APPLICATION OF ALGEBRA HYPER-CURVE NEURAL NETWORK IN SOIL NUTRIENT SPATIAL INTERPOLATION

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ABSTRACT

Study on spatial distribution and interpolation method of soil nutrient is the basis of soil nutrient management in precision agriculture. For study on application potential and characteristics of algebra hyper-curve neural network in delineating soil properties spatial variability and interpolation, total 956 soil samples were taken for alkaline hydrolytic nitrogen measurement from a 50 hectares field using 20m*20m grid sampling. The test data set consisted of 100 random samples extracting from the total 956 samples, and the training data set was extracted from the other samples using 20m*20m, 40*40, 60m*60m, 80m*80m, 100m*100m and 120m*120m grid sampling respectively. Using algebra hyper-curve neural network model, three training plans were designed including plan AHC1 using spatial coordinates as the only network input, plan AHC2 adding 4 neighboring points' information as network input and plan AHC3 adding 6 neighboring points' information as network input. Comparing interpolation precision using algebra hyper-curve neural network method with Kriging method, following conclusions can be reached: when the number of training samples is bigger, interpolation precisions between Kriging and algebra hyper-curve neural network were similar; when the number was smaller, the precisions of both methods declined. Since algebra hyper-curve neural network method has no request of data distribution, it is non-linearization of neutron input variables and more suitable to delineate spatial distribution of soil properties which are nonlinear also. Furthermore, algebra hyper-curve neural network has an advantage of model parameters adaptive adjustment which makes it effective for soil nutrient spatial interpolation. With comparisons of three indexes of mean absolute error $\overline{d}$, root mean square error RMSE, mean relative error $\bar{d}\%$ and the generated spatial distribution maps using different methods, results shown that it can not simulate the characteristics of soil nutrient spatial variability well using spatial coordinates as the only network input, and the simulation degree can be improved greatly after adding neighboring sample points' information, considering about the distance effect, as network input. When the number of samples was smaller, interpolation precision can be improve after proper increasing the number of neighboring sample points. Results also shown that evaluation on interpolation precision using conventional error statistic indexes was not complete, and the spatial distribution maps should be used as an important evaluation indexes.

Keywords: Algebra hyper-curve neural network, spatial interpolation, soil nutrients, spatial variability, Kriging interpolation

INTRODUCTION

The obvious difference of properties in same type of soil is an important feature of soil in a field. Even in an area in which texture of soil can be regarded as uniform, soil properties in different spatial locations are different. This is known as soil nutrient spatial variability (Xu Jiyan and Webster, 1983; Huang Shaowen and Jin Jiyun, 2001). In past, this variability was analyzed using traditional statistic method founded by Fisher. This method considered that samples were entirely independent and obeyed certain known probability distribution, so soil property spatial variability was delineated through calculating mean, standard deviation, variance and coefficient of variation of samples and conducting significance tests, which had some successful applications in soil research. However, recent research had found soil properties were not entirely independent spatially, but correlated spatially in some extent (Burrough, 1993). Obviously, study on soil property spatial variability for estimation of un-sampled points is the basis of soil nutrient management and scientific fertilization in precision agriculture.

Recent years, geostatistics method was widely used in quantitative analysis of soil nutrient spatial variability. However, application of Kriging interpolation method based on geostatistic has some important preconditions (Hou Jingru and Guo Guangyu, 1993). If these preconditions can not be satisfied in some cases, geosatistics can not be used reliably for spatial variability research (Yue Tianxiang and Liu Jiyuan, 2001).

