consuming to collect sufficient soil samples [5].

In recent decades, digital soil mapping (DSM) has been developed to estimate soil properties. Specifically, the discrete sampling points can be converted to a continuous surface using spatial interpolation approaches [6]. Odeh et al. [7] applied kriging interpolation with two data transformation methods to estimate soil PSF distribution. Zhang et al. [8] employed ordinary kriging, regression kriging, and compositional kriging for the mapping

of soil texture and PSFs. Zhao et al. [9] used universal kriging interpolation to generate multi-layer soil PSF maps for the Loess Plateau of China. Li et al. [10] evaluated kriging approaches with various log-ratio transformations for interpolating the soil PSFs and texture. Wan et al. [11] developed a co-kriging approach based on exploratory factor analysis to explore the spatial distribution of multi-layered soil PSFs. Furthermore, machine learning has been applied to estimate soil properties, examining the relations between soil observations and spatially continuous environmental variables [12–14]. In particular, random forest (RF), as an effective technique, has been employed for the estimation of soil texture and PSFs. Akpa et al. [15] depicted the superiority of RF in mapping the soil PSFs of Nigeria. Hengl et al. [16] mapped the soil PSFs of Africa and illustrated that the use of RF improved the DSM performance. da Silva Chagas et al. [17] showed that combining RF and remote sensing data can provide a satisfactory estimation result of soil texture in semi-arid areas. Liu et al. [18] employed RF to predict the spatial variation of soil PSFs as well as soil texture at multiple depths across China with a 90 m resolution. Zheng et al. [19] mapped the soil PSFs of cultivated land in Songnen Plain using RF and Sentinel-2 images. Cheshmberah et al. [2] evaluated 16 mathematical models for predicting soil PSF distribution and used RF to identify the relations between environmental variables and soil PSFs.

In soil science, soil PSFs are well-known compositional data, consisting of sand, silt, and clay [20]. The contents of the three components are related to each other and presented as percentages. Notably, log-ratio transformations have been applied in the interpretation of the compositional soil PSF data. Specifically, additive log-ratio (ALR), centroid log-ratio (CLR), and isometric log-ratio (ILR) are widely used transformation methods [21,22]. Moreover, log-ratio transformations and kriging-based interpolations have been combined for soil PSF mapping [7,23]. The soil PSF estimation performances obtained using log-ratio transformations with different machine learning approaches were compared [24,25].

Although log-ratio transformation guarantees that the sum of predicted sand, silt, and clay contents is 100%, the statistical distribution of transformed data is different from that of the untransformed original data. Zhang et al. [24] illustrated that log-ratio transformation made soil PSF data more symmetric with lower skews, and the transformed data showed greater kurtosis values than the original ones. Although the application of log-ratio transformation showed satisfactory soil PSF prediction results, data transformation could lead to biased estimates of PSFs [25]. The distribution of transformed data can be affected by outliers, which may influence the soil PSF mapping performance [23]. Therefore, to avoid the possible bias caused by data transformations, we pay attention to predicting soil PSFs based on the original untransformed data.

This study aims to predict and map the soil PSFs in the Loess Plateau, China, at a 30 m resolution using a DSM approach. To ensure that the sum of sand, silt, and clay content at each location is 100%, multivariate random forest (MRF) was employed to simultaneously predict the soil PSFs with the original compositional data for the first time. Specifically, MRF regards that the components of the compositional data are independent and simultaneously predicts the target variables, which can preserve the internal relations among sand, silt, and clay contents.

2. Materials and Methods

2.1. Study Area

The Loess Plateau, China, located in the middle reaches of the Yellow River, is the world's largest loess deposit [26]. Due to the limited and unbalanced precipitation, highly erodible loess soil, sparse vegetation cover, improper land use, and intensive human disturbance, this area has experienced severe land degradation and soil erosion [27,28]. The Loess Plateau belongs to the continental monsoon region [29], and most areas of the Plateau are dominated by semi-arid and sub-humid climates [28,30]. Its altitude ranges from 200 to 3000 m, and highly erodible loess layers cover most of the Plateau area. For the Plateau, the mean annual precipitation from northwest to southeast increases from 150 to

800 mm, and the mean annual temperature varies from 3.6 to 14.3 °C [31,32]. Notably, most precipitation occurs between June and September [33], and the concentrated high-intensity precipitations cause soil loss in the areas with steep slopes [34]. From the south to the north of the Loess Plateau, the dominant soil types are Haplic Luvisols, Terric Anthrosols, Calcic Chernozems, Aridic Leptosols, Calcic Regosols, Calcic Kastanozems, and Aridic Arenosols. The main geomorphic landforms are Yuans (large flat surfaces with little or no erosion), ridges, hills, and gullies [35].

