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Study on Site Quality Assessment of Afforestation Land Based on GA-RBF Neural Network

Chen Yuling, Wang Chengde, Wu Baoguo† and Liu Jiancheng
School of Information Science and Technology, Beijing Forestry University, Beijing 100083, China
†Corresponding author: Wu Baoguo

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ABSTRACT

The assessment of forest site quality at early stages of stand development is very essential for scientific afforestation and forest management. In order to enhance the accuracy of the existing models, a new site quality assessment model based on Genetic Algorithm-Radial Basis Function (GA-RBF) was proposed to predict site index (stand dominant height). Data used in this study came from 980 permanent sample plots for Chinese fir (*Cunninghamia lanceolata*) plantations in Fujian Province, China, which were randomly divided into the training dataset (786 plots) and the testing dataset (194 plots) with a ratio of 8:2. In this paper, the GA-RBF was compared with the radial basis function (RBF) and the traditional Quantitative Theory I (QT-I) method. The results indicated that the predicted accuracy was significantly increased by using the GA-RBF model. Furthermore, we used the existing site-specific site index table of Chinese fir to test the results of the GA-RBF and the agreement was 73.2%. Therefore, we recommend the GA-RBF for assessing site quality of afforestation land.

INTRODUCTION

Site quality assessment of afforestation land at early stages of stand development is very essential for scientific afforestation and forest management (Guo 2014, Bueis et al. 2016, Dau 2018). Site index (stand dominant height at a reference age, SI) is an important indicator to evaluate site quality and widely used because it strongly correlates to forest growth and yield (Mamo & Sterba 2006, McDill & Amateis 1992, Sharma 2017, Gonzalez-Benecke et al. 2017). Many researchers developed the dominant height model for forested land based on forest stand factors such as tree dominant height and tree age (Carmean 1975, Green 1989, Nothdurft et al. 2012, Yue et al. 2014, João 2017). However, forest site quality is usually estimated using site and stand factors, many studies examined the relationships between SI and site factors such as climate (Carlos 2017, Héctor 2018, Jiang et al. 2015, Mark 2017, Gonzalez-Benecke 2015), soil (Amuakwa-Mensah 2016, Rafael 2016) and topography (Stage & Salas 2007, Mitsuda & Ito 2015, Rafael 2016). Earlier attempts adopted a Quantitative Theory I (QT-I) method for both forested land and afforestation land (Chi 1995, Yang 2004). Due to the nonlinear and complex relationship between site factors, the estimation of QT-I may have biased estimation and low prediction accuracy. The artificial neural network (ANN) machine learning algorithm is easy to estimate the nonlinear relationship, and has the characteristics of fault tolerance, self-learning and self-adaptability. In forestry research, some studies have been performed and many different machine learning algorithms proposed. Huang (2006) and Gong (2013) used back propagation (BP) neural network model to evaluate the afforestation land. But the weaknesses of slow convergence speed, unstable fitting results and over-fitting of potential data, BP neural network have been rarely applied to site quality assessment of afforestation practice, making the traditional method always occupy a dominant position (Guo 2014). To solve the above problems, this paper introduced the Radial basis neural network (RBF) to improve. RBF, which takes the radial basis function as the basis of hidden layer neurons, has the advantages of strong generalization ability, fast learning convergence, and less computation. However, RBF is prone to fall into the local optimal solution (Yingwei 1998, Xiong 2015), while genetic algorithm as an optimization method imitating the biological evolution process has the ability to search for the global optimal solution (Maillard 1999, Cook 2000, Wu 2015). Genetic Algorithm-Radial Basis Function (GA-RBF) can combine the advantages of RBF and GA. The GA-RBF has not been used to derive the site quality assessment model.

The objective of this study was to develop a site quality assessment model to estimate SI for Chinese fir in Fujian Province using the GA-RBF.

