ORIGINAL PAPERS

Predicting soil elements spatial distribution with two models

Zheng Jia[1,2] · **Li Xiaochuan**[1] ·**Ding Xiaogang**[1] · **Mo Xiaoyong**[2] · **Zhang Yingzhong**[1] · **Zhao Zhengyong**[3] · **Zhang Xiangyu**[2] · **Qi Ye**[1]

Abstract The BP artificial neural network and the spatial interpolations model (Universal Kriging, Spline method and Inverse Distance Weighted) were used to predict the forest soil elements (exchangeable calcium, sulfur and exchangeable magnesium) spatial distribution in Yuncheng district and Yun'an district in Yunfu city, Guangdong province. It was showed that the highest content element in the forestry soil was exchangeable Ca (of 17.333—1 169.033 mg·kg^{-1}), followed by total S and exchangeable Mg with concentration of (60.787—354.600 and 8.320—51.580 mg·kg^{-1}, respectively. The coefficient of variation for the three elements varied from 33.43%—106.34%. The variation coefficient of exchangeable Ca in Yun'an district reached 106.34%, indicating high variation in the concentration of exchangeable Ca. Among three interpolation methods, deviation from the Universal Kriging was smaller than from other methods. But the Universal Kriging was unable to predict other elements well in the three elements, except exchangeable Mg. By comparison, we can conclude that the BP artificial neural network was the best model to predict the element spatial distribution in this study.

Keywords Forest soil · Elements · Spatial interpolation model · BP artificial neural network · Yunfu

Project funding Guangdong forestry science and technology innovation fund project investigation and evaluation on forest soil nutrients (2014KJCX022).

✉ Zheng Jia
710212087@qq.com

1 Guangdong Academy of Forestry, Guangzhou, Guangdong 510520, China

2 College of Forestry and Landscape Architecture, South China Agricultural University, Guangzhou, Guangdong 510642, China

3 College of Forestry, Guangxi University, Nanning, Guangxi 530004, China

Introduction

Forest is a biocenosis mainly featuring natural growth and arbors, it also represents a synthesis consisting of woods, microorganism, associated plants, animals, and soils (Brockerhoff et al.2008). Forest is equipped with a wide range of social values in terms of improving human living conditions, providing rich product resources, and conserving water sources. After a series of interactions, special forest soils came into being for forestry production, and the natural forest can be nurtured and developed at the same time. Medium elements such as calcium, magnesium, and sulfur are essential for the growth of plants, and they also meet the high demands for timber quality. Nowadays, people have been paying more attentions to the soil medium elements with better economic growth, land development, and management intensity (Chen et al.2010).

The scientific development of soils has been going on for a very long time in Guangdong, with major achievements being made in food safety (Li et al. 2010), environmental protection (Zhang et al. 2001 and Wang et al.2013), soil nutrients research (Yao et al.2006 and Lee 2009), reconversion of deteriorated lands (Shang and Qiu 2004), and maintenance of ecosystem stability (Liu et al. 2001). Nevertheless, Guangdong is still facing a series of issues, including small arable land per capita, limited reserve soil resources, reduced soil fertility, deteriorating soil environment, and severe water and soil loss (Wan et al.2011). The research into forest soil medium elements of Guangdong has been confined to urban forests and plantations due to the severe human interferences with forestry. Therefore, further studies are needed to figure out the distribution of medium elements of natural forests.

Based on the BP artificial neural network model and the spatial interpolation model, this paper comes to predict the spatial distribution of forest soil medium elements, along with the analysis of the features of such spatial distributions within the research area. To sum up, the research is generally aimed to reveal the distribution of forest soil medium elements of Yuncheng district and Yun′an district under current environmental conditions, which will act as references for the operation and management of local forests.

Material and methods

Research area

The Yuncheng district in Yunfu city of Guangdong province, China, is located in the western Guangdong province, with the latitude and longitude position of 111°56′—112°20′E, 22°43′—23°08′N. With a total area of 78 911 hm^2, and the total population of 317 600, Yuncheng features a subtropical monsoon climate. It enjoys mild climate, abundant rainfall, and ample sunshine. The annual average temperature of this region is 21.5 ℃, with the annual rainfall of 1 586.5 mm. It is a semi-hilly region.