Artificial neural network technology is a powerful tool to process nonlinear system which has been used in research of soil property spatial variability and achieved some ideal results (Shen Zhangquan, et al, 2004; He Yong, et al, 2004; Shen Zhangquan, et al, 2004; You Shucheng and Yan Tailai, 2000; T.P. Robinson and G. Metternicht, 2006). But these research work was based on back propagation (BP) neural network which is an algorithm developed from establishing configuration network of basic perceptron model. BP neural network, a multilayer feed-forward network with hidden-layer, is not useful in deciding the number of hidden-layer in multilayer network and the number of nodes in certain layer. Sometimes the number is decided based on experiences, so the design of network is not optimal. Moreover, there are still some problems with BP neural network such as low speed of learning and convergence, and the convergence can not ensure reach global minimum. Algebra hyper-curve neural network (AHCNN) develops basic perceptron model in terms of perceptron integrative function which adds some auxiliary units to basic perceptron model. These auxiliary units are quadratic value of each unit (i=1, 2, ⋯, n) in input vector of basic perceptron model, that is algebra hyper-curve neural network is non-linearization of neuron input variables. Therefore, algebra hyper-curve neural network is more ideal nonlinear computation tool suitable to delineate spatial distribution of soil properties which are nonlinear also. Furthermore, algebra hyper-curve neural network has an advantage of model parameters adaptive adjustment which, in some sense, overcomes the disadvantages of low learning speed and adjustment of many parameters in BP neural network (Liu Zhenyan and Wang Wansen, 2004).

In this article, algebra hyper-curve neural network model was used to analyze precision of soil nutrient spatial interpolation at conditions of different sampling density and adding neighboring sampling points' information as network input, and compared with algebra hyper-curve neural network with spatial coordinates as the only network input and ordinary Kriging method. Application potential and characteristics as well as problems of using algebra hyper-curve neural network in delineating soil properties spatial variability and interpolation were studied also.

MATERIALS AND METHODS

Materials

In this study, experimental base is located in National Precision Agriculture Demonstration Station in Xiaotangshang town, Beijing. Total 956 soil samples were collected from 0~20 cm plough horizon using 20m*20m grid sampling with Differential Global Positioning System (DGPS) at No. 1 50 hectares field in September, 2008. Each soil sample was mixed with 4 sample points' soil distributed on 10 meter diameter concentric circles and 1 sample point soil in the circle center. These samples were air dried and preserved in 24 hours after sampling. Then, nutrients of soil samples were measured after sieving.

The measurement results of alkaline hydrolytic nitrogen of soil using alkaline hydrolysis diffusion method were used as experiment data. In a diffusion container, as soil was hydrolyzed in alkaline condition, hydrolyzable nitrogen transformed easily into NH3 and was absorbed by H3BO3 after diffusion. Then NH3 in absorbing solution H3BO3 was titrated using standard acid, so content of alkaline hydrolytic nitrogen can be calculated.

In order to analyze precision of soil nutrient data interpolation using different interpolation methods at certain sampling precision, the total 956 sample points were divided into independent training data set with 856 sample points and test data set with 100 sample points. Field distribution consisted of entire training data set was Plan a, sampling interval was 20 m. Sampling points were extracted at the sample interval based on original field distribution. Plan b contained 217 sample points through interlacing extraction at horizontal and vertical direction and sampling interval was 40 m. Plan c extracted 107 sample points every two lines at horizontal and vertical direction and sampling interval was 60 m. Plan d extracted 57 sample points every there lines at horizontal and vertical direction and sampling interval was 80 m. Plan e extracted 44 sample points every four lines at horizontal and vertical direction and sampling interval was 100 m. Plan f extracted 28 sample points every five lines at horizontal and vertical direction and sampling interval was 120 m. The sample points' distributions of each plan were shown in Fig. 1.

