Preliminary note

Combination of Artificial Neural Network with Multispectral Remote Sensing Data as Applied in Site Quality Evaluation in Inner Mongolia

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Abstract

While abundant ground surface and site information is included in multispectral remote sensing data, traditional site quality evaluation system mainly uses artificial ground surface survey data. To construct an effective site quality evaluation system, this paper, with Wangyedian Forest Farm in Inner Mongolia as the object of study, has adopted an improved back propagation artificial neural network (BPANN) model based on a combination of multispectral remote sensing and surface survey data of the zone. With dahurian larch as an example, a neural network model based on a combination of remote sensing spectrum factor, site index and site factors has been constructed, which, applied in the site quality evaluation of sub compartments of the studied zone, has led to an optimized geographical position prediction model with an accuracy of 95.36%, and an increase of 9.83% as compared with neural network model based on traditional sub compartment survey data. The result indicates that multispectral remote sensing data is very suitable for forest site quality evaluation. Besides, the improved BP neural system features ideal accuracy of prediction, which testifies to the effectiveness and advantage of the methodology described in this paper.

Keywords: site quality evaluation, multispectral remote sensing, neural network

1. Introduction

The growth and productivity of forest is closely related to the environmental conditions of the site and their quality, hence better understanding and management of its health requires accurate knowledge of the relationship between environmental factors and forest growth. Site refers to the total of external environmental conditions, which considerably influence the growth and development of the forest within a given space and is constituted of four categories, namely: climate conditions, topographical conditions, soil conditions and biological conditions (Zhang et al. 1992, Meng 1996, Enset al. 2013). Site quality evaluation refers to the judgment and prediction of the suitability for forestry or potential productivity of a forest site, hence quantifying the productive potential of the land (Skovsgaard and Vanclay 2008, Bruce 1981).

The evaluation of site quality included two methods, direct evaluation method and indirect evaluation method. According to many researches, the most important and commonly used method is to use site index as an indicator to evaluated site quality (Zhang and You 1998). Site index was defined as the average height of dominant trees at the specific benchmark age in forest stand. However, using this indicator was extremely limited where the tree height could not be measured in non-forested land and of multiple tree species (Guo et al. 2012). Thus, the method of multivariate statistic mathematical modelling was adopted by Carmean, Louwa, Curt et al. to retrieve the relationship between site index and site factors, using site factors for indirect evaluation of site index. This method was extensively used as it has provided an effective solution for the difficulty in uniform evaluation of forested and non-forested land and of multiple tree species (Louwaand Scholes 2002, Carmean 1978, Curt et al. 2001, Farrelly 2011). However, many weaknesses in the design of analysis methods and the accuracy of prediction remain to be solved. For example, the use of stepwise regression analysis tends to incur biased estimation or ineffective prediction (Swenson 2005). Main component analysis method may effectively simplify the data structure, but the accumulated contribution rate of the first two main component factors is usually below 70% (Huang et al. 2006); while quantification theory applied analysis method enables effective handling of discrete property factors but relies on enormous data accumulated through long term observation (Waring 2006).

The above problems are either directly or indirectly resulted from the non-linear complicated relationship between various site factors. Artificial neural networks (ANN), on the other hand, have attracted much attention for their unique properties including self-organization, self-adaptation, self-learning and distribution parallel processing (Mutluet et al. 2012, López 2001, Francl and Panigrahi 1997). Especially, *BP* (backward propagation) neural network model, a type of feed forward neural network constituted by non-linear transfer function neuron, enables effective prediction function by adopting a learning algorithm of error backward propagation (Mutlu et al. 2012). However, few studies have been conducted in the application of neural network in site quality evaluation up to now. Luan Zhaoping has applied *BP* neural network in studying the extent of influence by various site environmental factors on the height of wild *Vaccinium uliginosum* (Luan 2011). Huang Jiarong et al. have chosen *Pinus massoniana* as an example in modelling the relationship between site factors and site index with the application of *BP* neural network for non-forested site quality prediction evaluation, with an average accuracy of 86.06%, higher than traditional multivariate regression model (Huang et al. 2006). All these site studies with *BP* neural network application have used traditional sub lot survey data, merely taking environmental factors of the site into consideration, without including bio vegetation factors, which most directly reflect site growth conditions into evaluation system, causing the prediction accuracy of the model to decrease. Meanwhile, most sub lot survey data are discrete non numerical data, causing convergence performance of model training and stability performance of prediction to deteriorate. Multispectrum remote sensing data include abundant ground surface bio vegetation information at low cost and with desirable availability, thus representing an improvement over the high demand for human and financial resources by traditional survey (Wu and Peng 2011, Niall et al. 2011). Ma Mingdong et al. have studied the correlation between remote sensing spectrum of plants and site index and established the site index inversion model of single vegetation index (Ma et al. 2006). However, the applicability of this method is constrained by the lack of universality of this estimation model semi-empirical formula, given the differences of surface and natural properties.

Therefore, for stable and effective forest site quality assessment, multispectral remote sensing data is introduced with 6 vegetation indexes closely related to forest productivity such as biological vegetation factor, which, combined with geographical topographical factor and soil factor, an improved *BP* neutral network with sensitiveness analysis and self-adapted *lr* decreasing gradient is applied in site quality evaluation. Four plans are proposed based on different combinations of neutral network models and input data sets in predicting the site index. Accuracy and effectiveness of each plan is then analyzed and assessed for an optimized result, aiming at providing a more effective method for forest site quality assessment.

2. Materials and methods

2.1 Background information of the study site and data retrieval

Wangyedian Experimental Forest Farm is located in the southwest of Kalaqin Qi in Inner Mongolia, Chifeng city at 118°09′–118°30′E, 41°21′–41°39′N with the central GPS coordinates 118.3825E, 41.5543N, between 500 and 1890 m above sea level with over 85% of its land classified as mountainous. The studied area is located in the mid temperate continental monsoon climate zone, with an average temperature of 6.2 ºC and 100–145 frost free days annually. Its soil types mainly include brown soil, cinnamon soil, meadow soil, black soil in mountainous area, among which brown soil covers most of the area. The annual hours of sunlight range between 2700 and 2900 hours, and main tree species include *Dahurian larch*, *Pinus tabuliformis*, *Birch*, *Populus davidiana*, *Xylosma racemosum*, etc. The name of the authority that issued the permit for each location is forestry bureau of Chifeng city in Inner Mongolia. We had a formal contract to help them to carry out forest inventory in Wangyedian Farm Land and they gave us the authority to publish any research articles using the sub lot data. In addition, there were no specific permissions required for these locations or activities. The field studies did not involve endangered or protected species.