Yun′an district is in the central and western part of Guangdong province, with the latitude and longitude position of 111°43′—112°10′E, 22°34′—23°08′N. With a total area of 117 240 hm^2, and the total population of 33.15 million, Yun′an features a subtropical humid monsoon climate. In spring, it rains a lot with little sunshine; while in summer and autumn, it rains a lot with high temperature; in winter, it is dry with little rainfall and ample sunshine. Yun′an features a topography of being high in east, south and west, but low in north, basing on hills and low mountains. Hills are throughout the district and even the town.

Collecting and determination of forest soil samples

This study adopts stratified random distribution sampling method, and the stratification basing on a 1: 1 million soil distribution maps. The collection of forest soil was in line with the standard LY/T 1210—1999 in collecting and preparing forest soil samples. A total of 100 forest soil samples were excavated from October to December in 2015, as shown in Figure 1. Before digging soil, pit and soil profile pictures were taken, GPS coordinates, slope, aspect, and vegetation types were recorded. For each soil pit soil samples were collected at the 0–20 cm, 20–40 cm, and 40–60 cm depth layers, respectively. The total sulfur was detected according to the determination standard LY/T 1255-1999 of total sulfur in forest soil. The exchangeable calcium and exchangeable magnesium were determined in accordance with the methods LY/T 1245-1999 of exchangeable calcium and exchangeable magnesium in forest soil.

Analysis of forest soil sampling data

Outlier processing

The outliers not only affect the accurate expression of soil elements distribution, but also distort the experimental semivariogram, obscuring the real distribution structure of soil nutrient space (Zhao 2010). So, the outliers need to be removed and replaced. This paper adopts the X±3S method to handle it, with X as the arithmetic

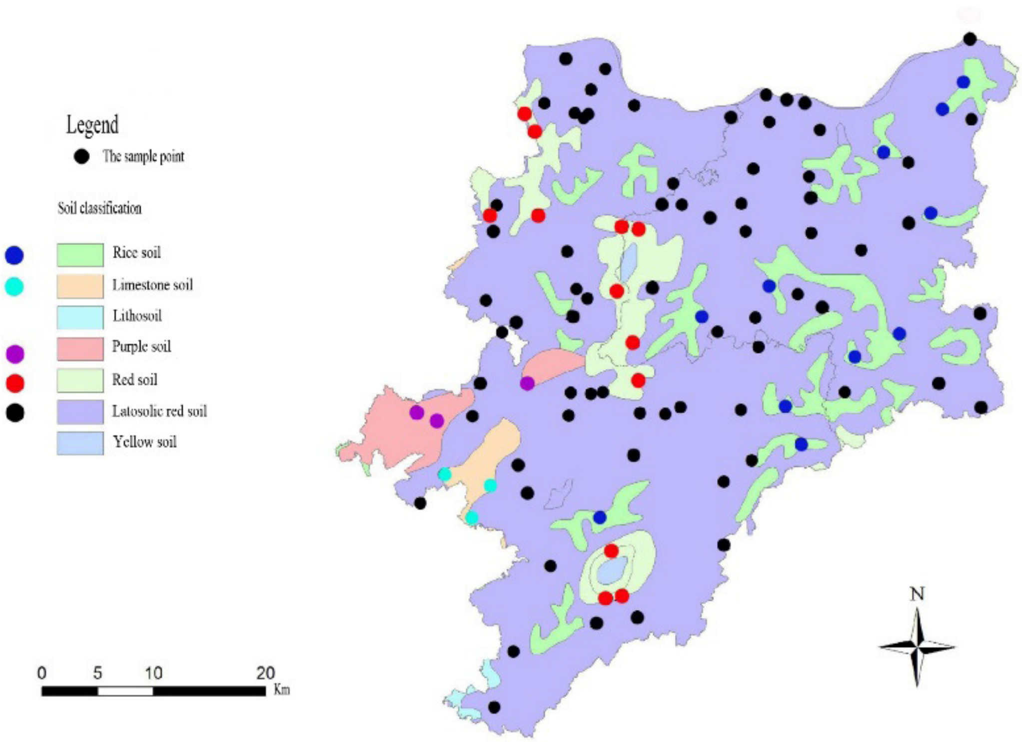

Figure 1 The forest soil sampling distribution in Yun'an and Yunfu district

mean value of the sample data and S as the standard deviation. When the outliers exceed X+3S, X+3S replaces them, and when the outliers are less than X-3S, they are substituted by X-3S (Wang 2008; Li 2014; Qian 2014).