2.2. Soil Data and Analyses

A total of 243 soil samples were collected at 0–40 cm in a typical region that is about 2/3 ($43 \times 104 \text{ km}^2$) of the Loess Plateau (Figure 1). To represent soil PSFs in this region, an intensive soil sampling method was used [9]. In each grid, the sampling site that can represent the dominant soil type, topography, and land cover within the field of view was selected. The distance between adjacent sites was approximately 40 km. In the areas with complicated geomorphology and landscapes, more sampling sites were added for better representation. To reduce the influence of transportation systems and human disturbance on the soil samples, the sampling sites were set at least 150 m away from the road. During the soil sampling, the position and land use of the site were recorded.

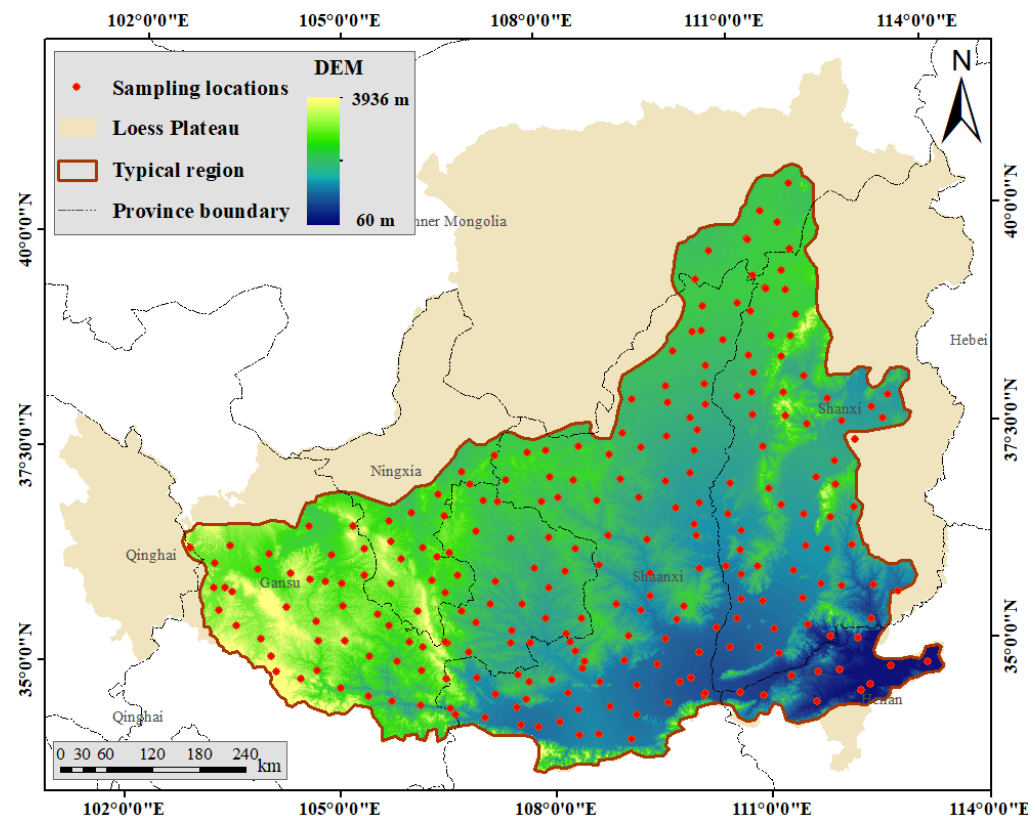


Figure 1. Locations of soil sampling points in the Loess Plateau, China.

In the laboratory, the collected soil samples were air-dried and then passed through a 2 mm mesh. The soil organic matter was removed by using hydrogen peroxide, and the soil samples were dispersed using sodium hexametaphosphate. The soil PSFs were measured using the Malvern Mastersizer 2000 laser diffraction particle size analyzer (Malvern Instruments, Malvern, UK).