According to the researches of site quality evaluation from Wu (2011), He (2012), Ma (2006) and Zhang (1998), *TM* remote sensing images were the traditional and best option for site quality study. Thus, the current research, with sub lot dominated by *Dahurian larches* as its object, uses *TM* images covering the area in April, 2010, with sun elevation angle of 64°, solar azimuth of 135°, with no enormous quantities of clouds or shadows guaranteeing desirable image quality. 1:10.000 topographical map is used for geometrical correction of image, with pixel root mean square error of 0.2, meeting the requirement for accuracy. Sub lot survey data, including site topographical information (altitude, aspect and slope) and soil information (soil type, soil thickness and humus layer thickness) with sub lot as unit of the studied area is also applied in the study.

2.2 Site information retrieval

The scope of the study presented in this paper is limited to Wangyedian Forest Farm, where site climate conditions show little fluctuation. Therefore, topography, soil and biology factors are dominating factors in influencing the forest site changes in the studied area. Factors of these three categories are selected in this paper, and site factors of the study area are retrieved with multispectral remote sensing data in combination with forest resource sub lot data, with sub lot defined as unit.

2.2.1 Spectrum information retrieval

As the band combination value of multispectral remote sensing data is closely related to the growth of ground surface vegetation, six representative vegetation indexes, i.e. difference vegetation index (*DVI*), ratio vegetation index (*RVI*), normalized difference vegetation index (*NDVI*), green vegetation information (*Gvi*), bright vegetation information (*Bvi*) and transformed soil adjusted vegetation index (*TSAVI*) are selected to retrieve the bio vegetation factors in the studied area.

⇒ *DVI* (Difference Vegetation Index)

This index indicates the difference between near visible light red band and infrared band values. For *TM* image, the calculation formula of *DVI* is:

$$DVI = TM_4 - TM_3 \qquad (1)$$

Where:

TM_4 near infrared band emission rate;

TM_3 red light band reflection rate.

This index effectively reflects the soil background of forest vegetation as well as changes in vegetation coverage (He 2012).

⇒ *RVI* (Ratio Vegetation Index)

Through gray scale ratio between near infrared band and red light band, this vegetation index expresses their difference in reflection rate. For *TM* image, the calculation formula of *RVI* is:

$$RVI = TM_4 \,/\, TM_3 \qquad (2)$$

RVI shows strong sensitivity towards green plants, while indicating significant correlation with forest parameters including biomass, leaf area index (*LAI*) and chlorophyll content, etc. (He 2012).

⇒ *NDVI* (Normalized Difference Vegetation Index)

For *TM* image, the calculation formula of *NDVI* is:

$$NDVI = \left(TM_4 - TM_3\right) / \left(TM_4 + TM_3\right) \qquad (3)$$

This vegetation index reflects the absorption of solar radiation by forest vegetation in photosynthesis as well as information of vegetation growth including vegetation growth rate (He 2012).

⇒ *Gvi* and *Bvi* calculated on the basis of *K–T* variation

$$Gvi = -0.284TM_1 - 0.243TM_2 - 0.543TM_3 + \\ + 0.724TM_4 + 0.084TM_5 - 0.180TM_7 \qquad (4)$$

$$Bvi = 0.303TM_1 + 0.279TM_2 + 0.474TM_3 + \\ + 0.558TM_4 + 0.508TM_5 + 0.186TM_7 \qquad (5)$$

Spectrum information of vegetation and soil is separated through *K–T* transformation, hence acquiring *Gvi* and *Bvi* components, which accurately reflect the variation in spectrum properties of forest vegetation and soil (Wu and Peng 2011).

⇒ *TSAVI* (Transformed Soil Adjusted Vegetation Index)

For *TM* image, the calculation formula of *TSAVI* is:

$$TSAVI = \\ = \left(TM_4 - TM_3 - 0.5\right) / \left(TM_4 + TM_3 + 0.5\right) \qquad (6)$$

By adding soil adjustment coefficient, this vegetation index has corrected the sensitivity of *NDVI* towards soil background, while explaining the characteristics of optical property variation of the background (He 2012).

2.2.2 Topography and soil information retrieval

Topography and soil information used in this study is retrieved from forest sub lot survey data. Eight properties, namely aspect, slope, elevation, soil type, soil thickness and humus layer thickness, are

Table 1 Sub lot

Sub lot ID	Aspect	Slope	Elevation, m	Soil type	Humus layer thickness	Soil thickness
283	Southeast	Mid slope	1300	Brown soil	4	Medium
281	Southeast	Level	1300	Brown soil	1	Medium
178	Northeast	Mild slope	1100	Brown soil	9	Medium
212	West	Slope	1200	Brown soil	3	Slight
9	South	Mid slope	1000	Brown soil	6	Thick
496	Northwest	Slope	1500	Brown soil	9	Medium
524	North	Slope	1000	Brown soil	9	Medium
826	Southeast	Steep slope	1500	Brown soil	3	Medium

retrieved from forest resource sub lot survey data sheet to constitute the *Dahurian larch* growth site information table; several examples are illustrated in Table 1 while all these site factors of 826 sub lots in this forest farm are presented in supplement data file.

3.1 *BP* neural network

In the light of the complicated non-linear relationship between multiple site factors and site quality, *BP* neural network (Back Propagation Neural Network), a multi-layer feed forward neural network capable of predicting based on multi scale data sources is adopted in this study.

As illustrated in Fig. 1, in multilayer feed forward network, the first layer is input layer, *L* layer is output layer, the mid layer is hidden layer. Suppose the neuron of layer l (l = 1, 2…, L) is the connection weight value of the *ist* neuron in layer l is $W_{ij}^{(l)}$ (i=1,2,…, n_l ; j=1,2,…, n_{l-1}), then the connection relation of this network is discovered.

$$x_i^{(l)} = f\left(S_i^{(l)}\right) = \frac{1}{1+e^{-S_i^{(l)}}} \tag{7}$$

i=1,2,$\cdots$, n_l ; j=1,2,$\cdots$, n_{l-1} ; l =1,2,$\cdots$,L

$$S_i^{(l)} = \sum_{j=0}^{n_{l-1}} W_{ij}^{(l)} x_j^{(l-1)} \left(x_0^{(l-1)} = \theta_i^{(l)}, \quad W_{i0}^{(l)} = -1\right) \tag{8}$$

Input and output samples of the given t group are set as $x_t^{(0)} = \left[x_{t1}^{(0)} x_{t2}^{(0)} \cdots x_{t,n0}^{(0)}\right]^T$, $d_t = \left[d_{t1} d_{t2} \cdots d_{t,\ na}\right]^T$ (t= 1, 2…, T).

