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EVALUATION OF SOIL SUITABILITY FOR CULTIVATION BASED ON BACK-PROPAGATION ARTIFICIAL NEURAL NETWORK: THE CASE OF JIANGXIA DISTRICT

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Abstract

In this paper, a model based on Back-Propagation (BP) artificial neural network was proposed, as a tool predict the soil suitability for cultivation in Jiangxia district. The model takes the soil nutrients indicators as the input and the level of soil suitability as the output. The correlation analysis showed that the correlation coefficient between expected output and actual training result is 0.99. The simulative results indicate that the learning and generalization ability of the model performed well and can adapt to different regions and requirements of samples. Hence, the model developed through the fully trained BP Neural Network can predict the level of soil suitability of Jiangxia district by a comprehensive evaluation leading to the value of 4, which means the nutrients content of soil in Jiangxia district is lower and make innapropriate the soil for for plants growth and development as it is, withouth supplements of nutrients.

Keywords: BP neural network, classification, Matlab, soil fertility, soil nutrients,soil suitability evaluation

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1. Introduction

Soil fertility can be defined as the ability of a soil to provide the substrate required for plants growth and development (Du and Zhou, 2009; Stockdale et al., 2002). Soil nutrients are the essential material foundation of soil fertility (Adjei-Nsiah et al., 2007; Izac, 2003). Because of the impact of natural and human factors, the nutrient levels which ensure soil fertility vary in different area. The spatio-temporal distribution features of soil nutrients affect the regional plants distribution, the composition and diversity of species and quality and quantity of the crop (Arnebrant et al., 1990; Neugschwandtner et al., 2017; Singh et al., 1989). The research on soil fertility is very complicated and cannot be measured directly, but can be evaluated via some soil properties (Bautista-Cruz, 2005).

Any classification of agricultural land suitability comprehensively reflects soil quality, soil workability and crop appropriateness. It is the most sensitive indicator mirroring dynamic change of soil fertility and productivity under the influences of human activities (Sanchez et al., 2003; Sicat et al., 2005). Nowadays, the Land Evaluation (LE) which was published by FAO (Food and Agriculture Organization of the United Nations) in 1976 has been the primary procedure used worldwide to address local, regional, and national land use planning. China had also published the classification standard of soil nutrients according to the second soil census in 1985. In either land suitability classification, it corresponds to evaluate a particular crop and the land-use option. Therefore, the level of agriculture land suitability classification determines the regional land-use option and can help famers on land management.

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For land suitability assessment, the development of relationships between the soil nutrients indicators and the soil suitability is the essential work. Hence, land suitability evaluation analysis serve as a first step towards developing an agricultural land suitability classification (De la Rosa et al., 2004). There are many scholars using the conventional evaluation methods to measure the soil fertility classification including Analysis Hierarchy Process (AHP), regression coefficient method and principle component analysis. For example, some scientists used the AHP method to evaluate the soil productivity for intensive agriculture in China (Nie et al., 2017; Zhang et al., 2004). Salehi et al. (2013) incorporate the fuzzy logic and AHP techniques to evaluate the soil fertility in Northen Iran. Halil et al. also used the AHP to determine suitable lands for agricultural in Turkey (Akıncı et al., 2013). The regression coefficient method and principle component method were widely used on soil quality assessment and precision soil management (Chang et al., 2001; Howard and Howard, 1990; Shepherd and Walsh, 2002; Swaine, 1996).

Some researchers also integrated the conventional methods with the Geographic Information System (GIS) and generated the land suitability maps. For example, Reshmidevi et al. (2009) presented a GIS-integrated fuzzy rule-based inference system for land suitability evaluation in agricultural watersheds. Davidson et al. (1994) used the Boolean and fuzzy set method and with the GIS as an aid to evaluate the land in Greece. Pereira and Duckstein (1993) put forward a multiple criteria decision-making approach with the GIS method to assess the land suitability. However, the conventional evaluation methods have the defects of narrow application range and human subjectivity and GIS technique also has limitation with the complex appraisal process, low efficient and only be used for specific environment.

In order to avoid the disadvantages of existing conventional methods, the BP neural network method was introduced to this field. There are some scholars who used the BP neural network method to study the soil water forecasting, soil erosion, and soil space variability (Kim and Gilley, 2008; Schaap and Bouten, 1996; Zhongyi, 2007). Ranmadan et al. (2005) applied the BP neutral network to predict the soil properties in environmental soil samples. Miao et al. (2006) used the artificial neutral network to identify the factors which influence the corn yield and grain quality variability.