2.3. Environmental Variables

For the prediction of soil PSFs, three types of spatially continuous environmental variables, including remote sensing data, terrain attributes, and climate variables, were

employed. To reduce the redundancy among the environmental variables, the Pearson correlation coefficient values were considered in the selection of variables. Specifically, variables with Pearson correlation coefficient values lower than 0.85 were selected. Table 1 records the 20 variables selected for the mapping of soil PSF distribution. For remote sensing data, the 30 m resolution Landsat 7 ETM+ data were employed to reveal the spectral reflectance of land surface, and a series of indexes were derived to represent the distribution of vegetation. Based on the ASTER Global Digital Elevation Model with a 30 m spatial resolution and $1^\circ \times 1^\circ$ tiles, the terrain attributes were generated using SAGA GIS software. Moreover, the climate variables covering the Loess Plateau of China with 1 km resolution were provided by the National Earth System Science Data Center, National Science and Technology Infrastructure of China (<http://www.geodata.cn> (accessed on 15 October 2022)), and the National Tibetan Plateau Data Center (<http://data.tpdc.ac.cn> (accessed on 10 October 2022)) [36–38]. To harmonize the spatial resolution of different variables, the climatic variables were resampled to 30 m by using bilinear interpolation.

Table 1. Environmental variables used for the spatial prediction of soil PSFs.

	Variable	Abbreviation	Brief Description
Remote sensing	Band 3	B3	Red band (0.63–0.69 μm)
	Band 4	B4	Near-infrared band (0.77–0.90 μm)
	Band 5	B5	Shortwave infrared band (1.55–1.75 μm)
	Normalized difference vegetation index [39]	NDVI	Quantifies vegetation by measuring the difference between near-infrared and red reflectance
	Enhanced vegetation index [40]	EVI	Quantifies vegetation using near-infrared, red, and blue reflectance
	Triangular vegetation index [41]	TVI	Quantifies vegetation using near-infrared, red, and green reflectance
	Elevation		Original value of the DEM
Terrain attributes	Slope		Rate of elevation change
	Aspect		Orientation of slope
	Slope length and steepness factor [42]	LS-factor	Describes effects of slope length and slope gradient on soil erosion
	Topographic wetness index [43]	TWI	Quantifies the topographic control on hydrological processes
	Valley depth	VD	Vertical distance to a channel network base level
	Flow accumulation	FA	Sum of all flows from upstream of a pixel
	Plan curvature	PC	Curvature along the horizontal plan
Climate variables	Multiresolution index of valley bottom flatness [44]	MrVBF	Describes the flatness and lowness characteristics of valley bottoms at a range of scales
	Wind exposition index	WEI	Expresses how open a location is to the wind
	Precipitation	Pre	Amount of precipitation in a year
	Evapotranspiration	ET	Total water loss to the atmosphere from the land surface
	Daytime land surface temperature	LST_D	Temperature of the Earth's lands during the daytime
	Nighttime land surface temperature	LST_N	Temperature of the Earth's lands during the nighttime

2.4. Multivariate Random Forest

To predict the multiple target variables as well as to model their compound dependencies, MRF is employed to estimate the components of soil PSFs in this study. MRF can be regarded as an extension of the widely used RF method. RF is a powerful ensemble learning method, which combines multiple regression trees to construct a stronger model [45]. Specifically, a regression tree is built by recursively partitioning samples into several groups using a top-down strategy [46]. The core of building a tree is to find the optimal partition rule, which depends on the selection of the feature and splitting points. The average of the predictions obtained from the generated trees can be used to yield the final RF output. To obtain an accurate RF model, not only the prediction error of individual trees should be low, but also the correlation among regression trees should be diminished [47]. Thus, the bagging strategy is used in RF, where each tree is built based on a bootstrap sample drawn with replacement from the training set.

MRF constructs a single model to simultaneously predict all the target variables, in which the internal relations among multiple targets are preserved [48]. In MRF, an ensemble

of multivariate regression trees is generated on the basis of bootstrap resampling and predictor subsampling [49]. The multivariate regression tree is an extension of the univariate regression tree for addressing the multioutput issue. Specifically, a multivariate regression tree exhibits several similar characteristics to a univariate regression tree [50,51]. Both of them are easy to be built, and the generated results are simple to interpret. The interactions between variables can be automatically detected by these trees. Meanwhile, the trees are robust to the noise response and can handle missing values in feature variables with minimal loss of information. Furthermore, compared to the separate prediction approach that builds individual models for each target variable, MRF has two main advantages [48]. Firstly, a single MRF is usually much smaller than the total size of the individual predictors for all variables. Secondly, the separate prediction approach ignores the correlation of compositional data, while MRF is able to exploit the compound dependencies among multiple target variables.