BP network is trained with this sample set, and this process enables the relation mapping between input and output through learning and adjustment of weight

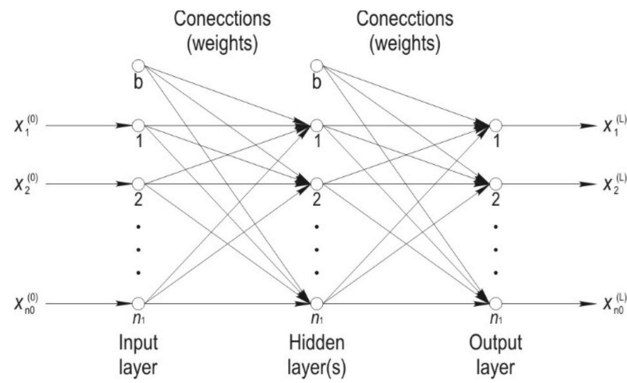

Fig. 1 Back propagation network structure

coefficient of network connection. The cost function is supposed as:

$$E_t = \frac{1}{2}\sum_{i=1}^{n_L}\left(d_{ti} - x_{ti}^{(L)}\right)^2 \tag{9}$$

For output layer *L*:

$$\frac{\partial E}{\partial W_{ij}^{(l)}} = \frac{\partial E_t}{\partial x_{ti}^{(l)}} \times \frac{\partial x_{ti}^{(l)}}{\partial S_{ti}^{(l)}} \times \frac{\partial s_{ti}^{(l)}}{\partial W_{ti}^{(l)}} = \\ = -(d_{ti} - x_{ti}^{(l)}) f'(S_{ti}^{(l)}) x_{ti}^{(t-1)} = -\delta_{ti}^{(L)} x_{ti}^{(L-1)} \tag{10}$$

Calculation $\delta_{ti}^{(L)}$ is conducted, $\delta_{ti}^{(L-1)}$ followed by the recurrence based on the above formula. The rest $\delta_{ti}^{(l)}$ and $\partial E_t / \partial W_{ij}^{(l)}$ may be derived by analogy. The expression $\delta_{ti}^{(l)}$ where recurrence continues until the total is calculated, contains derivatives $f'\left(S_{ti}^{(l)}\right)$. As $f\left(-\right)$ for *s* function is hypothesized, the derivative can be calculated as follows:

$$x_{ti}^{(l)} = f\left(S_{ti}^{(l)}\right) = 1/\left(1+e^{-S_{ti}^{(l)}}\right) \tag{11}$$

$$f'\left(S_{\mathrm{ti}}^{(\mathrm{l})}\right)=\frac{e^{-S_{\mathrm{ti}}^{(\mathrm{l})}}}{1+e^{-S_{\mathrm{ti}}^{(\mathrm{l})}}}=f\left(S_{\mathrm{ti}}^{(\mathrm{l})}\right)\left[1-f\left(S_{\mathrm{ti}}^{(\mathrm{l})}\right)\right]=$$

$$=x_{\mathrm{ti}}^{(\mathrm{l})}\left(1-x_{\mathrm{ti}}^{(\mathrm{l})}\right) \qquad (12)$$

On this basis the following network model is constructed:

$$W_{\mathrm{ij}}^{(\mathrm{l})}\left(k+1\right)=W_{\mathrm{ij}}^{(\mathrm{l})}\left(k\right)+\varphi D_{\mathrm{ij}}^{(\mathrm{l})}\left(k+1\right) \qquad (13)$$

$$D_{\mathrm{ij}}^{(\mathrm{l})}=\sum_{\mathrm{t=1}}^{\mathrm{t}}\delta_{\mathrm{ti}}^{(\mathrm{l})}x_{\mathrm{ti}}^{(\mathrm{l-1})} \qquad (14)$$

$$\delta_{\mathrm{ti}}^{(\mathrm{l})}=\left[\sum_{\mathrm{k=1}}^{\mathrm{n_{l+1}}}\delta_{\mathrm{k}}^{(\mathrm{l+1})}W_{\mathrm{ki}}^{(\mathrm{l+1})}\right]x_{\mathrm{ti}}^{(\mathrm{l+1})}\left(1+x_{\mathrm{ti}}^{(\mathrm{l})}\right) \qquad (15)$$

$$\delta_{\mathrm{ti}}^{(\mathrm{L})}=\left(d_{\mathrm{ti}}-x_{\mathrm{ti}}^{(\mathrm{L})}\right)x_{\mathrm{ti}}^{(\mathrm{L})}\left(1-x_{\mathrm{ti}}^{(\mathrm{L})}\right) \qquad (16)$$

$$l=L,\ L-1,\cdots,1;\ i=1,2,\cdots,n_1;\ j=1,2,\cdots,n_{\mathrm{l-1}}$$

With the method of universal approximation, approximation of any non-linear mapping relation is enabled.

3.2 Improved *BP* neural network

The improved neural network proposed in this paper is based on back propagation algorithm and, targeting at characteristics of the studied data sets, processing mechanisms of sensitivity analysis and self-adaptive *lr* decreasing gradient are introduced to filter out less influential factors, thus ensuring learning and convergence speed of the network.

As an excessive number of input data set shall result in excessive scale of neural network, sensitivity analysis algorithm is applied in this study for sorting the importance of properties of input data sets; therefore, by eliminating less important properties, a minimized and optimized data set is retrieved, enhancing the categorization accuracy and efficiency of neural network.

Model for Sensitivity Analysis (*SA*) can be expressed as follows: $y=f(x_1,x_2,\dots x_n)$, where x_i is the i^{th} property value of the model, sensitivity algorithm is the algorithm that allows each property to change within feasible scope of value, where the extent of influence of these changes on model output value is assessed and regarded as the sensitivity coefficient of such property. In sensitivity analysis, the quantified value of the relation between changes in input and changes in output is defined as sensitivity causal parameter (*SCP*). Suppose input vector is $\left[x_i\right]_1^{\mathrm{n}}$, where x_i is the i^{th} property of such input vector and *n* is the total number of samples. Therefore, for the output result *f*(*x*) of *BP* neural network, *SCP* is defined as follows:

$$SCP=\sum_{\mathrm{i=1}}^{\mathrm{N}}\left|f\left(x_{\mathrm{i}}\right)-f\left(x_{\mathrm{i}}+\Delta_{\mathrm{ij}}\right)\right|/N \qquad (17)$$

Where Δ_{ij} is the variation value and disturbed value in j^{th} component of x_{i}.

Based on sensitivity analysis, the properties showing weakest sensitivity in diversified forestry factor are excluded while the other properties showing strong sensitivity are preserved so as to reduce the number of dimensions of the original input data set, hence improving the training accuracy and efficiency of *BP* neural network.

The study adopts self-adaptive *lr* gradient descent method to adjust the learning speed during network training, hence accelerating the training speed of network and avoiding the problem of minimum. The algorithm procedures of this method are as below:

Step 1: check if the corrected value of weight reduced error function;

Step 2: if so, increase learning speed at fixed step (in which case the learning speed is insufficient);

Step 3: if not, decrease learning speed at fixed step (in which case the learning speed has been excessively adjusted);

Step 4: if new error value is lower than previous error value, increase learning speed at fixed step.