There are also some hybrid intelligent model with neural network proposed to estimate the nutrient concentrations in a biological wastewater treatment process (Cemek et al., 2013; Huang et al, 2015; Huang et al, 2016; Huang et al, 2017; Zhang et al., 2016). Keramati et al. (2014) also used data mining classification techniques including Artificial Neutal Network to predict the customer churn. From the related literature reviews, it resulted that the BP neural network can by applied to perform an accurate and efficient evaluation of soil fertility. The model built with BP neural network has wide applicability. Therefore, in this paper, a BP neutral network model for agriculture land suitability evaluation is presented and applied for he evaluation of agricultural soil quality in the Jiangxia district of Hubei in China.

2. Methodology

Back-Propagation Neural Networks is one of the most popular algorithm within Artificial Neural Networks. It was first promoted by Paul Werbos in 1974 and was applied in Linnainmaa's AD by Paul Werbosin in 1982. Rumelhart et al. (1986) ultimately described in detail the methodology. BP algorithm was built based on the gradient descent method and repeats a two phase cycle: forward propagation and back propagation. In the forward propagation, the input vector is propagated forward through the network, layer by layer, until it reaches the output layer. The output of the network is then compared to the desired output, if the output layer cannot generate the expectative output, the error values will then propagated backwards. Through modifying each of the neurons, the output error will decrease. Reiteration will continue until the output error achieves the given minimum value (Gong and Liu, 2013). Fig.1 shows the topology of the BP neural network that includes an input layer, a hidden layer and an output layer.

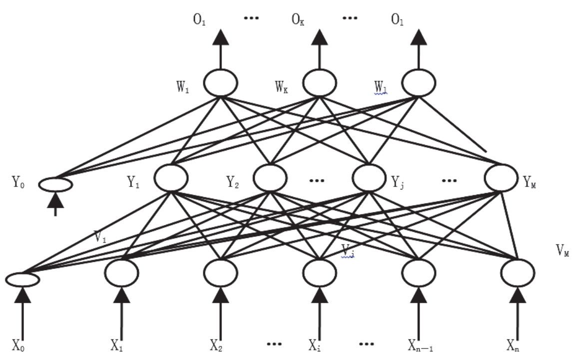

Fig. 1. Three-layered BP neural network model

The input vector is $X=(x_1,x_2,\cdots,x_i,\cdots,x_n)^T$, the output vector of hidden layer is $Y=(y_1,y_2,\cdots,y_j,\cdots,y_m)^T$,the output vector of output layer is $O=(o_1,o_2,\cdots,o_k,\cdots,o_l)^T$, and the expect output vector is $d=(d_1,d_2,\cdots,d_k,\cdots,d_l)^T$ 。The weight matrix between input layer and hidden layer represented symbolically by V, $V=(v_1,v_2,\cdots,v_j,\cdots,v_m)$. The weight matrix between hidden layer and output layer represented symbolically by $W=(w_1,w_2,\cdots,w_k,\cdots,w_l)$:

For output layer (Eqs. 1, 2):

$$o_k=f(net_k),\quad k=1,2,\cdots,l \tag{1}$$

$$net_k=\sum_{j=0}^{m} w_{jk}y_j,\quad k=1,2,\cdots,l \tag{2}$$

For hidden layer (Eqs. 3, 4):

$$y_j = f(net_j),\ j = 1, 2, \cdots, m \tag{3}$$

$$net_j = \sum_{i=0}^{n} w_{ij} x_i,\ j = 1, 2, \cdots, m \tag{4}$$

The activation function *f(x)* is sigmoidal function and can be expressed by Eq. (5):

$$f(x) = \frac{1}{1+e^{-x}} \tag{5}$$

When the output layer cannot generate the expectative output, the output error value can be expressed by Eq. (6):

$$E = \frac{1}{2}\sum_{k=1}^{l}[d_k - f(net_k)]^2 = \frac{1}{2}\sum_{k=1}^{l}[d_k - f(\sum_{j=0}^{m} w_{jk} y_j)]^2 \tag{6}$$

The input error value can be expressed by Eq. (7):

$$\begin{aligned} E &= \frac{1}{2}\sum_{k=1}^{l}\{d_k - f[(\sum_{j=0}^{m} w_{jk} f(net_j)]\}^2 \\ &= \frac{1}{2}\sum_{k=1}^{l}\{d_k - f[(\sum_{j=0}^{m} w_{jk} f(\sum_{i=0}^{n} v_{ij} x_i)]\}^2 \end{aligned} \tag{7}$$