Normal distribution of soil data

The Kriging interpolation requires that the data satisfy the normal distribution, which brings abundant convenience to the theoretical analysis and the estimation method for soil element treating, or scale effects would be caused, failing to authentically reflect the spatial distribution of soil elements content (Xu 2008 and Shi 2013).

In this paper, K-S (Kolmogorov-Smirnov) test method is applied to conduct normal distribution tests on the medium elements content of the forest soil in Yun′an district of Yuncheng. The results show that the P values of exchangeable calcium (0.057), exchangeable magnesium (0.064) and total sulfur (0.500) all exceed 0.05, consistent with the normal distribution.

Research methods

This study uses BP artificial neural network model and spatial interpolation model to predict the medium elements of forest soil, and select the optimum model.

Spatial interpolation model

(1) The Universal Kriging interpolation method (UK): It is targeted to the nonstationary phenomenon of the regionalized variables in the study area, under the precondition that the variation functions of the drift $\mathrm{E}[Z(u)] = m(u)$, and non-stationary random functions are $Z(u)$ and its variogram is $\gamma(h)$ given that the nonlinear estimation is there for the drift (Hou et al. 1998).

(2) The Inverse Distance to a Power method (IDW): As a weighted average interpolation method, it takes into account the distance between the actual soil sample point and the interpolation point, and then interpolates the distance. The weight coefficient is related to the distance from the measured point. The value of weight coefficient has something to do with the distance to the actual test point, and when the distance increases, the weight coefficient decreases (Shi 2013).

The formula is expressed as:

$$Z=\sum_{i=1}^{n}\frac{1}{(D_i)^p}Z_i/\sum_{i=1}^{n}\frac{1}{(D_i)^p}$$

Where Z is the predicted value of the interpolated point, D_i is the distance between the i test point and the interpolated point, n is the number of the test points involved in the calculation, and p is the power of the distance.

(3) The Cubic Spline Function Interpolation method: The higher order interpolation function has the characteristics of drastic oscillation, huge computation, and poor numerical stability, and continuous and non-commutability occurs in piecewise linear interpolation, with continuous first-order derivative in the three piecewise interpolations. The spline function solves this problem, making the interpolation function a low-order piecewise function and a smooth function, too. The cubic spline function interpolation method is a piecewise function constructed from the given function table, and to be a first-order and second-order derivative after passing the fixed point (Li 2008).

BP artificial neural network model

Artificial neural network (ANN) is a technology based on the physiological structure of the human brain simulating the information processing function of the human brain (Zhu 1999). ANN can be generally divided into managed artificial neural network and unmanaged artificial neural network. This paper adopts the typical managed neural network method, that is, back propagation artificial neural network (BP-ANN) (Gui 2004). The principle is, through the data normalization process, to input the matrix, set the parameters, and establish a three-tier neural network, so as to train the data and afterwards input the test data for testing, mainly for error analysis; the trained data is under the function simulation, and the simulation results are anti-normalized and the trained neural network is preserved for the use in subsequent forecast, where the forecast results can be obtained only if the data to be precast is input.

Comparison of prediction models

The Greate Subsets function of the ArcGIS geo-statistical analysis module is applied to select 70% of the 100 soil samples as the modeling points, and the rest 30% the verification points, with the mean absolute error (MAE) and the root mean square error (RMSE) to comparatively analyze the predicted value and the measured value of the verification points and the modeling points, thus the optimal method or model for accuracy is gained. The formulas respectively are:

$$MAE=\frac{1}{n}\sum_{i=1}^{n}\left|\hat{Z}_i-Z_i\right|$$

$$RMSE=\sqrt{\frac{1}{n}\sum_{i=1}^{n}\left(\hat{Z}_i-Z_i\right)^2}$$

Where $\hat{Z}_i$ is the predicted value of the i sample, Z_i is actual observed value, and n is the number of samples. The smaller the MAE and RMSE values, the smaller the error and the higher the simulation accuracy. The mean absolute error can reflect the measured error range of the predicted value. The root mean square error can reflect the prediction sensitivity and effect of the extreme value of the soil sample data (Zhang et al. 2008). The model is mainly based on the root mean square error, and the method is optimal when root mean square error is the smallest.