This mechanism ensures stable learning of the network at maximum learning speed, while maintaining descent error. Once excessive learning rate is the case, learning speed automatically reduces to maintain stability of error descent. The following equation is the self-adaptive *lr* descent adjustment model:

$$lr\left(k+1\right)=\begin{cases}1.05lr\left(k\right),\ SSE\left(k+1\right)<SSE\left(k\right)\\0.7lr\left(k\right),\ SSE\left(k+1\right)>1.04SSE\left(k\right)\\lr\left(k\right),\ other\end{cases} \qquad (18)$$

Where:

lr(k) learning step;

SSE(k) momentum factor.

Based on the above optimized algorithm and various site factors, four schemes are adopted in this paper for site index prediction using *BP* neural network. In this study, all of the schemes implementation and data analysis were completed with MatlaB 2010 software:

Scheme I: *BP* neural network + sub lot survey factors (*XB* factors, *XBF*): with topographical factors (elevation, aspect, slope) and soil factors (soil type, soil thickness, humus thickness) in traditional sub lot survey data as input data set, with site index selected as factor of output layer. Classic *BP* neural network is applied in prediction.

Scheme II: *BP* neural network + multispectral remote sensing bio factors (*RS* factors, *RSF*) + sub lot survey factors: Multispectral remote sensing bio factors (*DVI, RVI, NDVI, Gvi, Bvi, TSAVI*) are combined with topographical factors in traditional sub lot survey data (elevation, aspect, slope) and soifactors (soil type, soil thickness, humus layer thickness) as input data set, with status index selected as factor of output layer. Classic *BP* neural network is applied in prediction.

Scheme III: Improved *BP* neural network + sub lot survey factors: Output and input data sets are identical with Scheme I, with improved *BP* neural network applied in site index prediction.

Scheme IV: Improved *BP* neural network + multispectral remote sensing bio factors + sub lot survey factors: Output and input data sets are identical with Scheme II, with improved *BP* neural network applied in status index prediction.

4. Results and discussion

4.1 Sensitivity analysis

Sensitivity analysis is made on the basis of sub lot survey factor data set (hereinafter referred to as sub lot data set) and multispectral remote sensing biofactor + sub lot survey factor data set (hereinafter referred to as multivariate data set), wherein sub lot data set consists of six factors (elevation, aspect, slope, soil type, soil thickness, humus layer thickness) and multivariate data set consists of 12 factors (*DVI, RVI, NDVI, Gvi, Bvi, TSAVI*, elevation, aspect, slope, soil type, soil thickness, humus layer thickness). 100 groups of data are selected as training samples for sensitivity analysis to conclude the sensitivity of each factor in the two data sets, as illustrated in Fig. 2 and Fig. 3.

Fig. 2 shows that the sequential order of sensitivity of corresponding factors is: aspect, soil thickness, elevation, soil humus layer thickness, slope, soil type.

With the 1st and 2nd insignificant factors, namely soil type and slope factors removed, a filtered sub lot data set consisting of four site factors, i.e. aspect, soil thickness, elevation and soil humus layer thickness, is constructed, where the low sensitivity of soil type is the result of relatively uniform distribution of soil type in the studied area.

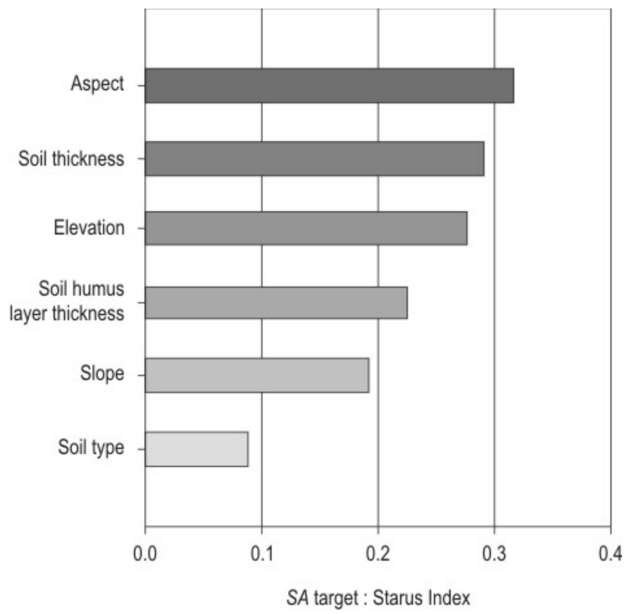

Fig. 2 Multivariate factor sensitivity analysis

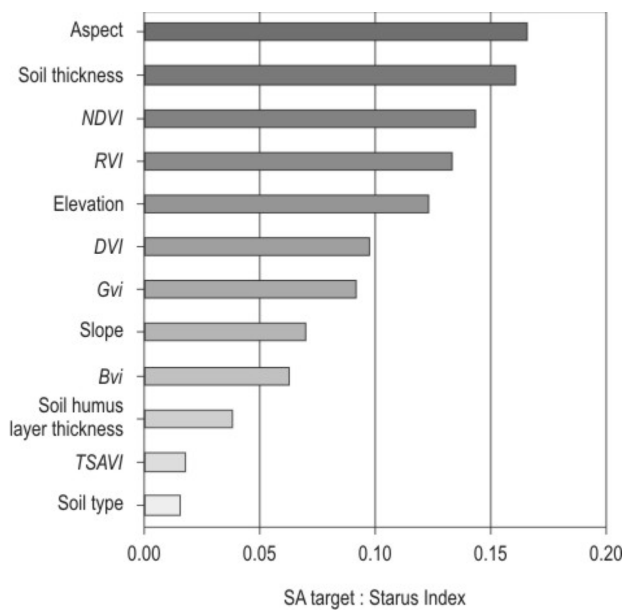

Fig. 3 Multivariate factor sensitivity analysis

Fig. 3 shows that the sequential order of sensitivity of corresponding factors is: aspect, soil thickness, *NDVI, RVI*, elevation, *DVI, Gvi*, slope, *Bvi*, soil humus layer thickness, *TSAVI*, soil type. Obviously, the vari-