MATERIALS AND METHODS

Data

Data for this study were collected from 980 National Forest

Inventory (NFI) permanent sample plots for Chinese fir plantations in the central and western Fujian Province. The data were randomly divided into the training dataset (786 plots) and the testing dataset (194 plots) with a ratio of 8:2. For each plot, the site measurement factors (Table 1) included landform (DM), elevation (HB), aspect (PX), slope (PD), slope position (PW), soil type (TRMC) and soil thickness (TCHD). The stand measurement factors included dominant species, stand age, stand height (HT) and stand diameter at breast height (DBH).

Due to the measurement of stand dominant height (HTT) was not included in the NFI plots. For site quality assessment, the HTT can more accurately reflect the production potential of sample plots. Therefore, we established 132 temporary sample plots to derive the HTT and the equation developed was: HTT = 3.048+0.932*HT ($R^2 = 0.967$).

Table1: The site overview of NFI permanent sample plots.

Site Factors	Description
DM	Middle Mountain; Low Mountain; Hills
PX	South, Southeast, Southwest, North, Northwest, Northeast, East, West
PW	Ridge; Uphill; Middle Slope; Downhill; Valley
PD (°)	4 (minimum), 49 (maximum),27 (mean), 7 (standard deviation)
HB (m)	41(minimum), 1114 (maximum), 443(mean), 90(standard deviation)
TRMC	Yellow Soil; Red Soil; Yellow-Red Soil
TCHD (cm)	10 (minimum), 250 (maximum), 98(mean), 20(standard deviation)

Note: DM is the landform; PX is the aspect; PW is the slope position; PD is the slope; HB is the elevation; TRMC is the soil type; TCHD is the soil thickness.

Methods

Quantitative Theory I (QT-I) Model

The site quality evaluation of afforestation land can be speculated by the forestland with the same characteristics of site factors. Quantitative Theory I (QT-I) Model is multiple regression analysis scheme for deducing the relationship between a quantitative variable and qualitative variables. In this study, the site factors were quantified by dummy variable method. Taking the dominant average height as dependent variables and the site factors and the corresponding age as independent variables, the quantitative theory I model was established (Li 2009) as follows:

$$y_t = \sum_{i=1}^{m} \sum_{j=1}^{k} X_t(i,j) b_{ij} + b_0 \mathrm{A} + \varepsilon_i \qquad \ldots(1)$$

Where, y_t denotes the stand dominant height from the plot t; $X_t(i,j)$ denotes the j^{th} categorical observation of the i^{th} site factor from the plot t; A is the stand age; b_{ij} is the coefficient of the $Xt(i,j)$; b_0 is the coefficient of the A; m is the number of site factors; k is the categorical index; and ε_i is an error term.

The entire manipulation procedure, including four steps, is described as follows:

Step 1: Initially, dummy variables were generated according to the categories of site factors. Data were divided into the training dataset (786 plots) and the testing dataset (194 plots) with a ratio of 8:2.

Step 2: The prediction equation of dominant height was developed based on the Equation 1 using the training dataset. Furthermore, the quantitative scoring table of site factors was derived.

Step 3: In order to scientifically and objectively evaluate the reliability of the prediction result based on the QT-I model, a *t*-test was conducted for the complex correlation coefficient and partial correlation coefficient of the equation.

Step 4: The standard age (20-year) of Chinese fir was substituted into the estimated Equation 1 to obtain the prediction of dominant height. Furthermore, the testing dataset was used to verify the accuracy.

Radial Basis Function (RBF) Neural Network Model

Radial Basis Function (RBF) used as the transformation function of the hidden layer of the neural network is a forward-looking neural network, which generally has three layers of network structure. RBF is not a global response function but a local response function, and is a non-negative linear function with radial symmetry and attenuation at the centre point (Fu 2017). The structure of RBF neural network is shown in Fig. 1.