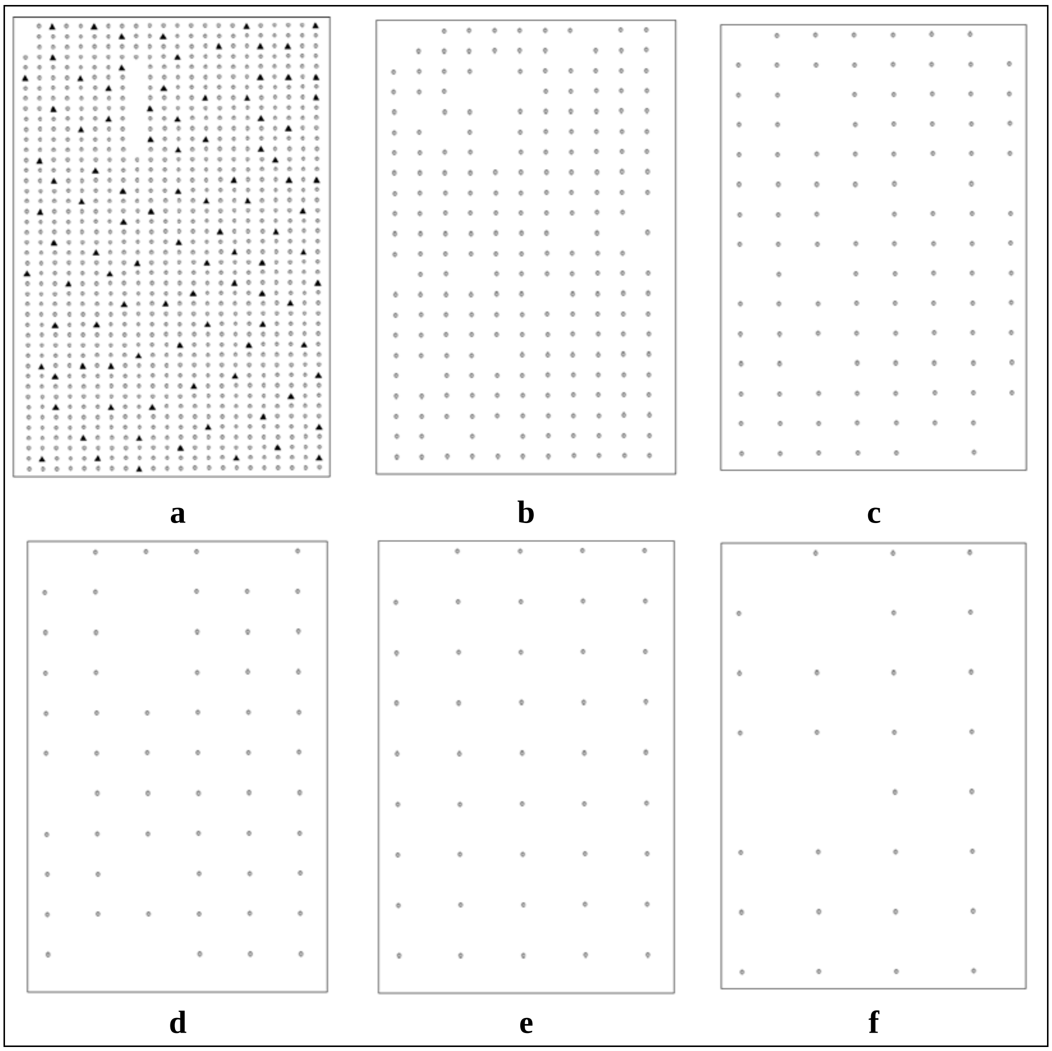

Fig. 1. The sample points' distributions of plan a to f. (.: training points ➤: test points)

Methods

Kriging

Firstly, skewness and kurtosis tests of training sample data were conducted. If it didn't obey normal distribution, then logarithmic transformation was used to make it obey lognormal distribution. Then, with semi-variance analysis, basic parameters for Kriging interpolation can be calculated by using theoretical semi-variance model with relative high fitting degree to fit semi-variance function. Finally, ordinary Kriging interpolation was finished in ArcGIS9.0.

Algebra Hype-curve Neural Network Method

Fig. 2 shown two-dimension algebra hype-curve neural network model. At the basis of two nodes x_1 and x_2 in input vector, three auxiliary input nodes f_1, f_2 and f_3 were added. The order of the two-dimension algebra hype-curve neural network model was 2, and the degree of polynomial was 2 also. Given $f_1 = x_1^{\ 2}$, $f_2 = x_1 \cdot x_2$ and $f_3 = x_2^{\ 2}$, the output of perception can be calculated through following formula:

$$\begin{aligned} Z &= f\left(\sum_{i=0}^{2} w_i x_i + w_3 f_1 + w_4 f_2 + w_5 f_3\right) \\ &= f\left(-w_0 + w_1 x_1 + w_2 x_2 + w_3 x_1^{\ 2} + w_4 x_1 x_2 + w_5 x_2^{\ 2}\right) \qquad (1) \end{aligned}$$

Hyperbolic tangent sigmoid function was used as transformation function at hidden-layer and linear function at output layer. Before training neural network with these training data, the [-1, 1] normalization processing of training data was conducted for fast convergence. The δ learning rules was used, which was continuous perceptron learning rule.