Hence, the formulas of adjusting the weight are expressed by Eq. (8, 9):

$$\Delta w_{jk} = -\eta \frac{\partial E}{\partial w_{jk}},\ j = 0,1,2,\cdots,m; k = 1,2,\cdots,l \tag{8}$$

$$\Delta v_{ij} = -\eta \frac{\partial E}{\partial v_{ij}},\ i = 0,1,2,\cdots,n; j = 1,2,\cdots,m \tag{9}$$

Eqs. (1-9) constitute the basic BP algorithm. The minus sign in the function indicates that the gradient descends, and the constant $\eta \in (0,1)$ is the proportionality coefficient which represents the learning rate in training.

3. Case study

3.1. Regional overview

Jiangxia district (29° 58′ 05″ ~30° 32′ 18″ N, 114° 01′ 52″ ~ 114° 35′ 38″ E) situated in the Wuhan city, Hubei province and on the south bank of middle Yangtze proper. The total area is 201457.87 hm^2, and the farmland area is about 90813.90 hm^2. It features a subtropical monsoon climate with distinct seasons. An annual average temperature of the district is 16.7°C and the annual precipitation is 1260.5 mm.

3.2. Data sources

According to the location and area of administrative region, we collected 538 representative soil nutrients samples during spring and autumn of 2015, spread on the whole Jiangxia district. The collected samples can fully reflect the features of soil in Jiangxia district. The soil sampling depth is 0~20cm.

3.3. Soil suitability evaluation by BP neural network model

3.3.1. Selection of evaluation indicators

The essence of soil suitability evaluation is the pattern recognition problem, by compareing the simulation results of the model with the actual results of the evaluated system. The most relevant simulation result fitting with the actual result is the final recognition of the model accuracy. Measuring the soil nutrients needs to follow the corresponding grading standers. According to the Chinese soil fertility classification based on the second soil census as shown Table 1, this paper selects the available nitrogen, available P, available K, and organic matter as relevant soil suitability evaluation indicators.

3.3.2. BP Neural Network building

In the BP neural network topology, the number of hidden layers will directly affect the training performance of the network. Increasing the hidden layer can reduce network error, but it also complicates the network and increases the training time, so that a "over fitting" tendency. In general, it is easier to achieve the lower error and better training effect by increasing the number of hidden nodes than increasing the hidden layer number. Hence, the soil suitability evaluation model was designed as a three-layer BP neural network with an input layer, a hidden layer and an output layer. The nodes of input layer are decided by the practical issue.

There are four soil evaluation indicators in the classification standers, hence the nodes of input layer in the BP neural network is four. The output target of the model is the evaluation level of soil suitability, and the corresponding expected output values are '1','2','3','4','5','6'. The value equals '1' represents the highest level of the soil suitability evaluation which means the best quality of soil, by that analogy, the '6' stands for the lowest grade and means poor quality of soil.

Therefore, the node of output layer can be defined as one. The selection of nodes in hidden layer may influence the accuracy of the prediction of BP neural network. If the number of nodes in hidden layer was too small, it will reduce the forecast precision of model. If the number of node in hidden layer was too many, it will result in a longer training time and poor performance.

The formula about the selection of number of nodes in hidden layers is as follows (Eq. 10):

$$L = \sqrt{m+n} + a \tag{10}$$

According to the formula, the range of nodes in hidden layer is from 3 to 10.

Table 1. Chinese soil fertility classification standards

Evaluation indicator	***Rank***					
	I	***II***	***III***	***IV***	***V***	***VI***
Available Nitrogen（mg/kg）	>150	120~150	90~120	60~90	30~60	<30
Available P（mg/kg）	>40	20~40	10~20	5~10	3~5	<3
Available K（mg/kg）	>200	150~200	100~150	50~100	30~50	<30
Organic Matter（g/kg）	>40	30~40	20~30	10~20	6~10	<6

When the number of nodes in hidden layer is 6, the BP neural network training test showed that optimal result with highest speed and precision. Therefore, the topology of soil suitability evaluation based on BP neural network model can be determined that 4-6-1 and shown as Fig. 2.