Microsoft excel 2010 respectively calculates the three methods of spatial interpolation model, and the most representative absolute interpolation method is obtained by comparing the mean absolute error with the root mean square error. For the most suitable model, not only the great ability to predict is necessary, but also stability and promotion. The two-tailed correlation degree test is performed on the model. If the correlation between the measured value and the predicted value of the model's test points and the verification points is significant, and their difference in correlation index is weak, the model is the optimal.

Results

Analysis of statistical characteristics of secondary element in forest soil sampling point

The results in Table 1 show that the average value of exchangeable calcium, exchangeable magnesium, and total sulfur in medium elements of forest soils in Yun′an district are higher than those in Yuncheng district, the former being 273.689, 18.373 and 197.098 mg·kg^{-1}, and the latter 202.141, 16.004 and 170.648 mg·kg^{-1}, respectively. The contents of soil exchangeable calcium, exchangeable magnesium and total sulfur in the whole study area are between 17.333–1169.033, 8.320–51.580, and 60.787–354.600 mg·kg^{-1}, respectively, the highest among them being exchangeable calcium, followed by total sulfur and exchangeable magnesium.

If the variable coefficient is less than 10%, it belongs to lower variability. When the variable coefficient is between 10% to 100%, it is considered medium variability. When the variable coefficient exceeds 100%, it is defined as strong variability (Wang 2009). Table 1 shows that the variable coefficients of exchangeable magnesium and total sulfur of forest soils in Yun′an district are 54.95% and 33.43%, respectively, all being medium variability, and the variable coefficient of exchangeable calcium is 106.34%, which belongs to strong variability. The variable coefficients of exchangeable calcium, exchangeable magnesium, and total sulfur of forest soil in Yun′an district are 98.19%, 39.76% and 38.70%, respectively, which belong to medium variation, and the variation of exchangeable calcium is the largest.

Selection with optimal interpolation method of spatial interpolation model

Comparison of three interpolation methods

It can be known from Table 2 that the mean square error and the mean absolute error value of the total sulfur, the exchangeable calcium and the exchangeable magnesium are the lowest in the verification points with the universal Kriging interpolation method, respectively 0.020 0, 0.020 0; 0.380 0, 0.280 0; 0.020 0, 0.010 0. So the universal Kriging interpolation method is optimal in verification points.

In the modeling points, the root mean square error and the mean absolute error of the total sulfur, exchangeable calcium and exchangeable magnesium of the reverse distance weighted interpolation method are the

Table 1 Statistical characteristics of secondary element in forest soil in Yuncheng and Yun’an district

Study area	Soil nutrient	Maximum / (mg·kg^{-1})	Minimum / (mg·kg^{-1})	Mean / (mg·kg^{-1})	Standard deviation	Coefficient of variation / %
Yun’an district	Exchangeable calcium	1169.033	17.333	273.689	291.041	106.34
	Exchangeable magnesium	51.580	8.320	18.373	10.096	54.95
	Total sulfur	354.600	62.098	197.098	65.890	33.43
Yuncheng district	Exchangeable calcium	895.286	21.469	202.141	198.482	98.19
	Exchangeable magnesium	30.807	8.614	16.044	6.363	39.76
	Total sulfur	318.483	60.787	170.648	66.041	38.70

Table 2 The accuracy of three interpolation methods

Soil nutrient	Interpolation methods	Modeling point		Verification point	
		MAE	RMSE	MAE	RMSE
Total sulfur	IDW	0.0100	0.0300	0.0600	0.0700
	UK	0.0416	0.0341	0.0200	0.0200
	Spline	0.0448	0.0345	0.0800	0.1300
Exchangeable calcium	IDW	0.0600	0.0344	0.6600	0.9600
	UK	0.4150	0.2459	0.2800	0.3800
	Spline	0.4250	0.2454	0.6900	1.0900
Exchangeable magnesium	IDW	0.0030	0.0048	0.0300	0.0500
	UK	0.0214	0.0149	0.0100	0.0200
	Spline	0.0229	0.0149	0.0400	0.0700

Note:The MAE means the mean absolute error value. The RMSE means the mean square error value.

smallest, respectively, 0.030 0, 0.010 0; 0.034 4, 0.060 0; 0.004 8, 0.003 0. Therefore, in the three methods, the cubic spline interpolation method is excluded, and the comparison is further made between the universal Kriging interpolation method and the inverse distance interpolation method.

