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Spatial Prediction Method for Digital Soil Mapping

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Abstract: The spatial distribution of soil information is the basic data required for ecological hydrological simulation, global change research, and resource and environmental management. Digital soil mapping (DSM) is an efficient way to obtain and express soil spatial distribution information. This paper introduces the theories and principles of DSM, compares the principles, characteristics, and applicable conditions of spatial prediction methods widely used in DSM, and proposes a selection strategy for spatial prediction methods for DSM, which provides a reference for the promotion of DSM.

Keywords: Digital Soil Mapping, Spatial Distribution, DSM.

1. Introduction

High precision soil properties and their spatial distribution information are essential data for scientific research and production activities, such as regional farmland fertility evaluation, soil improvement and utilization, precision agriculture practice, and ecological environment protection, etc.

In the past, soil experts formed soil-landscape model in their minds through field investigations. They drew soil map manually taking polygon as unit based on topographic maps, aerial photographs, or satellite images[1]. In the past 30 years, with the development of geographic information systems, data mining, and acquisition technology of surface data, digital soil mapping (DSM) has become an emerging and efficient method for expressing soil spatial distribution[2][3].

DSM is a modern technology system that integrates spatial analysis and mathematical model for soil investigation and mapping, which is different from traditional one. The implementation process of DSM is to generate soil map in digital format based on environmental covariate data and soil survey. Alternatively, the spatial distribution of soil is generated by geostatistical method based on the spatial auto-correlation characteristics of soil properties. The soil map generated by DSM usually express the spatial pattern of soil using a raster data, which can provide more details of soil spatial variation information.

The birth and development of computer technology and geographic information system (GIS) have promoted the development of DSM. In 1975, the first International Soil Information System Conference was held in Wellington, New Zealand, and a corresponding working group was established. The working group was subsequently absorbed into the 5th Group (the group of soil genesis, classification, and geography) by the International Soil Society. Subsequently, the digital expression of soil information developed rapidly. In 1990, the Pedometrics Professional Committee was established in the International Union of Soil Sciences. In 2005, the Digital Soil Mapping Working Group was established. In February 2009, the Global Digital Soil Mapping Program was officially launched in the United States.

On the basis of introducing the theories and principles of DSM, this paper compares the principles, characteristics, and applicable conditions of spatial prediction methods widely used in DSM, proposes a selection strategy of spatial prediction methods for DSM.

2. Theories and Principles of Digital Soil Mapping

DSM reflects the spatial distribution characteristics and laws of soil, mainly based on two theories, namely the theory of soil formation factor and the first law of geography. The theory of soil formation factor holds that soil is the product of the combined effects of five soil formation factors, i.e. parent material, climate, biology, topography, and time [4]. In recent years, human activities have also become an important environmental factor in changing the direction and intensity of soil formation [2]. The soil in a certain region is formed by a series of physical, chemical, and biochemical processes of soil parent material under certain hydrothermal conditions, biological factors, and human factors. The spatial distribution of soil and environmental covariates has a synergistic relationship [5]. According to the first law of geography, the continuous gradient of soil spatial distribution is attributed to the spatial continuity of environmental factors [6][7]. The closer the spatial distance, the more similar the soil properties are. There is often no clear boundary between adjacent soil types in space, but rather a transitional zone [8].

DSM follows the following three principles. (1) The principle of scale effect of soil spatial variation. The soil variation at a certain scale can only be revealed at the corresponding scale. Soil spatial distribution at large-scale is mainly adapted to the bioclimatic conditions, and the one at small-scale is mainly influenced by local topography, parent materials, and other factors. (2) The principle of adapting to local conditions. A relatively mature and accurate method should be determined based on the scale and characteristics of the mapping area, combined with the density and uniformity of soil samples. (3) The principle of soil attribute suitability. Soil physical properties are greatly influenced by natural factors, while the abundance of nutrient elements in soil is significantly influenced by agricultural management practices.

3. Spatial Prediction Methods Widely Used in Digital Soil Mapping

The spatial prediction methods widely used in DSM can be

divided into five categories, i.e. mathematical statistics, deterministic interpolation, geostatistics, machine learning, and fuzzy inference.