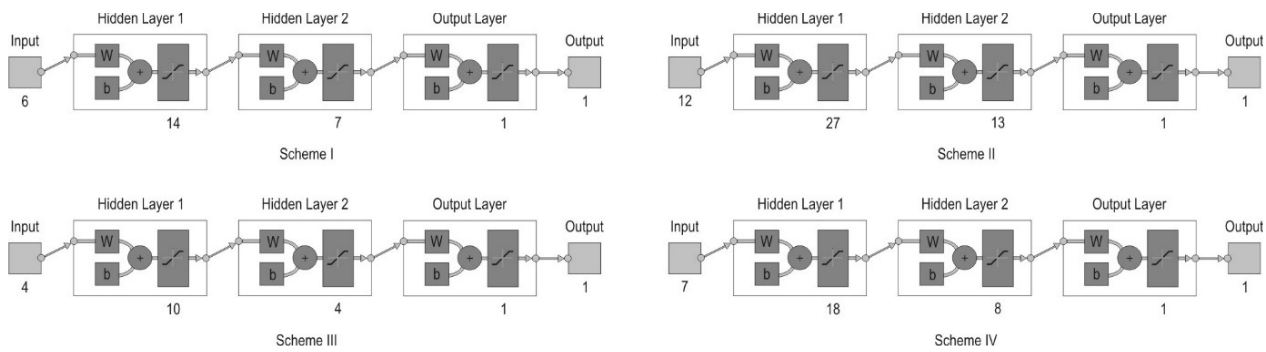

Fig. 4 BP neural network model of each scheme

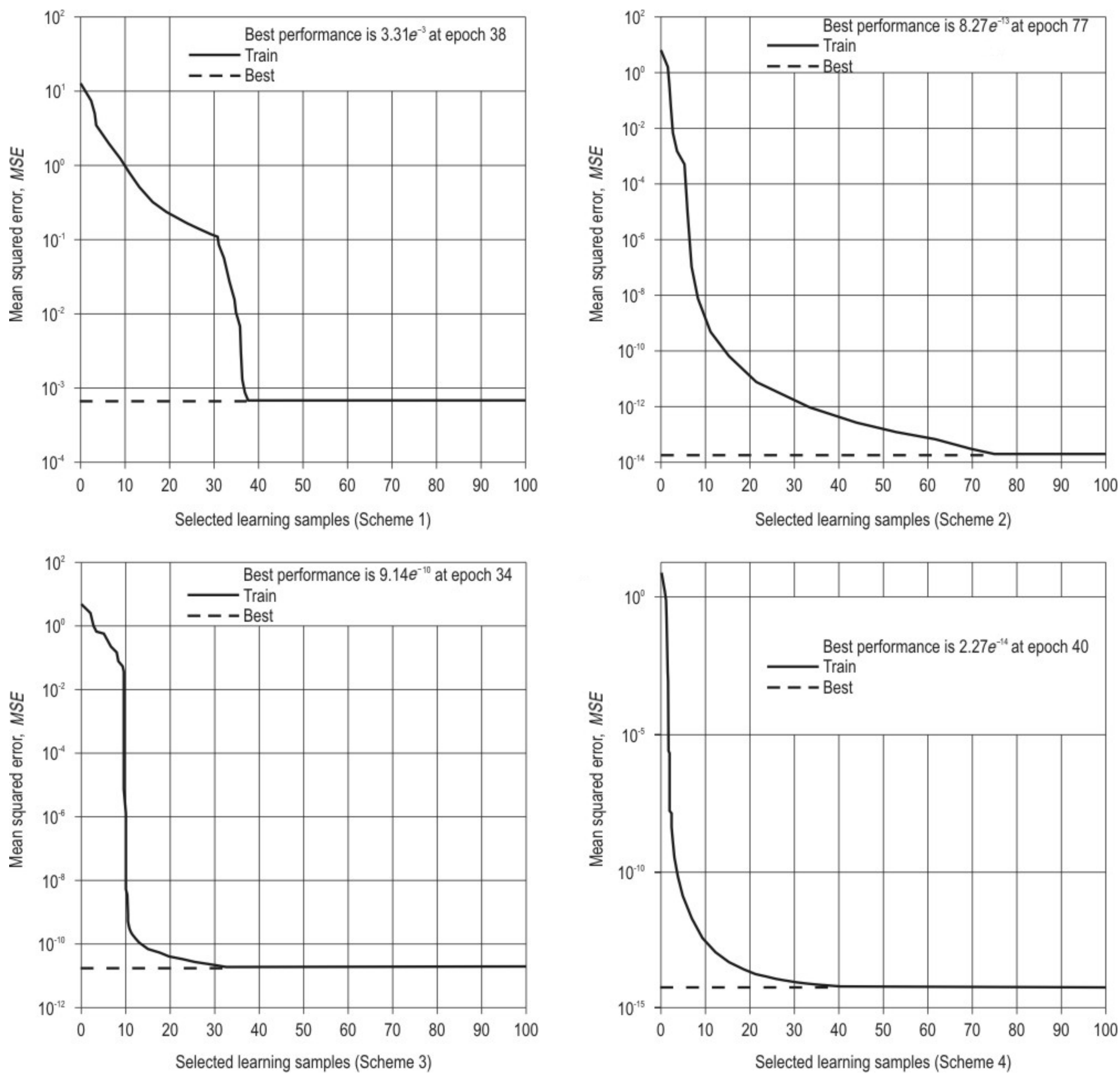

Fig. 5 Curve of training *MSE* for each scheme

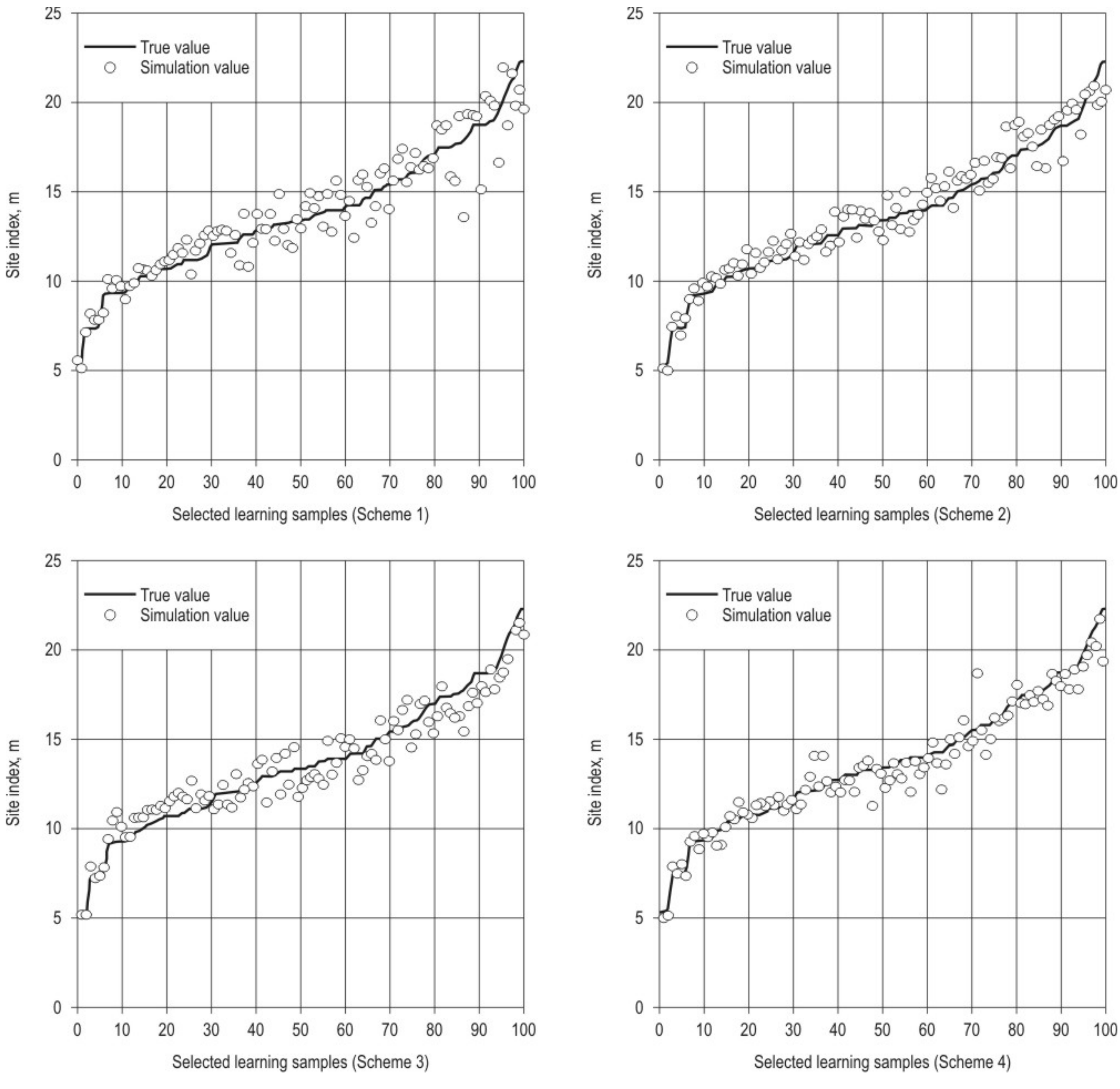

Fig. 6 Fitting curves of prediction accuracy

ous vegetation indexes acquired from multispectral remote sensing data show higher sensitivity.

With five factors: slope, *Bvi*, soil humus layer thickness, *TSAVI* and soil type, which show low sensitivity removed, a filtered multivariate factor data set is concluded, including aspect, soil thickness, *NDVI, RVI,* elevation *DVI* and *Gvi*.

According to the results of sensitivity analysis, the input data sets of Scheme III and Scheme IV were determined. Four sub lot survey factors were selected for Scheme III and seven multispectral remote sensing bio factors + sub lot survey factors were used for Scheme IV, separately (Fig. 4). The above sensitivity analysis mechanism has effectively removed factors with weak or no correlation, hence providing a solution to the redundant size and low efficiency of neural network, and improving the prediction efficiency and accuracy of neural network.

4.2 Parameter definition and modelling

As the prediction of site index essentially boils down to function fitting, therefore, an artificial neural