The construction of multivariate regression tree starts with all samples in the root node, and then the split and partitioning of nodes are recursively performed until meeting the predefined stopping criterion. Based on the multivariate response, the node impurity measure is defined as the sum of squared error, which should be minimized in each split. In a multivariate regression tree, each leaf is depicted by the multivariate mean of the samples at the leaf [48]. For each tree in MRF, the samples will be assigned to a certain terminal leaf. By combining the decisions of different multivariate regression trees, the final regression result can be obtained. As the internal relations of multivariate response are considered in the building of trees, MRF can retain the data correlation in the prediction process [52]. For soil PSFs, the sum of sand, silt, and clay content is 100% for each input sample. Therefore, the output estimates of the three components can be calculated using the multivariate mean of the input samples at the same leaf, which satisfies the constraint of summing to 100%. In addition, the importance of feature variables can be obtained and ranked to identify those most influencing MRF prediction [49].

2.5. Evaluation Criteria

The collected 243 samples were split into a training and a test set randomly. Specifically, 182 samples (75%) were utilized to construct the model, and 61 samples (25%) were utilized for evaluation. For each model, the grid search and 5-fold cross validation were used to adjust the number of trees in the forest (n_trees) and the maximum depth of each tree (max_depth). Statistics including the coefficient of determination (R^2), root mean square error (RMSE), mean absolute error (MAE), and Lin's concordance correlation coefficient (CCC) were used to evaluate the models' performance.

$$R^2 = 1 - \frac{\sum_{i=1}^n (o_i - p_i)^2}{\sum_{i=1}^n (o_i - \bar{o})^2} \quad (1)$$

$$RMSE = \sqrt{\frac{1}{n} \sum_{i=1}^n (o_i - p_i)^2} \quad (2)$$

$$MAE = \frac{1}{n} \sum_{i=1}^n |o_i - p_i| \quad (3)$$

$$CCC = \frac{2r\sigma_o\sigma_p}{\sigma_o^2 + \sigma_p^2 + (\bar{o} - \bar{p})^2} \quad (4)$$

where o_i and p_i are the observed and predicted values of sample i , $\bar{o}$ and $\bar{p}$ are the means of the observed and predicted values, σ_o and σ_p are their standard deviations (SDs), n denotes the number of test samples, and r represents the correlation coefficient between o_i and p_i .

3. Results and Discussion

3.1. Descriptive Statistics of Soil PSFs

As shown in Figure 2, most of the collected samples are classified as silt loam soil in texture according to the USDA soil taxonomy. Table 2 demonstrates that the training and test soil samples showed similar PSFs statistics. The mean and median contents of silt were higher than those of sand and clay. Compared to silt and clay, sand showed higher variability with coefficients of variation (CV) of 0.73 and 0.65 for the training and test samples, respectively.

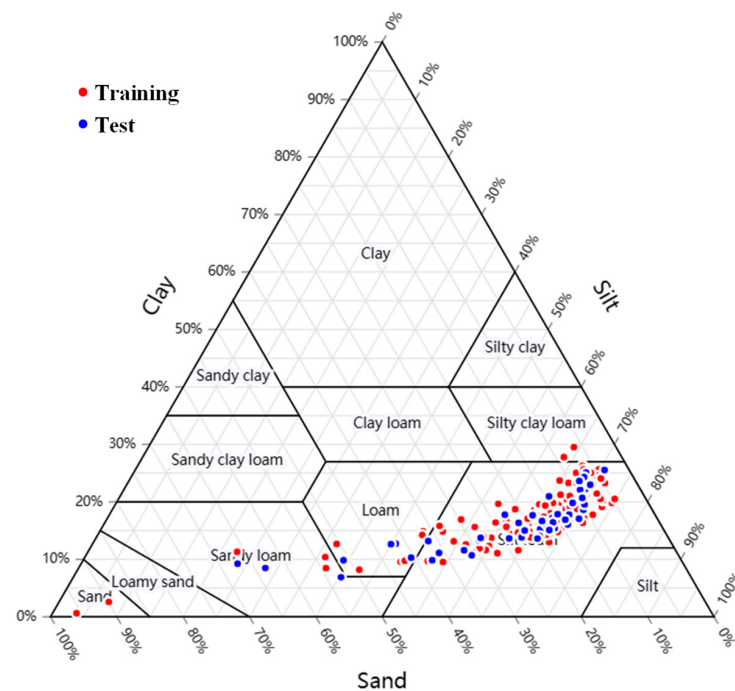


Figure 2. Soil texture classes of soil samples in the USDA texture triangle.

Table 2. Descriptive statistics for the PSFs of soil samples in the training and test sets.