Comparison of correlation significance between the universal Kriging interpolation method and the inverse distance interpolation method

The significance test is performed on the correlation significance between the precast values and the measured values of the universal Kriging interpolation method and the inverse distance interpolation method, with the results as shown in Table 3. There is a significant correlation between the measured values and the precast values of the medium elements in the modeling point with the inverse distance weighted interpolation method ($\alpha = 0.01$). Three elements display significant correlations in the modeling points of the universal kriging interpolation method, and the exchangeable magnesium and sulfur correlates significantly ($\alpha = 0.01$), so does the exchangeable calcium ($\alpha = 0.05$).

The correlation index differences between the modeling point and the verification point of exchangeable calcium, exchangeable magnesium and total sulfur in the inverse distance weighted interpolation method are 1.072, 0.613 and 0.708 respectively, and those of the universal Kriging interpolation method are 0.334, 0.022 and 0.241, respectively. The difference of the three kinds of medium elements in the universal Kriging interpolation method is smaller than that of the inverse distance weighted interpolation method, indicating that the former method has better predictability than the latter. Except that the difference of exchangeable magnesium is small relatively, the correlation coefficients of other verification points are smaller than that of the modeling point, implying that the universal Kriging interpolation method has great predictability for exchangeable magnesium, but slightly poor predictability for exchangeable calcium and total sulfur.

In summary, among the three interpolation methods, the universal Kriging interpolation method shows great predictability for exchangeable magnesium, and slightly poor predictability for exchangeable calcium and total sulfur. But only if the three medium elements have equal sampling density can this effect be achieved.

Selection of the optimal model

Spatial distribution of the universal Kriging interpolation method and BP artificial neural network model

The universal Kriging interpolation method and BP artificial neural network model are applied to predict the medium elements of forest soil, whose spatial distribution precast is as shown in Fig. 2-3, non-forest areas being not excluded, so the medium elements distribution covers the whole Yuncheng district and Yun′an district, but this paper only analyzes the distribution of the medium elements in forest soils.

It can be seen from Fig. 2 and Fig. 3 that the highest and lowest values of exchangeable calcium, exchangeable magnesium and total sulfur of the study area are distributed in a bulk manner both in the universal Kriging interpolation and BP artificial neural network. What’s different is that the spatial distribution trend predicted with the universal Kriging interpolation is not as obvious as BP artificial neural network. The distribution of exchangeable calcium displays a trend of first increasing then steadily decreasing and gradually increas-

Table 3 The correlation analysis between the universal Kriging interpolation method and the inverse distance interpolation method

Soil nutrient	The inverse distance interpolation method		The universal Kriging interpolation method	
	Modeling point	Verification point	Modeling point	Verification point
Exchangeable calcium	0.894**	–0.178	0.248*	–0.086
Exchangeable magnesium	0.922**	0.309	0.344**	0.322
Total sulfur	0.844**	0.136	0.315**	0.074

Note:“**” indicats a significant correlation at 0.01 level; “*” indicats a significant correlation at 0.05 level.

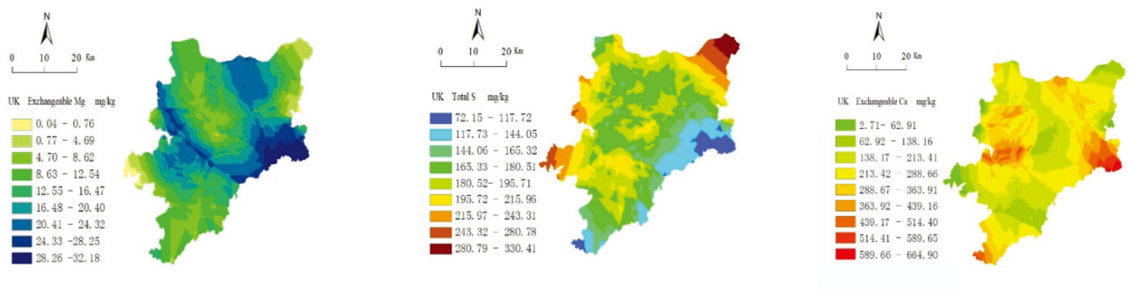

Fig.2 The space distribution of secondary element in forest soil in Yuncheng and Yun'an district by the universal Kriging interpolation method