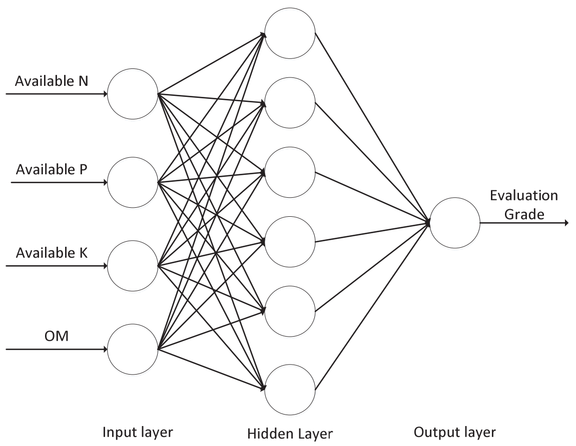

Fig. 2. Topology diagram of soil suitability evaluation BP network model

In order to ensure the non-linearization of BP neural network model, using sigmoid function from input layer to hidden layer and adopted the purlin function from hidden layer to output layer. The training function is trainlm.

4. Training and validation

4.1. BP neural network training

Using the formulated transfer function for the structure of soil suitability based on BP neural network model, we have evaluated the quality of 538 soil samples from Jiangxia district, from which we have selected 400 subsets for data training and the remaining 138 data as the test set. Setting the maximum number of iteration as 1000, the goal of error performance is 0.01, the minimum training rate is 0.01 and the dynamic parameter is 0.9.

By the command *input=mapminmax(input_train), output=mapminmax (output_train)* the training set was normalized; by the command *net=newff (inputn, output, 6,{'tansig' 'tansig'}, 'traingdx')* a feed-forward neural network was built; using the command *[net,tr]=train(net,inputn,outputn)* the training of model was performed. The command of *simout=sim (net, input_test)* performed the verification of the model.

The error performance of BP neural network training of shown in Fig. 3: after 11 iterations, the network can reach the level of expected error, which showed that the convergence speed of the model is fast.

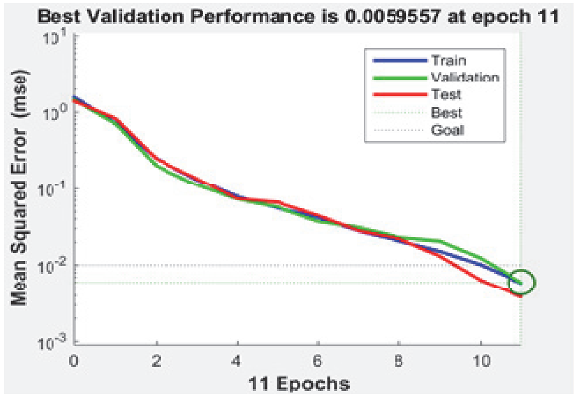

Fig. 3. The training error performance of soil suitability evaluation model

The regression data is shown in Fig. 4: the effect of regression between the expected responses and simulated output was significant, the coefficient of correlation is up to 0.9, which means that the model has resulted in high fit degree and can satisfy the forecast of the soil suitability evaluation.

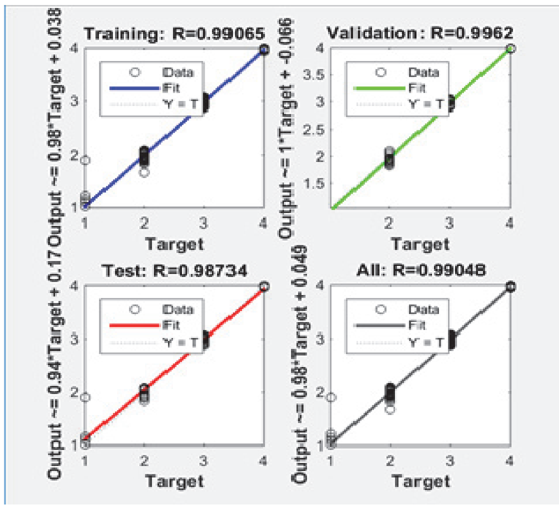

Fig. 4. Data regression of soil suitability evaluation model

4.2. BP neural network validation

We selected 138 samples from the 538 soil quality samples as the testing set. Using the four soil nutrients indicators of each sample as the input data we found the simulation outputs based on fully trained network evaluation model. The simulation result are shown in Fig. 5.