Generally, the activation function of RBF can be expressed as Equation 2. In this study, self-organizing centre selection learning method was used to evaluate the quality of afforestation land. Gauss function (equation 3) was used as the RBF model.

$$R(dist) = e^{-\gamma dist^2} \qquad \ldots(2)$$

Where *dist* is the distance between the input vector x and the classification node c_i, i.e. $dist = x - c_i$.

$$R(x_p - c_i) = exp\left(-\frac{1}{2\sigma^2}\|x_p - c_i\|^2\right) \qquad \ldots(3)$$

Where $\|x_p - c_i\|$ is the Euclidean norm; c_i is the centre of Gaussian function; σ is the variance of Gaussian function.

Firstly, the RBF neural network which organizes the relationship between site factor and tree height is an unsupervised learning. By learning, the network can solve the

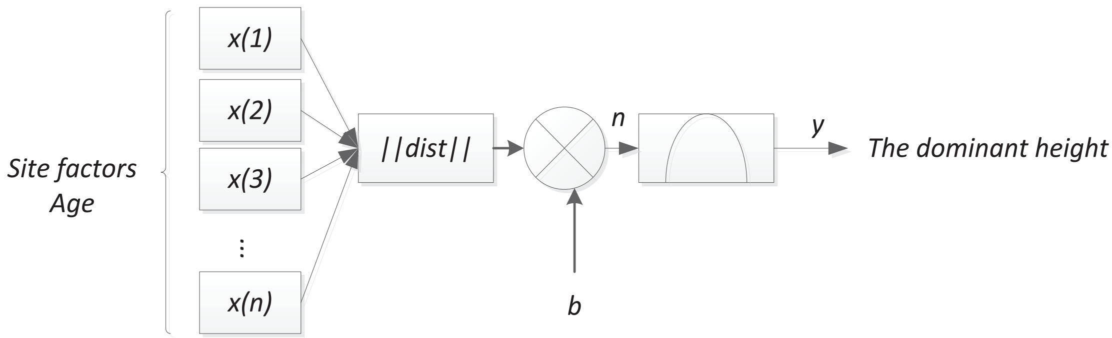

Fig. 1: The structure of RBF neural network.

centre and variance of the underlying layer basis function and determine the learning quantity. Secondly, the network was put into the process of supervised learning. The weight between the hidden layer and the output layer was obtained according to the centre and variance of the hidden layer basis function. The output expression of corresponding network can be expressed as Equation 4.

$$y_j = \sum_{i=1}^{h} \omega_{ij} exp\left(-\frac{1}{2\sigma^2}\|x_p - c_i\|^2\right) \qquad j = 1,2,3,\ldots,n \quad \ldots(4)$$

$$\sigma = \frac{1}{P}\sum\nolimits_j^m \|d_j - y_j c_i\|^2 \qquad \ldots(5)$$

Where, y_j is the jth output node of the network. The vector $x_p = \left(x_1^p, x_2^p, x_3^p, \ldots, x_m^p\right)^T$ is the pth ($p=1,2,3\ldots,N$) input sample, and it represents the vector of the site factor from each plot. N is the total number of samples. c_i is the centre of network hidden layer node. w_{ij} ($i=1,2,3,\ldots,h$) is the connection weight from the hidden layer to the output layer. i represents the node sequence of the hidden layer and h is the number of nodes in the hidden layer. If d is the expected output of the sample, the variance of the basis function can be expressed as Equation 5.

The entire manipulation procedure of RBF neural network, including seven steps, is described as follows:

Step 1: The site and stand factors were input for unsupervised learning, and the base function centre c was obtained based on the K-means clustering method.

Step 2: Initially, the h nodes were randomly selected from the input data as clustering centres c_i ($i=1, 2, 3,\ldots, h$).

Step 3: The training dataset was grouped according to the nearest rule. The site factor vector x_p was distributed to each cluster set $\vartheta_p\left(p = 1,2,3,\ldots,P\right)$ of the input sample according to the Euclidean distance between the site factor vector x_p and the K-means clustering centre c_i.

Step 4: The clustering centre was simultaneously readjusted based on the learning situation to calculate the new clustering centre ci of training samples in all clustering sets ϑ_p. If the new clustering centre was not changed, the c_i obtained was the ultimate basis function centre of RBF. Otherwise, the Step 2 was carried out to select the clustering centre c_i again.