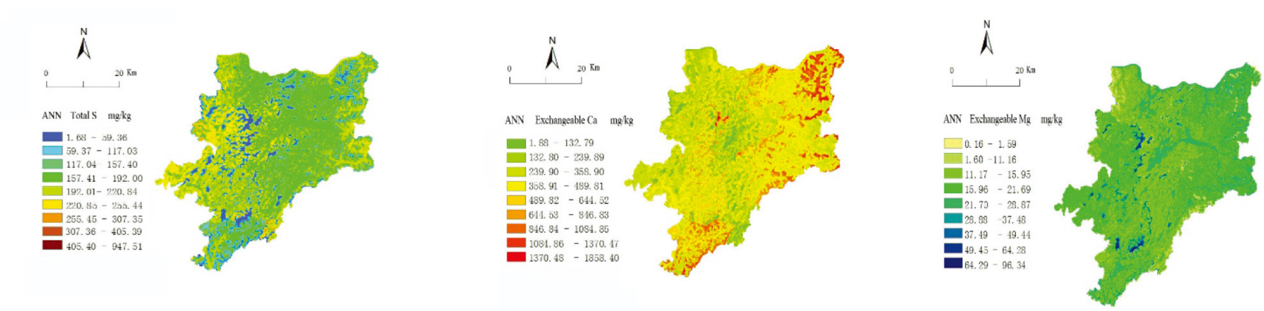

Fig. 3 The space distribution of secondary element in forest soil in Yuncheng and Yun'an district by the BP artificial neural network model

ing from west to east, the high-value zones are mainly distributed in bulk in the eastern and southern parts of the study area, a few being scattered in the northwest. The low-value zones are presented in an irregular belt manner crossing through the entire study area, and covered by the high-value zones in the east. The distribution of exchangeable magnesium offers a trend of first gradually decreasing and then increasing from west to east, with high-value zones scattered in the south and west; The distribution of low-value zones is striped from north to south crossing from the central through the entire study area; the total sulfur shows a trend of gradually decreasing and then rising from west to east, and most of the high-value zones are concentrated in the west. For the situation where the high-value zones cover the low-valued zones in the soil medium elements, it can be seen from the Google Earth satellite map that the two types of zones show marked topographical changes. Thanks to the differences in rainfall erosion, altitude, slope and so on, significant domain differences occur between the hill and slope toe. Li Qiquan et al (2013) found in the prediction of soil nutrients of hills that BP artificial neural network could better reveal the complex relationship between soil nutrients and environmental factors under complex terrain conditions in hilly areas. BP artificial neural network model can reflect the detailed information of the detailed terrain changes when carrying out soil nutrient predictions.

Comparison of correlation significance between the universal Kriging interpolation method and the BP artificial neural network model

The BP artificial neural network model and the universal Kriging interpolation method are used to analyze the prediction and the measurements of the three soil nutrient indexes (Table 4).

From Table 4, it can be inferred that the correlation between the modeling point and verifications of the universal Kriging interpolation method is reflected as: a significant correlation between the two of exchangeable magnesium and total sulfur (α = 0.01), the two of exchangeable calcium (α = 0.05), the two of total sulfur (α = 0.01), the two of exchangeable magnesium and exchangeable calcium (α = 0.05) as well as the two of

Table 4 The correlation analysis between the universal Kriging interpolation method and the BP artificial neural network

Soil nutrient	The universal Kriging interpolation method		The BP artificial neural network	
	Modeling point	Verification point	Modeling point	Verification point
Exchangeable calcium	0.248*	–0.086	0.290*	0.771**
Exchangeable magnesium	0.344**	0.322	0.278*	0.520**
Total sulfur	0.315**	0.074	0.370**	0.699**

Note: "**" indicates a significant correlation at 0.01 level; "*" indicates a significant correlation at 0.05 level.

the predicted values and the measured values ($\alpha = 0.01$). The BP artificial neural network model is optimal for the prediction of exchangeable calcium, exchangeable magnesium, and total sulfur content. Based on the correlation analysis, the BP artificial neural network model shows the optimal prediction for the soil exchangeable calcium, exchangeable magnesium, and total sulfur.