Mathematical statistics method fits mathematical functions to predict the spatial distribution of soil properties by exploring the statistical relationship between soil properties and environmental covariates in soil samples. Mathematical statistical methods are simple and intuitive, and can effectively express the correlation between soil properties and environmental factors. However, this method assume a linear correlation between soil properties and environmental covariates, and requires a large soil sample size to extract this linear relationship. In a large-scale region, soil properties and environmental variables are often not simply linearly related. Therefor, compared to in large-scale region, this method has higher prediction accuracy in small-scale region. The mathematical statistical method includes multiple linear regression (MLR), generalized multiple linear regression (GMLR), and discriminant analysis (DA), etc.

Deterministic interpolation method create a soil spatial distribution map based on the similarity or smoothness of soil samples in the study area. The inverse distance weighting method, nearest neighbor method, and spline interpolation method are all deterministic interpolation methods.

Geostatistical method is a spatial interpolation of soil samples using the spatial variation function (the spatial auto-correlation relationship of target soil property). Geostatistical method include Kriging interpolation and its derivative methods, such as ordinary Kriging (OK), universal Kriging (UK), regression Kriging (RK), geographically weighted regression Kriging (GWRK), co-Kriging (CK), etc. Except for OK and UK, other Kriging derivative methods improve prediction accuracy by using the correlation between target soil property and environmental covariates. OK has been widely used for a long time, but there is a smoothing effect, which may result in inaccurate predictions for regions with significant local variations.

As the name suggests, machine learning method predicts soil spatial distribution utilizing machine learning and data mining techniques. Compared with geostatistical and mathematical statistical methods, machine learning models can solve nonlinear relationship between soil properties and environmental variables, and do not require the distribution of soil property. Common machine learning models include artificial neural networks (ANN), classification and regression tree (CART), and random forest (RF), etc.

Fuzzy inference method expresses the relationship between soil and environmental variables as membership values. This method infers the spatial variation of the soil target variable utilizing the spatial representativeness of a single soil sample. The output depends on the reliability of soil sample.

The comparative analysis of different spatial prediction methods for DSM is shown in Table 1.

Table 1. Comparative analysis of different spatial prediction methods for DSM

		Mathematical statistics	Deterministic interpolation	Geostatistics	Machine learning	fuzzy inference
Principle		Mathematical function is fitted based on the statistical relationship between soil properties and environmental covariates.	Soil spatial distribution map is generated based on the similarity or smoothness of soil samples.	A spatial interpolation of soil samples using the spatial variation function.	The relationship between soil and environmental variables is extracted by utilizing machine learning and data mining techniques	The relationship between soil and environmental variables is indicated as membership values, which is used to infer the soil property.
Model	spatial auto-correlation of soil property	\	inverse distance weighting method (IDW), nearest neighbor method, spline interpolation method	ordinary Kriging (OK), universal Kriging (UK)	\	\
	correlation between soil and environment	multiple linear regression (MLR), generalized multiple linear regression (GMLR), discriminant analysis (DA)	\	regression Kriging (RK), geographically weighted regression Kriging (GWRK), co-Kriging (CK)	artificial neural networks (ANN), classification and regression tree (CART), random forest (RF)	Fuzzy C-means (FCM), stepwise fuzzy clustering method, fuzzy clustering method based on objective function
Characteristics		This method assume a linear correlation between soil properties and environmental covariates, and requires a large soil sample size to extract this linear relationship. Therefore, the mapping area should not be too large.	This method is applicable to small-scale areas with relatively uniform and stable soil properties.	This method is easy to operate and the results are relatively reliable, but the data needs to meet relevant mathematical assumptions and there is a smoothing effect.	This method solve nonlinear relationship between soil properties and environmental variables, and do not require the distribution of soil property.	This method takes into account the spatial distance between the sample site and the predicted site, as well as the similarity of the environment, and heavily relies on the reliability of soil sample.

4. Selection of Spatial Prediction Methods for Digital Soil Mapping

Here we proposes a strategy for selecting spatial prediction methods for DSM (Figure 1), based on the theory and principle of DSM and the characteristics of different spatial prediction methods, which includes the following four steps:

Step 1: Analysis of mapping conditions. At this stage, we need to analyze the spatial scale and environmental characteristics (e.g., terrain, climate, parent material, agricultural management practices, etc.) of the mapping area, target soil attribute characteristics (e.g., descriptive statistical features, semi variance functions, etc.), the number and distribution of soil samples, and the quantity and quality of environmental variables.