Method 1 (AHC1): With spatial coordinates' value as network input, the relation was established only between spatial coordinates and soil properties' information value which can be described using following formula:

$$Z = f\left(X, Y\right) \qquad (2)$$

In this formula, X and Y are spatial coordinates of sample point or predicted points. AHC neural network used X and Y as network input and corresponding soil properties' information value as network output, that is 2 nodes in input layer and 1 nodes in output layer .

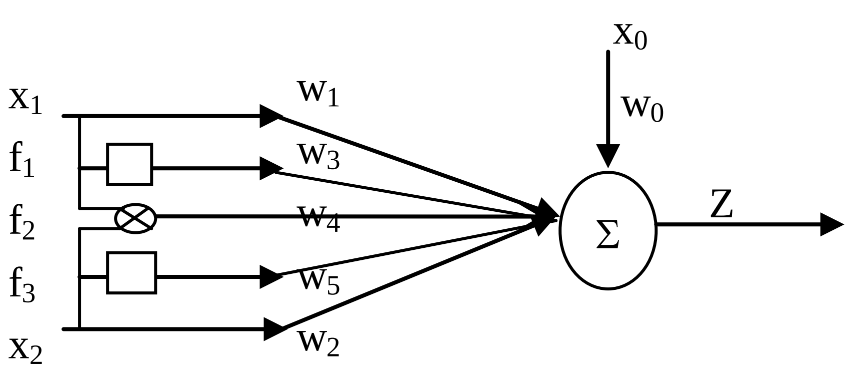

Fig. 2. Two-dimension algebra hype-curve neural network model.

Method 2 (AHC2): With spatial autocoorelation as theoretical basis (Zhu Huiyi, 2004), the function of soil nutrient spatial distribution can be expressed as following:

$$Z = f\left(X, Y, A_1, A_2, \cdots, A_n\right) \tag{3}$$

Where, Z is the value of soil property; X and Y are spatial coordinates; A_1, A_2, $\cdots$, and A_n are n values of soil property of sample points closest to interpolation point. The spatial coordinates X and Y, and the n sample points closest to the interpolation points were used as network input, so the number of nodes in network input was $2+n$ in which the first and second neurons are input coordinates X and Y respectively.

According to the spatial distance decay law, the effect of sample point on interpolation point declines as the distance between them increases. Considering about the effect of distance, in algorithm program the third neuron in network input layer was set as value of soil property of the sample point closest to the interpolation point, and the fourth neuron in network input layer was set as value of soil property of the sample point second closest to the interpolation point and so on. In this study, n was 4 and total nodes of network input layer was 6.

Method 3 (AHC3): In order to compare effects of different number of neighboring sample points on results of neural network interpolation, the interpolation results were calculated using 6 neighboring sample point data.

Evaluation on the Interpolation Precision

In this study, mean absolute error $\bar{d}$, root mean square error RMSE and mean relative error $\bar{d}\%$ were used to evaluate the interpolation precision. The three indexes can be calculated using following formulas:

$$\bar{d} = \frac{1}{n}\sum\left|\left(\hat{Z}_i - Z_i\right)\right| \tag{4}$$

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}\left(\hat{Z}_i - Z_i\right)^2} \tag{5}$$

$$\bar{d}\% = \frac{1}{n}\sum_{i=1}^{n}\frac{\left|\hat{Z}_i - Z_i\right|}{Z_i}\times 100\% \tag{6}$$

Where, $\hat{Z}_i$ is estimation value, Z_i is actual measured value, n is the number of training samples or test samples. Obviously, the smaller of $\bar{d}$, RMSE and $\bar{d}\%$, the smaller of error, and the better of interpolation precision.

RESULTS AND DISCUSSION

Comparison of interpolation precision of test data set using Kriging and algebra hyper-curve neural network based on test data set of different plans with different sampling intervals was shown as Table 1.

As shown in Table 1, when the number of training samples was bigger, interpolation precisions between Kriging and algebra hyper-curve neural network were similar. When the number was smaller, the precisions of plan d, e and f declined.