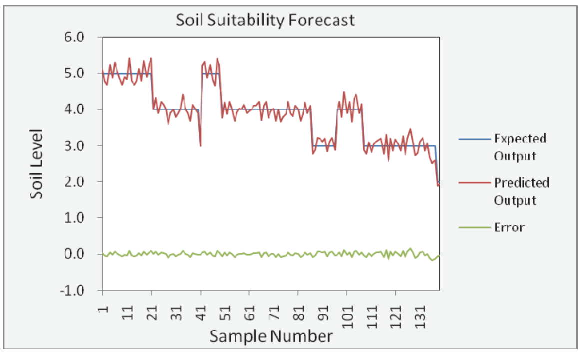

Fig. 5. Simulation result of the soil suitability evaluation forecast

5. Model result analysis

According to the simulation result of the model, the 138 samples from Jiangxia district can be divided into 6 levels. There are 2 samples belonging to the second class, 41 samples belonging to the third class, 60 samples belonging to the fourth class, and 28 samples belonging to the fifth class. Parts of the evaluation results are shown in Table 2.

Therefore, the overall soil suitability evaluation of the Jiangxia district is composed by medium suitability soil primarily, and some of the soil in exceptional areas has higher suitability. The evaluation results are shown as Table 2.

The correlation analysis showed that the correlation coefficient between expected output and actual training result is 0.99, which means the results have a high degree relationship and relative small error. Meanwhile, the result also showed that the model of soil suitability evaluation based on BP neural network has higher generalization ability, and can be adapted to different regions and requirements of samples. The error analysis is shown as Table 2.

6. Conclusions

In this paper, we build a BP Neural Network model for land suitability evaluation based on the soil nutrients classification standers and using the fully trained model simulated the soil nutrients of Jiangxia district.

The result showed that the model of soil suitability evaluation based on BP neural network has higher generalization ability, which can adapt to different regions and requirements of samples.

Table 2. Training result and Error analysis of the soil suitability evaluation model

No	*Available Nitrogen*	*Available P*	*Available K*	*Organic Matter*	*Expected Output*	*Training Result*	*Error*
1	118.9	41.6	149.0	24.83	3.0	3.968548	-0.0314518
2	126.0	23.0	73.2	29.40	4.0	3.999995	-5.08E-06
3	159.7	66.3	159.3	31.43	4.0	3.040568	0.04056753
4	118.9	34.0	138.6	28.69	4.0	3.040568	0.04056753
5	129.5	21.4	66.3	27.45	3.0	3.067595	0.06759483
6	212.9	20.3	73.2	35.17	3.0	3.999996	-3.79E-06
7	167.1	33.3	67.4	19.90	3.0	3.02383	0.02383044
8	115.3	43.4	338.4	26.82	4.0	2.103368	0.10336825
9	99.4	17.8	214.4	27.64	3.0	3.032711	0.03271091
10	79.9	19.9	100.7	20.29	2.0	3.03433	0.03433035
11	104.7	44.1	128.3	26.38	3.0	3.023164	0.02316419
12	113.6	26.1	80.1	31.91	3.0	3.999996	-3.95E-06
13	85.2	37.2	259.2	22.76	3.0	3.070627	0.07062739
14	108.2	40.8	152.4	26.55	4.0	3.954197	-0.0458025
15	97.6	43.2	214.4	22.29	3.0	3.999996	-3.94E-06
16	78.1	22.8	107.6	20.65	4.0	3.024385	0.02438463
17	108.2	14.9	49.0	35.62	4.0	3.954197	-0.0458025
18	159.7	17.4	49.0	45.96	3.0	3.024385	0.02438463
19	65.7	21.5	104.2	19.61	4.0	3.023164	0.02316419
20	115.3	35.8	117.9	24.28	3.0	3.032711	0.03271091
21	113.6	31.6	107.6	29.82	3.0	3.999995	-5.38E-06
22	69.2	32.9	341.9	17.18	3.0	3.999996	-1.0000039
23	145.5	17.0	38.7	39.07	4.0	2.952124	-0.0478759
24	126.0	27.5	107.6	34.76	5.0	3.024385	0.02438463
25	58.6	11.1	59.4	12.63	3.0	3.999996	-3.94E-06
26	63.9	10.4	62.8	16.58	3.0	3.067595	0.06759483
27	191.6	21.4	62.8	44.78	4.0	3.999995	-5.38E-06
28	127.8	25.7	131.7	31.16	3.0	3.034848	0.03484839
29	119.0	25.1	120.1	39.60	4.0	3.070627	0.07062739
30	152.6	27.3	100.7	45.97	3.0	3.999996	-3.96E-06

The level of soil suitability comprehensive evaluation of Jiangxia district is 4, which means the nutrients content of soil in Jiangxia district is lower and hard to be directly utilized. Hence, the evaluation results have a good reference value to government on the land management and also can give a good guidance to the farmers.

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