Step 5: The equation 5 was used to solve the variance σ_i of Gauss function (basis function). The expression of σ_i can be expressed as Equation 6.

$$\sigma_i = \frac{c_{\max}}{\sqrt{2h}} \qquad i = 1,2,3,\ldots,h \qquad \ldots(6)$$

Where c_{max} is the maximum distance of the selected centres.

Step 6: The neuron connection weight (Equation 7) between the hidden layer and the output layer was calculated by the least squares framework.

$$\omega = \exp\left(\frac{h}{c_{\max}^2}\|x_p - c_i\|^2\right) \quad i = 1,2,3,\ldots,h; p = 1,2,3,\ldots,P \qquad \ldots(7)$$

Step 7. After learning, the results of SI were obtained based on the input of site factors and the stand age.

Genetic Algorithm-Radial Basis Function (GA-RBF) Model

Genetic algorithm is a parallel and stochastic search optimization method used to simulate biological evolution process by computer technology (Liu 2013). After the initial population was set, the GA optimizes through the population search strategy and covers many individual situations in the process of inheritance, crossover and mutation (Xie 2014). In this paper, GA was applied to optimize the learning parameters of RBF model such as centre value, width of base function and connection weight between the hidden layer and the output layer. A modified Genetic Algorithm-Radial Basis Function (GA-RBF) model was applied to the study of the site quality assessment of afforestation land. The optimization process of GA-RBF includes population initialization, fitness function, selection operation, cross operation and mutation operation. The entire algorithm procedure is shown in Fig. 2.

Model Evaluation

In this paper, three different strategies (the QT-I, the RBF and the GA-RBF) were compared to select the optimal one. Furthermore, the existing SI tables of Chinese fir in Fujian were used to test the accuracy of prediction. The tables were divided into three grades: Low level (SI is between 8 and 12), Medium level (SI is between 14 and 18), and High level (SI is between 20 and 22). Mean deviation (MEP), mean squared error (MSEP) and mean absolute deviation (MAEP) were used to evaluate the performance. The model that had the smallest MEP, MSEP and MAEP performed best. The functions are shown as Equations (8)-(10).

$$MEP = \sum_{i=1}^{n} \frac{y_i - \hat{y}_i}{n} \qquad \ldots(8)$$

$$MSEP = \sum_{i=1}^{n} \frac{(y_i - \hat{y}_i)^2}{n} \qquad \ldots(9)$$

$$MSEP = \sum_{i=1}^{n} \frac{|y_i - \hat{y}_i|}{n} \qquad \ldots(10)$$

Where, y_i is the observation of the i^{th} plot; $\hat{y}_i$ is the predicted value of i^{th} observation; n is the number of plots; $\bar{y}_i$ is the mean value of the observation.

RESULTS

Analysis of QT-I Model

The items of site factors were quantified and expressed by matrix expression $X*b=Y$. Where, X was the data matrix of site factors and age, also the criterion variable independent variables; Y was the dominant height matrix; b was the score value. The score values of various items estimated by the MATLAB are given in Table 2.

The maximum score value was 2.221534 when the dummy variable of HB was higher than 500. For category X2 the score value of DM increased with terrain declining. For category X3 the dummy variable Sunny-Slope had the maximum score value. For category X4, score values were higher when the slope is smaller. For category X5, the result demonstrated a negative correlation between the slope position and the score value. For the soil thickness factor, the score value increased with the increase of the soil thickness. And the score value of red soil in category X7 was the maximum. Among the seven site factors, the higher score factor was elevation, soil thickness and landform, which indicated that the site factors correlated to forest tree could be determined by the score values of various categories. We concluded that the site conditions such as elevation higher than 500 m, hilly landform, sunny slope, steep slope 15-25, valley of slope, soil thickness >=80, and red soil were more conducive to the Chinese fir. The conclusions were consistent with the actual afforestation experiences.