From the precision indexes listed at Table 1, following results can be deduced: With neighboring points as neural network input, interpolation precisions were improved using both AHC2 and AHC3 compared with using ACH1 in plan a, b and c when the number of training samples was bigger. However, when the number of training samples was smaller, interpolation precisions were declined using both AHC2 and AHC3 compared with using ACH1 in plan d, e and f. Meanwhile, the number of neighboring points such as 4 or 6 had little effect on interpolation precisions.

Table 1. Comparison of interpolation precision of test data set using Kriging and lgebra hyper-curve neural network (soil alkaline hydrolytic nitrogen, mg/kg)

Plan	Number of samples	Kriging			AHC1			AHC2			AHC3		
		$\overline{d}$	RMSE	$\overline{d}$%	$\overline{d}$	RMSE	$\overline{d}$%	$\overline{d}$	RMSE	$\overline{d}$%	$\overline{d}$	RMSE	$\overline{d}$%
a	856	6.37	8.14	8.52	8.52	10.30	11.05	7.66	9.43	9.86	7.14	9.04	9.30
b	217	6.92	8.84	9.33	8.38	10.27	11.27	7.21	9.40	9.78	7.45	9.69	10.10
c	107	7.21	9.18	9.55	8.49	10.13	11.04	7.93	9.93	10.44	8.02	10.04	10.67
d	57	7.89	10.01	10.68	8.47	10.48	11.59	10.49	12.50	13.95	10.45	13.31	14.16
e	44	7.10	8.94	9.60	8.68	10.95	12.06	10.75	13.94	14.50	10.45	13.46	14.28
f	28	7.62	9.49	10.24	9.12	10.85	12.09	8.73	11.25	11.73	9.65	11.78	12.39

Kriging interpolation for estimated value of alkaline hydrolytic nitrogen of 100 test sample points using different methods was finished and fitting results of alkaline hydrolytic nitrogen spatial distribution in soil were shown in interpolation maps. Comparison of interpolation results using algebra hyper-curve neural network and actual measurement data of plan c and f was shown in Fig. 3.

The simulation of alkaline hydrolytic nitrogen spatial distribution using AHC1 was fairly bad, as AHC1 was based on relation only between spatial coordinates and value of alkaline hydrolytic nitrogen in soil. The fitting degree of interpolation result spatial distribution was improved as adding the number of neighboring points, which was more obvious in plans with smaller number of training samples such as plan f.

Field nutrient precision management is very important in precision agriculture which is based on soil nutrient spatial distribution. So, ensure fitting precision of soil nutrient spatial distribution is the aim of research on scientific sampling and interpolation method. At this point, evaluation on interpolation using AHC1, which is based on relation between spatial coordinates and value of soil properties, is feasible according to conventional statistics; however, having little meanings in research of precision agriculture.