	PSFs	Max	Min	Mean	Median	SD	CV
Training	Sand	95.74	3.77	18.45	15.39	13.47	0.73
	Silt	74.79	3.62	63.72	66.73	9.93	0.15
	Clay	29.53	0.63	17.83	17.97	4.57	0.25
Test	Sand	67.17	3.72	21.17	17.25	13.92	0.65
	Silt	71.16	23.57	62.30	66.65	10.30	0.16
	Clay	26.33	6.89	16.53	16.12	4.62	0.28

3.2. Performances of Different Approaches

To test the effectiveness of MRF in soil PSF prediction, three widely used log-ratio transformation approaches, namely, ALR, CLR, and ILR, were considered, where RF was used as the base predictor. Table 3 summarizes the R^2 , RMSE, MAE, and CCC of different approaches for predicting soil PSFs. Compared to the transformation approaches, MRF exhibited higher R^2 and CCC with lower RMSE and MAE. For the transformation approaches, CLR outperformed ALR and ILR in terms of the evaluation metrics. Wang and Shi [53] pointed out that the changes in the composition arrangements may influence the data transformation as well as the estimation result. In ALR, the arbitrary selection of the divisor may cause the changes in the distances among samples in the transformed space [54]. To overcome the problem in compositional data analysis, CLR takes the geometric mean into account. Meanwhile, the comparative approaches gave different results for sand, silt,

and clay. Specifically, the R^2 and CCC of clay were higher than those of sand and silt. The RMSEs of clay obtained using different approaches were lower than 2.8%, and the corresponding MAEs were lower than 2.3%. The obtained optimal RMSEs for sand and silt were 8.53% and 7.04%, and the corresponding MAEs were 5.64% and 4.66%, respectively.

Table 3. R^2 , RMSE, MAE, and CCC achieved using different approaches.

	R^2			RMSE (%)			MAE (%)			CCC		
	Sand	Silt	Clay	Sand	Silt	Clay	Sand	Silt	Clay	Sand	Silt	Clay
MRF	0.62	0.53	0.73	8.53	7.04	2.40	5.68	4.66	1.96	0.74	0.66	0.83
ALR	0.56	0.44	0.65	9.23	7.71	2.75	5.79	4.86	2.26	0.69	0.59	0.76
CLR	0.60	0.49	0.69	8.76	7.35	2.59	5.46	4.71	2.04	0.72	0.63	0.80
ILR	0.53	0.36	0.69	9.59	8.24	2.59	5.90	5.31	2.08	0.67	0.53	0.80

3.3. Importance of Environmental Variables

Soil PSFs are typical compositional data in soil science, where the three components are dependent on each other. The approaches based on transformed data used multiple predictive models to estimate soil PSFs separately. In each model, the environmental variables showed a different contribution, making it difficult to accurately identify the importance of variables in predicting the compositional PSF data. Conversely, MRF uses a single model to simultaneously predict the soil PSFs, and the relative importance of different variables is shown in Figure 3.