Table 2 Predicted results of comparison of four sc

Scheme	Datas	Model	*MSE*	Average accuracy, %
1	XBF	*BP*	3.31e^{-3}	85.53
2	*XBF+RSF*	*BP*	8.27e^{-13}	90.97
3	XBF	Improved *BP*	9.14e^{-10}	88.71
4	*XBF+RSF*	Improved *BP*	2.77e^{-14}	95.36
1	XBF	*BP*	3.31e^{-3}	85.53
2	*XBF+RSF*	*BP*	8.27e^{-13}	90.97

MSE means square error

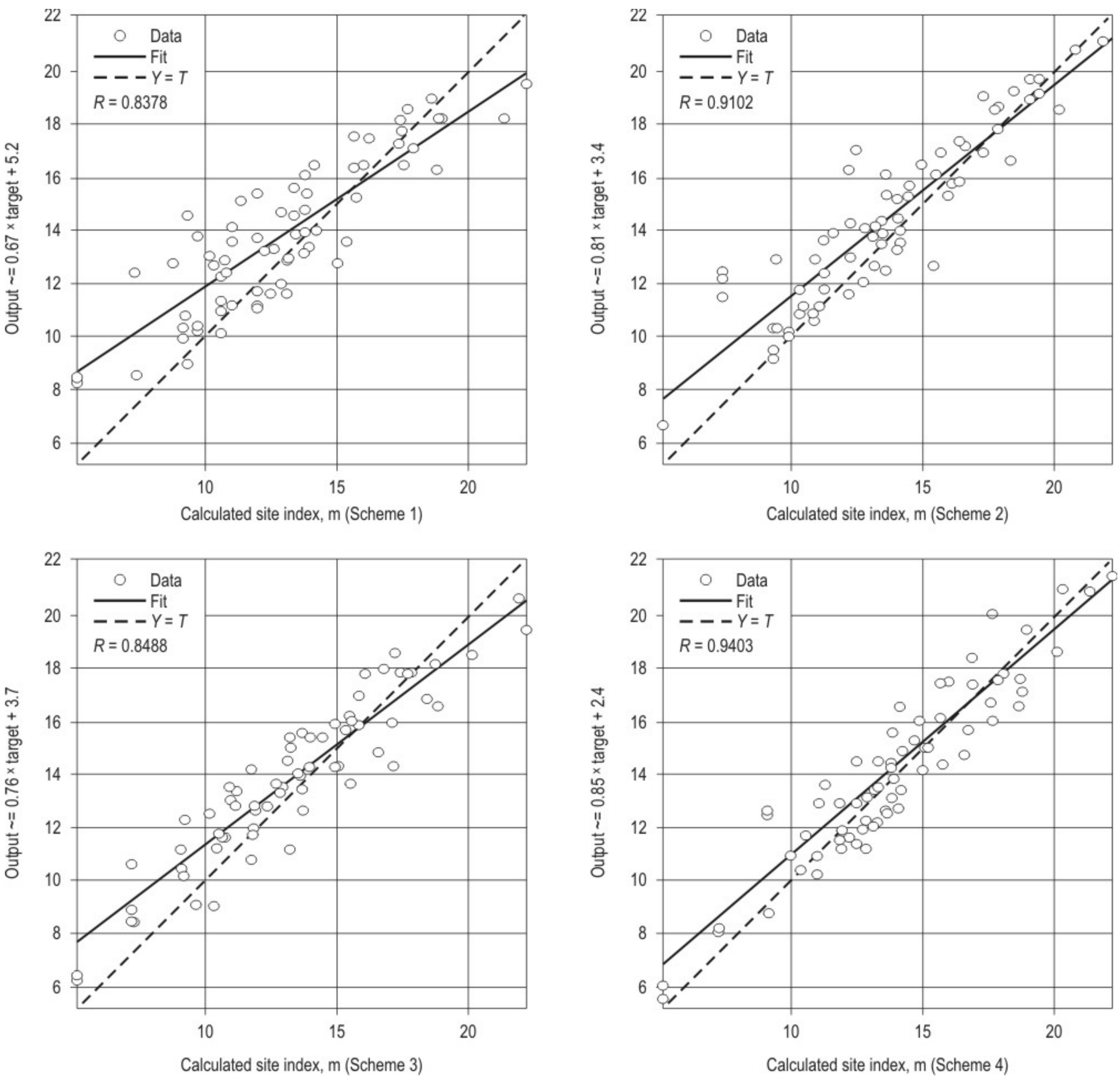

Fig. 7 Correlation analysis between predictive value and calculated value

network with 3 layer topology consisting of two hidden layers and one output layer is adopted in this study, where the constructed *BP* neural network model has selected 100 record entries from the above input data set as learning samples, while the number of neurons is adjusted based on the convergence of evaluation network training in order to determine the number of neurons of each hidden layer. To reproduce modelling results, random seeds are input in the neural network model of each scheme to determine the connection weight [1; 0; 0], connection bias [1; 1; 1] and layer connection weight [000; 100; 010] of the network. With Msereg as performance function and Initlay as initialization function, *BP* neural network models are illustrated in Fig. 4 based on the four schemes.