From the perspective of correlation analysis, the universal Kriging interpolation method can achieve the current known accuracy and spatial distribution map for the prediction of the study area beyond the sampling area only when it's placed under the same sampling density. The BP artificial neural network model has studied and trained the soil samples in the study area at the early stage, plus its associative memory function, it has had the "reasonable" rule of actual cases (Wang et al.2006), so it can predict with no sample data for the spatial distribution of the study area beyond the sampling area (especially the study area with similar environmental conditions). The BP artificial neural network model has no such strict requirements for the sampling samples as the universal Kriging interpolation method. Therefore, the BP artificial neural network model is the optimal model in this experiment.

Conclusion and discussion

This experiment is only for different methods and models of space prediction for the content of middle elements such as exchange calcium, exchange magnesium and total sulfur in the forest soil. It can be seen from the spatial interpolation model precision table that the optimal interpolation methods of the modeling point and the verification point are different, which indicates the optimal interpolation methods of different soil elements are not the same. This is consistent with Wang et al. (2000) in the interpolation prediction of soil potassium, which shows that the accuracy of the universal Kriging interpolation method is higher than that of spline interpolation and inverse distance weighted interpolation. Based on the three methods of multiple linear regression, the regression Kriging and ordinary Kriging, Shao et al. (2015), predicts the total nitrogen content in the soil of Hainan island. The result is consistent with the optimal ordinary Kriging interpolation method. Therefore, different elements should be used to interpolate with the appropriate method. However, from the practical application perspective, if the predicted soil nutrient species increase, it will increase the actual cost by looking for the best method to interpolate. As a result, in terms of the prediction of soil nutrients, it is necessary to find a highly promotional, highly predictive methods or models to solve this problem.

The number of samples in this experiment is 100, and the comparison of the optimal sampling number is not carried out, and the number of samples is directly related to the prediction accuracy. In theory, increasing the sampling density and the number of soil samples is the best choice for improving accuracy, but this is not the most viable option in practice. In the study of sampling methods, it is found by Li (2015) that soil sampling is a long-time, overloaded, and funds consumption process subject to weather and time constraints. Under the premise of obtaining a representative soil samples without increasing the sampling density as far as possible can really solve the problems that science of soil is currently facing. Therefore, the optimal sampling number and prediction accuracy of soil samples are the difficult problems to be overcome in the future.

The result shows that: (1) Among the 100 soil samples collected, the content of exchange calcium in the whole study area is relatively high, and the sequence is: exchange calcium> total sulfur> exchange magnesium; (2) In addition, in terms of variable coefficient of nutrients, the exchange calcium in Yun'an district belongs to strong variability and the other two elements belong to the middle variation, indicating that the spatial distribution of exchange calcium in the soil is uneven, and that of the other two elements in the soil is relatively stable. (3) Among the three interpolation methods, the universal Kriging interpolation method is superior to the inverse distance interpolation method, but it is better only for predicting the exchange magnesium, and the prediction of the exchange calcium and total sulfur is poor.

The result shows that the BP artificial neural network model is the best by comparing the correlation between the universal Kriging interpolation method and the BP artificial neural network model predictive value and the measured value. In other words, in the future forest soil survey, predicting the studying areas outside the sampling point, especially in similar environmental conditions without soil samples will be necessary. And the trained BP neural network can be used directly to predict middle elements, which will greatly reduce the field sampling workload, improving the efficiency of forest soil survey, avoiding environmental disruption in the sampling, and making a significant role in environmental protection.