Step 2: Selection of candidate models. Candidate models (generally no less than 3) should be selected taking into account the characteristics and applicability of different spatial prediction methods, as well as mapping conditions (step 1 for details).

Step 3: Evaluation of candidate models. The performance of spatial prediction candidate model is evaluated using metrics, e.g., coefficient of determination (R^2), root mean square error (*RMSE*), and Lin's concordance correlation coefficient (*LCCC*), etc.

Step 4: Determination of the optimal model. The optimal spatial prediction model is determined from the candidate models following the principle of larger R^2 and *LCCC*, and the smaller *RMSE*.

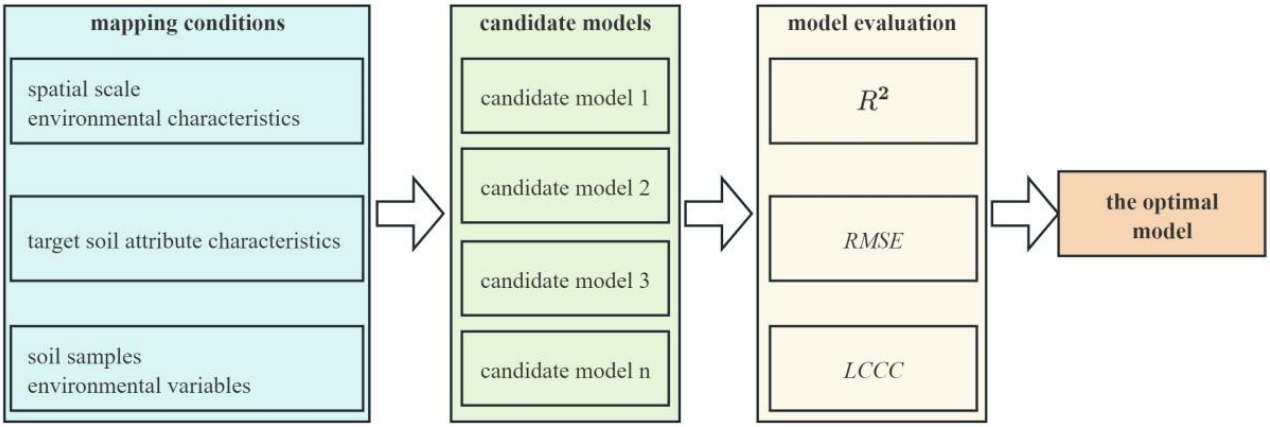


Figure 1. The strategy of selecting spatial prediction methods for DSM

5. Conclusions

There are significant differences in the principles, characteristics, and applicable conditions of spatial prediction methods for DSM, e.g., mathematical statistics, deterministic interpolation, geostatistics, machine learning, and fuzzy inference. The determination of the optimal model requires comprehensive consideration of the spatial scale and environmental characteristic of the mapping area, target soil attribute, and environmental variables.

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References

[1] Hudson B D. The soil survey as paradigm-based science[J]. Soil Science Society of America Journal, 1992, 56(3): 836-841.

[2] McBratney A B, Mendonça Santos M L, Minasny B. On digital soil mapping[J]. Geoderma, 2003, 117(1-2): 3-52.

[3] Hengl T, de Jesus J M, Heuvelink G B M, et al. SoilGrids250m: Global gridded soil information based on machine learning[J]. PLoS One, 2017, 12(2): e0169748, doi:10.1371/journal.pone.0169748.

[4] Jenny H. Factors of soil formation: A system of quantitative pedology[M]. New York, NY: McGraw-Hill, 1941.

[5] Zhu A X, Liu J, Du F, et al. Predictive soil mapping with limited sample data[J]. European Journal of Soil Science, 2015, 66(3): 535-547.

[6] Tobler W R. A computer movie simulating urban growth in the Detroit region[J]. Economic Geography, 1970, 46(S1): 234-240.

[7] Wilding L P, Jones R B, Schafer G M. Variation of soil morphological properties within miami, Celina, and Crosby mapping units in West-Central Ohio[J]. Soil Science Society of America Journal, 1965, 29(6): 711-717.

[8] Zhu A X, Li B L, Pei T, et al. Jingxi shuzi turang pucha moxing yu fangfa[M]. Beijing, China: Science Press, 2008.