The above illustration shows that the hidden layer and output layer in each layer of neural propagation function of each model are both Tansig neurons.

4.3 Training result analysis

Training is conducted with network initial values set on the basis of the above parameters. Fig. 5 illustrates the error variation curves of the four schemes, from which the variation law between numbers of training and network output error of each scheme is determined.

It is seen that the training convergence speed of Scheme III and Scheme IV, where improved neural network is adopted, is obviously more desirable than Scheme I and Scheme II. Respective comparison of Scheme I and Scheme III, using the same category of input data set, shows that the optimal prediction accuracy of Scheme III is $9.14e^{-10}$, considerably higher than $3.31e^{-3}$ in Scheme I; while a comparison between Scheme II and Scheme IV shows that optimal prediction accuracy has increased from $8.27e^{-13}$ to $2.27e^{-14}$, proving the effectiveness of the improved neural network as proposed in this paper.

Fig. 6 and Fig. 7 illustrate the test results of 100 groups of data in the four schemes as well as correlation analysis of predictive value and calculated value.

Table 2 is based on a comparison of the results of the above neural network experiments.

Results of the four schemes are compared. From the perspective of input data set, the average prediction accuracy of Scheme II and Scheme IV has both exceeded 90%, significantly higher than Scheme I and Scheme III, indicating that the introduction of multispectral remote sensing biological factor shall significantly enhance the prediction accuracy of status index. Analyzed from the perspective of neural network application, the prediction accuracy of Scheme III and Scheme VI is 88.71% and 95.36%, respectively, a significant improvement from 85.53% and 90.97%, respectively, of Scheme I and Scheme II. Meanwhile, the model convergence speed of Scheme III and Scheme VI is 34 and 40, respectively, notably more desirable than 38 and 77, respectively. of Scheme I and Scheme II, proving that improved *BP* neural network applied in this paper features better prediction accuracy and learning performance. With the optimized scheme determined as above, where multispectral remote sensing data is combined with sub lot survey data applied, the site index of *Dahurian larch* sub lot in Wangyedian Forest Farm in Inner Mongolia is predicted using ArcGIS 10.2 software. Eventual prediction results obtained in this paper are compared with the test data and illustrated in Fig. 8. The legend of Fig. 8 presents the site index, which means the average height of dominant tree larches at the specific benchmark age in forest stand. All the test data of site index was provided by Wangyedian Forest Farm.

5. Conclusions

This paper studies the site quality assessment with multispectral remote sensing data combined with sub lot survey data of *Dahurian larch* in Wangyedian Natural Reserve in Inner Mongolia. Unlike the traditional method of using Richards growth function to build guiding curve model, *BP* neural network, which is capable of reflecting more complicated non-linear relationships, is used in the study to predict the site index. Meanwhile, based on the characteristics of forest resources data, an improved *BP* neural network model is proposed to improve the prediction accuracy of status index and training speed of network. To obtain the most effective site quality evaluation system, site index prediction is conducted by combining different input data set and neural network models in this study, formulating four site quality evaluation schemes, whose prediction accuracy and performance are compared and analyzed.

The study shows that among the four schemes, the *Dahurian larch* site index prediction model determined by improved *BP* neural network with multispectral remote sensing data plus sub lot survey data applied features highest prediction accuracy of 95.36%. While the topographical and soil factors in traditional sub lot survey data and classic *BP* neural network was applied in prediction, the prediction accuracy was only up to 85.53%, which means an increase of 9.83% was achieved. Meanwhile, a comparison between improved *BP* neural network and classic *BP* neural net-