References

Brockerhoff EG, Jactel H, Parrotta JA, Quine CP, Sayer J (2008) Plantation forests and biodiversity: Oxymoron or Opportunity. Biodiversity and Conservation 17: 925-951

Chen HS, Liu DH, Liu GS (2010) Spatial variability of soil available calcium, available magnesium, and available Sulphur in Xiangcheng Tobavvo planting fields, Henan Province. Chinese Journal of Soil Science 41 (3): 582-589

Gui XC (2004) Realization of BP network and their applications in MATLAB. Journal of Zhanjiang Normal College 25 (3): 81-85

Hou JR, Yin Z N, Li W M, et al. Applied geostatistics [M]. Beijing: Geological Publishing House, 1998 (in Chinese)

Lee M (2009) Analysis of soil nutrient status and its relationship with tobacco lead quality in Guangodng tobacco growing areas. Journal of Anhui Agricultural Science 37 (2): 699-700

Li H (2008) Study of cubic splines interpolation in power exponent form. Beijing: Beijing Jiaotong University

Li MJ (2014) The different types of spatial variability of soil nutrients in Xunyang dam area. Xian: Shanxi Normal University

Li Q, Wang CQ, Zhang WJ, Yu Y, Li B, Yang J, Bai GC, Cai Y (2013) Prediction of soil nutrients spatial distribution based on neural network model combined with goestatistics. Chinese Journal of Applied Ecology 24 (2): 459-466

Li Y, Zhou YZ, Dou L, Du HY, Huang YH, Lai QH, Fan R, Du M, He X, Wei ZC (2010) Prediction and early-warning for health safety of lead in soil and vegetable system, the Pearl River Delta Plain, southern China. Geological Bulletin of China 29 (11): 1662-1676

Li ZJ (2015) Research of soil spatial heterogeneity and soil sampling method in karst area. Guiyang: Guizhou University

Liu JX, Zhou GY, Wen ZD, Chu GW (2001) Properties of surface soil on selected forest ecosystem affected by acid deposition in Guangdong. Agro-environmental Protection 20 (4): 231-234

Qian LG (2014) Based on GIS Fulin farm soil heavy metal spatial distribution of ecological risk assessment and. Yangzhou: Yangzhou University

Shang ZH, Qiu SJ (2004) Causes of water and soil loss in red weathered regolity regions of Guangdong province —— A Case Study of Wuhua County. Journal of Geological Hazards and Environmental Preservation 15 (4): 15-18

Shao N, Zhang RL, Zhang WL, Zeng JH, Fu CL, Xie LS, Xu AG (2015) Spatial prediction of soil total nitrogen by different methods in large scale—A case study of Hainan island. Soils and Fertilizers in China 2015 (6): 9-17

Shi WW (2013) The studies of forest soil nurtrient spatial variation in Guangxi. Nanchang: Jiangxi agricultural University

Wan HF, Yang GY, Zhou JM, Zhang TB, Luo w (2011) Processes, issues and propects in the development of soil science in Guangdong. Ecological Science 2011 (S1): 69-72

Wang CM, Gao YH, Zhang DW, He QJ, Lv Y (2013) Investigation and assessment of heavy metals in soil and plants from a sealed landfill in Zengcheng, Guangzhou, China. Journal of Agro-Environment Science 32 (4): 714-720

Wang FC (2009) The research on the evaluation and spatial variability of soil heavy metals and nutrients —— A casr stugy in Daxing District of Beijing. Beijing: the Capital Normal University

Wang HB, Zhang LY, Hu ZJ (2006) Theory on Artificial Neural Network and Its Application. Shanxi Electronic Technology 2006 (2): 41-43

Wang J (2008) Spatial distribution and pollution evaluation of heavy metal pollution soil beside highway based on GIS. Wuhan: Huazhong agricultural University

Wang K, Xu HW, Shi z, Bailey SJ, Jordan C (2000) Soil potassium spatial variability and comparison of several interpolation methods. Plant Nutrition and Fertilizer Science 6 (3): 318-322

Yao LX, Zhou XC, Peng ZP, Li GL (2006) Soil nutrient fertility in citrus orchards of Guangdong Province. Chinese Journal of Soil Science 37 (1): 41-44

Zhang HZ, Shi XZ, Yu DS, Wang HJ, Zhao YC, Sun WX, Huang BR (2008) Spatial prediction of soil temperatures in China using different methods. Geographical Research 27 (6): 1299-1307

Zhao LR (2010) Spatial variability of soil nutrients under different parent materials. Chongqing: Southwest University

Zheng HD, Xiao HL, Ye XY, Zheng XJ (2001) Soil problems occurring in the economic development of Guangdong and the tactics of resolution. Soil and Environmental Sciences 10 (3): 230-233

Zhu DM (1999) Study on structure learning algorithm and problem solving of artificial neural network. Beijing: Institute of computing technology, Chinese Academy of Sciences