The standard age (20-year) of Chinese fir in Fujian Province was introduced into the prediction equation of the dominant height, and the SI model was obtained:

SI = 2.148271 * X11 + 2.016107 * X12 + 2.221534 * X 13 + 0.367009 * X22 + 0.437051 * X23 - 0.06996 * X31 + 0.24483 * X32 + 0.75086 * X42 + 0.692169 * X43 - 0.57385 * X51 - 1.71536 * X52 - 0.8834 * X53 - 0.72789 * X54 + 0.759626 * X62 + 2.162782 * X63 + 1.53225 * X71 - 0.10188 * X73 + 6.73746 …(11)

The model was further evaluated by correlation matrix, complex correlation coefficient, partial correlation coeffi-

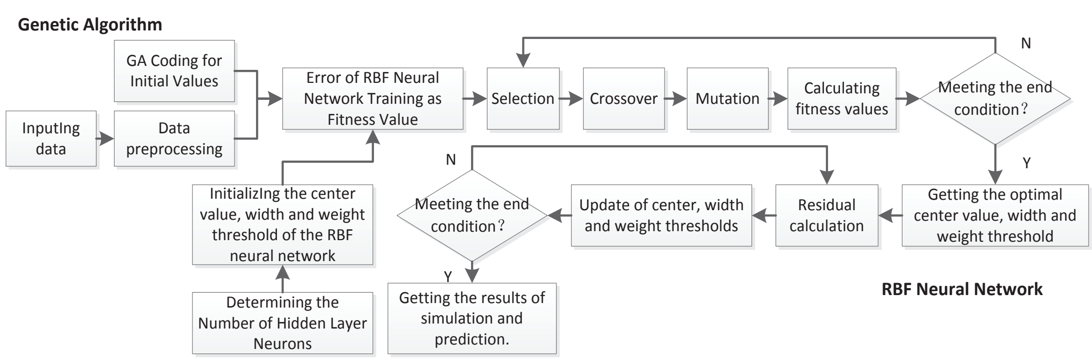

Fig. 2: Entire algorithm procedure of GA-RBF.

Table 2: The quantified scores of site factors.

Item variables	Dummy Variables	Categories	Parameters	Score Values
HB(X1)	<=300	X11	b11	2.148271
	300-500	X12	b12	2.016107
	>=500	X13	b13	2.221534
DM(X2)	Middle-Mountain	X21	b21	0
	Low-Mountain	X22	b22	0.367009
	Hills	X23	b23	0.437051
PX(X3)	Shady-Slope (north, northwest, northeast)	X31	b31	-0.06996
	Sunny-Slope (south, southeast, southwest)	X32	b32	0.24483
	Half-Sunny-Slope (east, west)	X33	b33	0
PD(X4)	Gentle-Slope <=15	X41	b41	0
	Steep-Slope 15-25	X42	b42	0.75086
	Incline >=25	X43	b43	0.692169
PW(X5)	Ridge	X51	b51	-0.57385
	Uphill	X52	b52	-1.71536
	Middle-Slope	X53	b53	-0.8834
	Downhill	X54	b54	-0.72789
	Valley	X55	b55	0
TRHD(X6)	Thin<=40	X61	b61	0
	Middle 40-80	X62	b62	0.759626
	Thick >=80	X63	b63	2.162782
TRMC(X7)	Red-Soil	X71	b71	1.53225
	Yellow-Red-Soil	X73	b73	-0.10188
	Yellow-Soil	X76	b76	0
A	-	A	b0	0.336873

Table 3: Correlation matrix of 7 site factors.