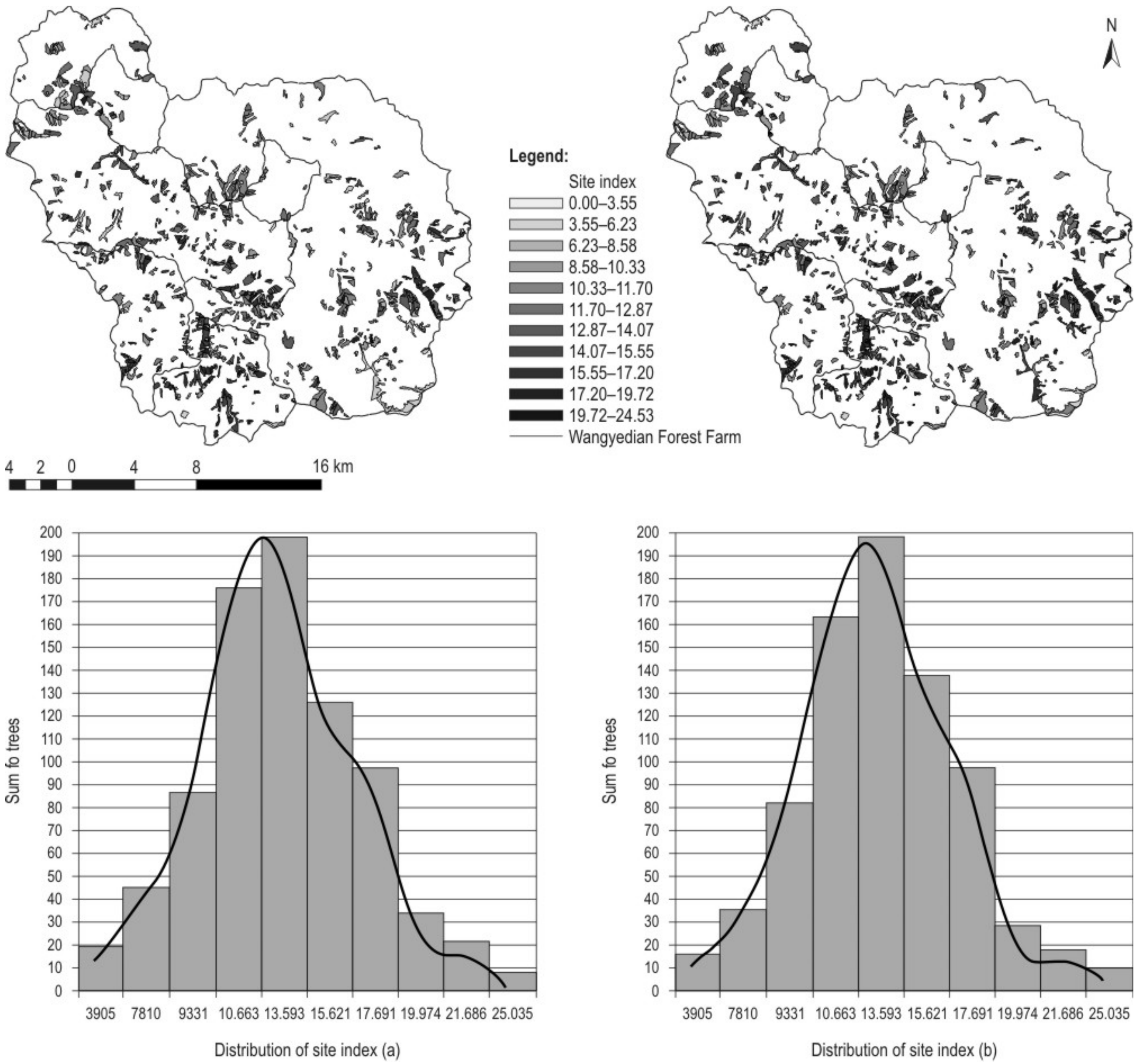

Fig. 8 Simulated results compared with test results; (a) is test result; (b) is prediction result

work indicates that the convergence speed of network training has effectively increased in improved *BP* neural network. The model convergence speed of Scheme III and Scheme VI is 34 and 40, respectively, notably more desirable than 38 and 77, respectively, of Scheme I and Scheme II.

Results of the study indicate that multispectral remote sensing data is highly applicable in forest site quality evaluation, as it has expanded the quantity of information on site factors, while ensuring sufficient time dimension with potentials for prediction over large areas, thus capable of providing effective evidence for forest site quality evaluation.

Further study shall develop a technical system of forest site quality evaluation fully based on remote sensing data, while using multispectral remote sensing data to retrieve soil and topographical factors of forests, hence reducing the cost for artificial sub lot survey, while increasing the extent and scope of forest site quality evaluation.

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6. Reference

Bruce, F., 1981: The use of overlays in site quality mapping. Canadian Journal of Forest Research 11(2): 362–370.

Carmean, W.H., 1978: Site index curves for northern hardwood sinnorthern Wisconsin and upper Michigan. New York, Department of Agriculture 3–18.

Curt, T., Bouchaud, M., Agrech, G., 2001: Predicting site index of Douglas fir plantations from ecological variables in the Massif Central area of France. Forest ecology and management 149(1): 61–74.

Ens, J., Farrell R.E., Bélanger, N., 2013: Effects of edaphic conditions on site quality for *Salix purpurea* »Hotel« plantations across a large climatic gradient in Canada. New Forests 44(6): 899–918.

Farrelly, N., Dhubháin, Á.N., Nieuwenhuisb, M., 2011: Site index of Sitka spruce (*Picea sitchensis*) in relation to different measures of site quality in Ireland. Canadian Journal of Forest Research 41(2): 265–278.

Francl, L.J., Panigrahi, S., 1997: Artificial neural network models of wheat leaf wetness. Original Research Article. Agricultural and Forest Meteorology 88(1–4): 57–65.

Guo, Y.R., Wu, B.G., Liu, Y., 2012: Research Progress of Site Quality Evaluation. World Forestry Research 25(5): 47–52.

Huang, J.R., Ma, T.X., Wang, Y.M., 2006: Forest site evaluation model studies on the basis of *BP* Neural Network. Journal of Mountain Agriculture and Biology 25(6): 479–483.

He, Z.H., Chen, X.X., Liang, H., 2012: Study of Remote Sensing Monitoring of Karst Basin Water-holding Dynamic Changing Based On Vegetation Indices Taking Guizhou Province as a Case. Territory&Natural Resources Study 4: 48–51.

López, G., Rubio, M.A., Martínez, M., Batlles, F.J., 2001: Estimation of hourly global photo synthetically active radiation using artificial neural network models Original Research Article. Agricultural and Forest Meteorology 107(4): 279–291.

Louwa, J.H., Scholes, M., 2002: Forest site classification and evaluation: a South African perspective. Forest Ecology and Management 171(1–2): 153–168.

Luan, Z.P., 2011: Study on growth site conditions of wild Benedict bilberry based on the *BP* neural network. Shandong Forestry Science and Technology 195(4): 11–16.

Ma, M.D., Jiang, H., Liu, S.R., 2006: The preliminary analysis of forest ecosystem site index using remote sensed data. Acta Ecologica Sinica 26(9): 2810–2816.

Meng, X.Y., 1996: Forest measurements. The second edition. Beijing: China Forestry Publishing House 99–106.

Mutlu, A.C., Boyaci, I.H., Genis, H.E., 2006: Prediction of wheat quality parameters using near infra-red spectroscopy and artificial neural networks. European Food Research and Technology 233(2): 267–274.

Niall, F., Áine, N.D., Maarten, N., 2011: Site index of Sitka spruce (*Picea sitch*ensis) in relation to different measures of site quality in Ireland. Canadian Journal of Forest Research 41(2): 265–278.

Skovsgaard, J.P., Vanclay, J.K., 2008: Forest site productivity: a review of the evolution of dendrometric concepts for even-aged stands. Forestry 81(1): 13–31.

Swenson, J.J., Waring, R.H., Fan, W., 2005: Predicting site index with a physiologically based growth model across Oregon. Canadian Journal of Forest Research 35(7): 1697–1707.

Waring, R.H., Milner, K.S., Jolly, W.M., 2006: Assessment of site index and forest growth capacity across the Pacific and Inland Northwest U.S.A. with a MODIS satellite-derived vegetation index. Forest Ecology and Management 228(1–3): 285–291.

Wu, J., Peng, D.L., 2011: Advances in researches on hyperspectral remote sensing forestry. Spectroscopy and Spectral Analysis 31(9): 2305–2312.

Wu, J., Peng, D.L., 2011: Tree Species information extraction of farmland returned to forests based on improved support vector machine algorithm. Spectroscopy and Spectral Analysis 31(4): 1038–1041.

Zhang, W.R., Sheng, W.T., Jiang, Y.X., 1992: Classification of Forest Site System in China. Forest Research 5(3): 251–262.

Zhang, X.L., You, X.X., 1998: Application of 3S Technology to Forest Site Type Classification and Site Quality Evaluation in Beijing. Journal of Remote Sensing 2(4): 292–296.

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