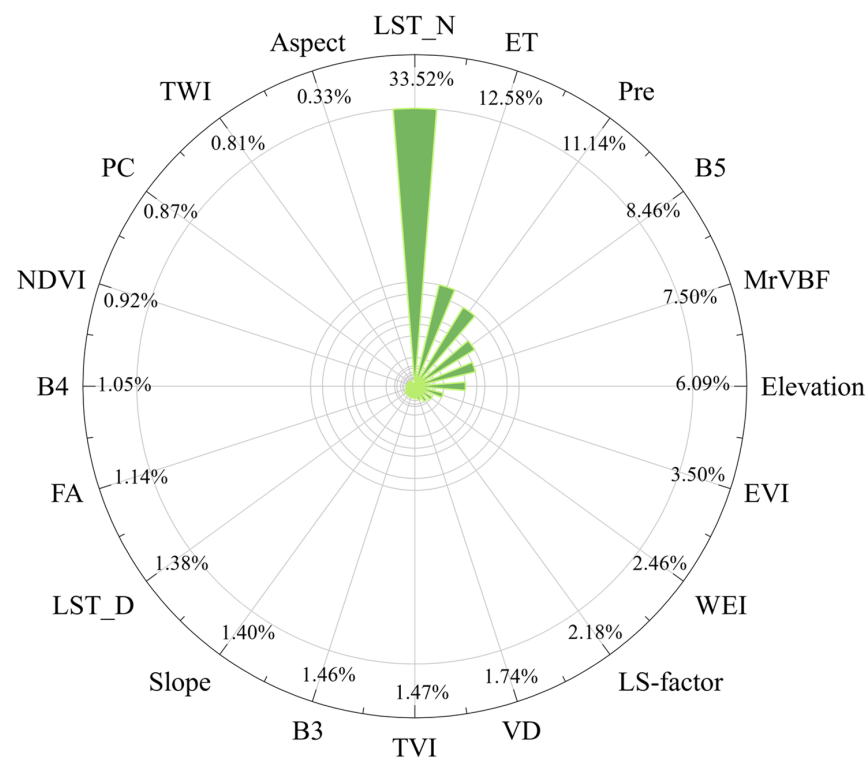


Figure 3. Environmental variable importance for soil PSF prediction with the MRF model.

Among the 20 environmental variables, LST_N showed the highest importance with 33.52%, followed by ET and Pre with 12.58% and 11.14%. It is evident that the climatic variables exhibit higher contribution than the other selected variables to the soil PSF prediction. The thermal infrared emissivity of bare soils is influenced by soil texture, which determines the LST [55]. Also, soil texture controls the available water content and affects the thermal inertia signature related to surface temperature patterns [56]. Osińska-Skotak [57] pointed out that soil texture and water content influence the land surface

temperature (LST). Also, soil PSFs and LST are highly correlated [58]. Sayão et al. [59] found that clayey soils showed higher LST, while sandy soils showed lower LST. Meanwhile, soil PSFs and texture determine water transfer and retention capacity, which have a significant effect on ET [60]. The consideration of soil texture will support the estimation of ET, since the relation between actual and potential ET is related to the soil texture and soil water content [61]. In particular, the finest texture showed greater surface per unit volume, which allows the greater adsorption of soil particles to water films [62]. If the water is heavily retained in soils, the absorption by plant roots will be limited, resulting in the decrease of plant transpiration rate. Additionally, loam soils with a large number of micro- and macro-pores show high water availability for plants, while coarse soils show a low available water capacity. For soil PSF prediction in loess deposition areas, the high importance of Pre can be attributed to the intensive water erosion with the transportation and sorting of soil particles in relation to rainfall [18]. Moreover, Liu et al. [63] emphasized the importance of precipitation and temperature in soil texture determination.

The contributions of B5 and MrVBF were ranked fourth and fifth among the twenty variables. In arid regions of Iran, B5 and MrVBF were also regarded as important variables for the estimation of soil PSFs [64]. B5 recorded the reflectance in the shortwave infrared band. Shortwave infrared reflectance is sensitive to soil available water capacity as well as soil texture [65]. Meanwhile, soil texture influences the shortwave infrared reflectance, as the fine and coarse soil particles exhibit different scattering properties. Stenberg et al. [66] argued that soil textures always show a stronger correlation to infrared bands than to visible bands. Topography affects water flow and material transport, and thus soil properties are related to terrain attributes [67]. MrVBF is an index designed to recognize valley bottoms and represent areas of deposited material. It depicts potential zones of transport for sediment and other materials, and is effective in explaining the soil texture distribution [68]. Due to the erosion and transportation processes, the soils in the hill slopes show a coarse texture. Meanwhile, owing to the deposition process, the soils in the valleys and plains show a fine texture [69].

3.4. Distribution of Soil PSFs

The soil PSF maps generated using MRF are shown in Figure 4. It can be observed that the silt content is much higher than the sand and clay contents in most areas of the Loess Plateau, China. According to the USDA soil taxonomy, the soil texture types of each point can be classified based on the estimated sand, silt, and clay contents. In Figure 5, the predicted soil texture map of the Loess Plateau, China, is presented, showing that silt loam is the main soil texture class.