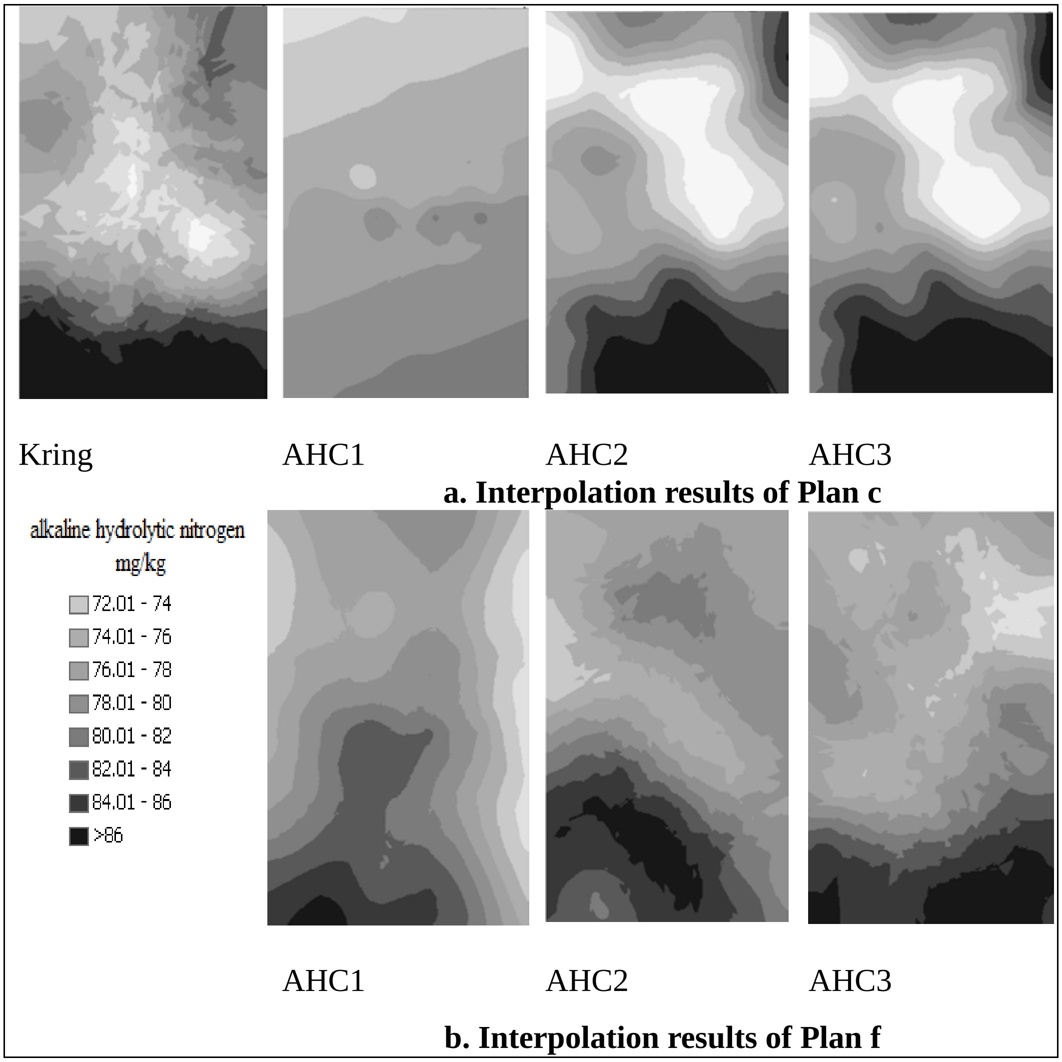

Fig. 3. Comparison of interpolation results using algebra hyper-curve neural network and Kriging method of plan c and f

CONCLUSIONS

1. Application of algebra hyper-curve neural network in research and interpolation of soil nutrient spatial variability is feasible and it has no special request of data distribution. Algebra hyper-curve neural network model is non-linearization of neutron input variables suitable for prediction of nonlinear system such as soil nutrient. In fact, the integrative function of algebra hyper-curve neural network model is a polynomial. The degree of this polynomial and the coefficient of each term can be obtained automatically through learning. Moreover, if network modeling was unsuccessful in lower degree, the degree of this polynomial can be raised using adaptive degree raising which is useful for fast determination of the order of algebra hyper-curve neural network model and higher efficiency of learning and modeling.

2. The precision of soil nutrient interpolation mode is determined by the reflection degree of this model on soil nutrient spatial variability and spatial

correlation, which means that the selected regression elements and interpolation elements should have high correlation degree (Mac Eachren and Davidson,1987; Fred and Paul, 1996). The selection of input parameters is very important in application of artificial neural network for soil nutrient spatial interpolation. Since there is no correlation between the value of spatial coordinates and the value of soil nutrient, the error would be great if using spatial coordinates of soil nutrient as the only input. Using ordinary error evaluation method, the error is relative small; but in terms of spatial interpolation map, the simulation of soil nutrient spatial distribution is fairly bad. So, conventional error statistic index such as RMSE can not be used as the only index for interpolation results' comparison. Compared with using spatial coordinates as the only network input, the simulation degree of soil nutrient spatial distribution was greatly improved using algebra hyper-curve neural network with auxiliary information of neighboring sample points as network input which considered about the distance effect. These conclusions agree with Li Qiquan et al.(2008)who concluded that the error of interpolation of three soil properties in an experiment field was greatly reduced when added the information of neighboring sample points, considering about the distance effect, as radial basis function neural network (RBFNN) input.