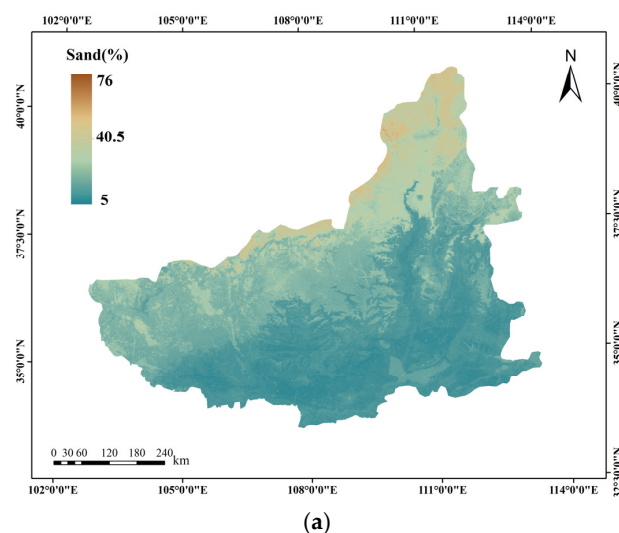
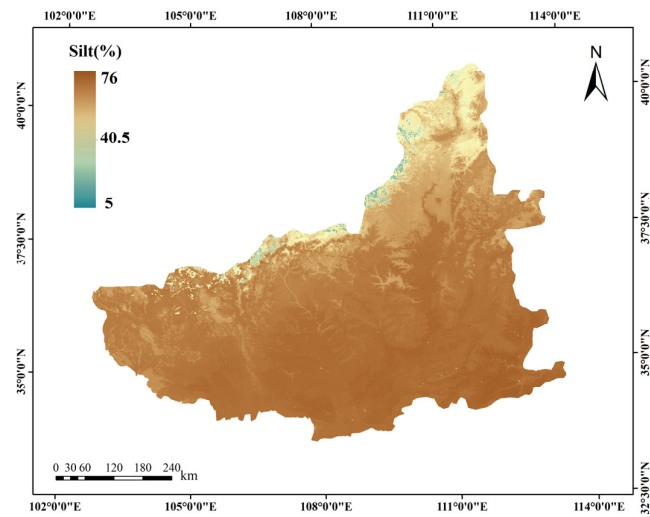
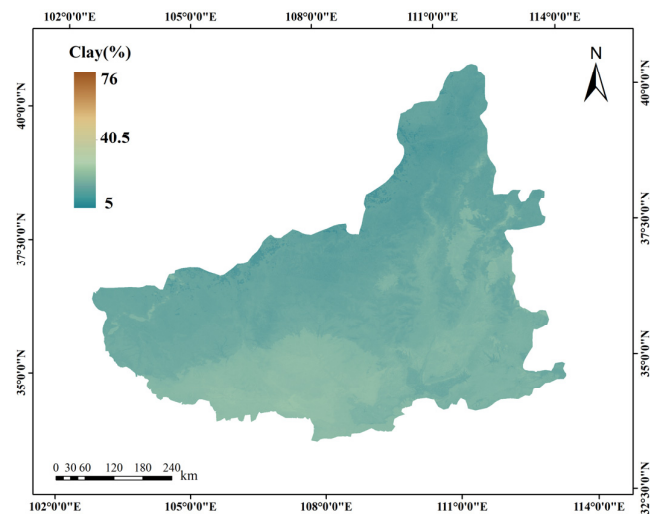


Figure 4. Cont.



(b)



(c)

Figure 4. Spatial distribution of (a) sand, (b) silt, and (c) clay content.

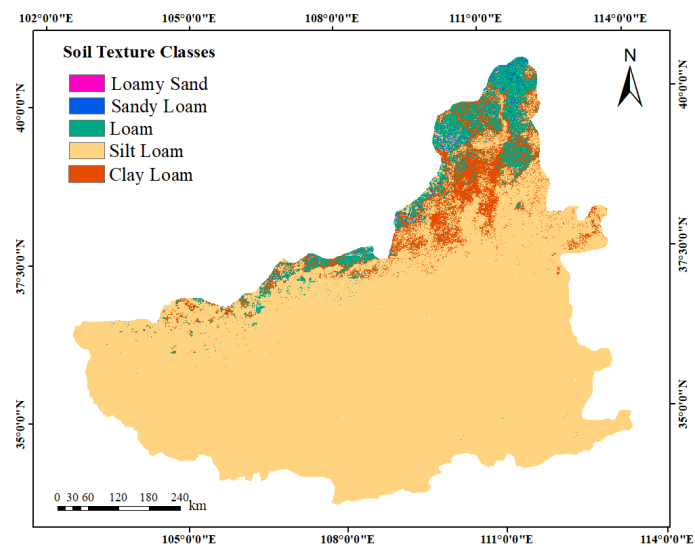


Figure 5. Digital map of soil texture in the typical Loess Plateau region.

The soils are sandy in the northwest and clayey in the southeast of the Loess Plateau. The Gobi Desert and the sand deserts located in the northwest of the Loess Plateau provide the loess source [70]. Loess with different sizes was carried to the plateau by the prevailing wind, monsoon wind, and dust storm. When the energy of the wind decreased, the largest and heaviest particles were first deposited. The northwesterly wind transported loess to the Plateau, and the coarser materials were deposited in the northwestern region [71]. The finer loess materials were brought and deposited in the southeast of the Loess Plateau. In the southeast of the Plateau, the climate is warm and wet. The strong weathering process driven by heat and water affected soil formation by increasing the clay content. In certain regions, the platy structures, that are the result of the combined effect of sedimentation, geomorphology, and topography, disrupted the continuing distribution of soil PSFs [9].

3.5. Soil Erosion Management

The high-resolution maps of soil PSFs can be a prerequisite to support soil erosion management decisions for the Loess Plateau, China, as the soil erosion rate is influenced by soil texture and PSFs [72]. As one of the most severely eroded regions, the Loess Plateau contributes approximately 90% of sediment sources in the Yellow River [73]. The severe soil erosion threatens land conditions for human survival, which reduces land productivity and exacerbates rural poverty [74,75].

To limit soil erosion and land degradation, a series of soil erosion control practices, such as soil management techniques, engineering techniques, and ecological restoration programs, have been conducted since 1950 [76]. Soil management techniques, including conservation tillage and mulching, aim to maintain soil structure and fertility. Conservation tillage justifies the soil texture and available water capacity, thereby reducing soil erosion [77]. Mulching protects the soil against raindrop impact and increases roughness, which further reduces the overland flow generation rates and velocity [78]. Engineering techniques prevent soil erosion by constructing terraces, which avert rainfall runoff on slopes, and check dams, which retain the sediments transported into the rivers [79,80]. As essential soil erosion control practices, ecological restoration programs have received the attention of decision-makers [1]. In particular, the Grain for Green Program and Natural Forest Conservation Program are the most famous national ecological restoration programs [76]. Increasing vegetation cover has been proven a useful practice to prevent soil erosion. The transport capacity of runoff water depends on the land cover types. Also, the energy of raindrops striking the land surface is reduced by vegetation, since trees, shrubs, and grasses with a dense vegetation canopy decrease the velocity of raindrops [81]. Meanwhile, the overland water flow is slowed down by dense vegetation, and the root systems of vegetation decrease runoff [82]. Notably, the programs promote the local economic development and reshape rural socio-economic structures.

For regional sustainable development, the trade-offs between ecosystem benefits and soil erosion management should be taken into consideration. Although the practices reduce soil loss, the water yield is concurrently reduced [73]. Excessive afforestation consumes deeper soil water resources, resulting in soil desiccation and the formation of a dry soil layer. The decrease in soil water storage capacity limits the growth of trees and threatens the ecosystem's health [83,84]. Hence, it might not be a good choice to plant short-lived and fast-growing vegetation in arid and semi-arid regions. A trait-based community that combines optimal species to maximize multiple ecosystem services should be considered for ecological restoration [85]. Moreover, the costly and labor-intensive maintenance is a major challenge for soil erosion management. Soil erosion management is a long-term plan, which requires sustainable management. To integrate the requirements of governments and farmers, soil management should be resilient and adaptive, and ecological, social, and economic benefits should be taken into account [76].

3.6. Limitations

This study mapped the soil PSFs and texture of a typical region in the Loess Plateau, China, but there is still room for further research. The 243 soil samples were mainly collected from the south of the Plateau, and few samples were collected from the northern region. Hence, more samples could be collected across the Loess Plateau to improve the DSM performance. For the conservation and responsible management of soils, the soil chemical properties could be predicted and mapped with a high spatial resolution in a future study [86]. In this study, Landsat data, terrain attributes, and climatic variables were employed as environmental variables to map soil PSFs, but in future, more variables associated with the formation, accumulation, and transportation processes of soil could be taken into account.

4. Conclusions

The soil PSFs in the Loess Plateau, China were simultaneously predicted and mapped at a 30 m resolution using environmental variables and MRF. Specifically, Landsat data, terrain attributes, and climatic variables were utilized for the high-resolution DSM. MRF used a single model to predict the three components of soil PSFs simultaneously, capturing the internal relations among the sand, silt, and clay contents. The results illustrated that MRF gave a satisfactory soil PSFs prediction performance in terms of high R^2 and CCC as well as low RMSE and MAE values. Among the environmental variables, climatic variables showed higher importance in the prediction of soil PSFs, where LST_N was the most important variable to the MRF model. Moreover, 30 m resolution maps of soil PSFs across the typical region in the Loess Plateau were generated, which can provide insightful information for soil erosion management, ecosystem conservation, and agricultural development. Future work will focus on the spatial prediction of the chemical properties of soil across the Loess Plateau, where more machine learning approaches and environmental variables could be taken into consideration.

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