3. Certain noise data is allowable in algebra hyper-curve algorithm (i.e., not all sample in training sample set was used successfully in modeling), which can reduce the time of learning in one hand. In the other hand, modeling can be successful in lower degree and need no degree raising of polynomial, which reduces effect on the accuracy of model. More research work on anti-noise performance of algebra hyper-curve algorithm needs to be done in future. In terms of multi-source information fusion, nonlinear mapping relation between soil properties and neighboring sample point information, and soil forming factors such as parent material, terrain and climate can be established to delineate spatial distribution of soil properties using nonlinear computation ability and expansiveness of artificial neural network. This provides a solution for large scale study and accuracy improvement of research result. This provides a solution for accuracy improvement of research result.

ACKNOWLEDGEMENTS

This research was supported by The National Natural Science Foundation of China (30600375) and the National High Technology Research and Development Program of China (2006AA10A306, 2006AA10Z271). We would like to thank the National Experimental Station of Precision Agriculture of China.

REFERENCE

Burrough P. A. 1993. Soil variability: a late 20th century view. Soils and Fertilizers. Vol. 56(5): 529-562.

Fred C. Collins Jr. and Paul V. Bolstad. 1996. A Comparison of Spatial Interpolation Techniques in Temperature Estimation. http://www.ncgia.ucsb.edu/conf/SANTA_FE_CD-ROM/sf_papers/

collins_fred/collins.html.

He Yong et al., 2004. Interpolation method of field information based on the artificial neural network. Transactions of the Chinese Society of Agricultural Engineering. Vol. 20(3): 120-123. (in Chinese)

Hou Jingru and Guo Guangyu, 1993. The Theory and Practice of Statistical Prediction and Geostatistics for Mineral Deposits. Metellurgical Industry Press, Beijing, p325-327. (in Chinese)

Huang Shaowen and Jin Jiyun, 2002. Advance in Study on Spatial Variability of Soil Properties. Soils and Fertilizers. Vol (1): 8-14. (in Chinese)

Li Qiquan et al., 2008. Error Analysis of Soil Property Spatial Interpolation with RBF Artificial Neural Network with Different Input Methods. Acta Pedologica Sinica. Vol. 45 (2): 360-365. (in Chinese)

Liu Zhenyan et al., 2004. Research of Nonlinear Neural Network. Computer Engineering and Applications. Vol. 40(3): 42-44. (in Chinese)

Mac Eachren A. M and Davidson J. V., 1987. Sampling and Isometric Mapping of Continuous Geographic Surfaces. The American Cartographer. Vol. 14 (4): p299-320

Shen Zhangquan et al., 2004. Spatial Variety of Soil Properties by BP Neural Network Ensemble. Transactions of the Chinese Society of Agricultural Engineering. Vol. 20 (3): 35-39. (in Chinese)

Shen Zhangquan et al., 2004. Study on Spatial Variety of Soil Properties By Means of Generalized Regression Neural Network. Acta Pedagogica Sinica. Vol. 41 (3): 471-475. (in Chinese)

T.P. Robinson and G. Metternicht, 2006. Testing the performance of spatial interpolation techniques for mapping soil properties. Computers and Electronics in Agriculture. Vol. 50 (2): 97-108

Xu Jiyan and R. Webster, 1983. Optimal Estimation of Soil Survey Data by Geostatistical Method -- Semi-Variogram and Block Kriging Estimation of Topsoil Nitrogen of Zhangwu County. Acta Pedologica Sinica. Vol. 20 (4): 419-430.

You Shucheng and Yan Tailai, 2000. A Study on Artificial Neural Network Based Surface Interpolation. Acta Geodaetica et Cartographica Sinica. Vol. 29 (1): 30-34. (in Chinese)

Yue Tianxiang and Liu Jiyuan, 2001. Multi Sources Information Fusion Data Model. World Science-Technology R&D. Vol. 23 (5): 1-4. (in Chinese)

Zhu Huiyi et al., 2004. Problems of the Spatial Interpolation of Physical Geographical Elements. Geographical Research. Vol. 23 (4): 425-432. (in Chinese)