	HTT	HB	PD	PW	TRHD	TRMC	DM	PX
HTT	1	-0.06436	-0.12558	0.230546	0.090517	-0.14277	0.147322	-0.0393
HB	-0.06436	1	0.202681	-0.15513	-0.35159	0.514141	-0.78383	0.070276
PD	-0.12558	0.202681	1	-0.02356	-0.14961	0.215486	-0.17755	0.021609
PW	0.230546	-0.15513	-0.02356	1	0.051953	-0.07262	0.085855	-0.10104
TRHD	0.090517	-0.35159	-0.14961	0.051953	1	-0.3302	0.322621	0.077797
TRMC	-0.14277	0.514141	0.215486	-0.07262	-0.3302	1	-0.38228	0.045046
DM	0.147322	-0.78383	-0.17755	0.085855	0.322621	-0.38228	1	-0.13762
PX	-0.0393	0.070276	0.021609	-0.10104	0.077797	0.045046	-0.13762	1

cient and *t*-test. From the correlation matrix (Table 3), the higher correlations between the dominant height and the site factors were the slope position, topography and soil thickness. And the correlation between the elevation and soil type of was the highest value of 0.514141.

The complex correlation coefficient was calculated, indicating that the dominant height of Chinese fir had a correlation degree of 0.6354 with 7 site factors and stand age. The complex correlation coefficient demonstrated that the site factor and stand age had effects on the dominant height growth. The partial correlation coefficients between each site factor and the dominant height and their significance test results at a 95% confidence interval are given in Table 4. According to the partial correlation coefficient, the importance of influencing the site quality was as follows: HB (elevation), DM (landform) and PW (slope position).

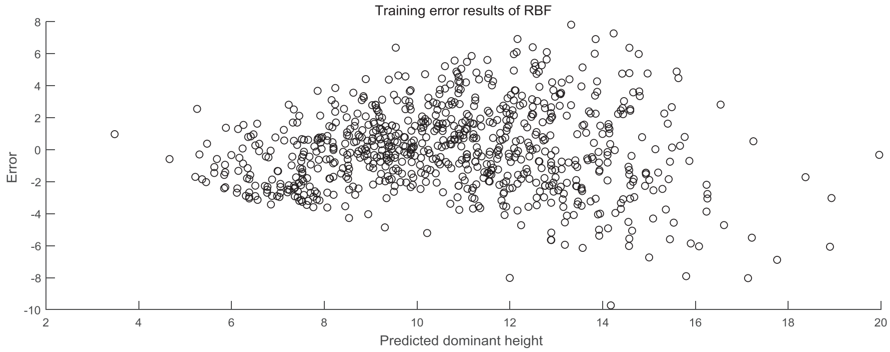

Fig. 3: Training error results of RBF neural network.

Table 4: The results of partial correlations.

Site factor	Correlation coefficient	P value
HB	0.171	0.019
DM	0.175	0.017
PX	0.009	0.908
PD	-0.098	0.183
PW	0.241	0.001
TRHD	0.029	0.691
TRMC	-0.122	0.096

Analysis of RBF Neural Network Model

The training dataset (786 plots) were used to establish the RBF model and the testing dataset (194 plots) were used to evaluate the accuracy. Twenty four notes in the input layer and 1 node in the output layer were obtained after processing of the 7 site factors through dummy variable method. The function established by the RBF neural network model was:

$$rbfnet=newrb\ (Input,Output,Goal,Spread,MN,DF) \quad \ldots(12)$$

Where the goal of network learning $goal=0.03$, the spread speed of radial basis function $spread$=1.1, the maximum number of neurons in RBF network MN=600, and the output interval of network DF=50. The target error MSE of 0.03 was achieved after 485 training sessions and the training error results are shown in Fig. 3. Results indicated that the RBF neural had better performed.

The RBF network was optimized by genetic algorithm. The parameters were set as population size of 10, evolution times of 50, crossover probability of 0.4, and mutation probability of 0.2. The GARBF neural network training results is shown in Fig. 4.

Model Evaluation

In this study, three models of QT-I model, RBF neural network and GA-RBF neural network were used to predict the dominant height according to the testing dataset. The predicted results are shown in Fig. 5. We concluded that the predicted output of RBF and GARBF were more precise than that of QT-I. The evaluation indexes of three models are given in Table 5. The GA-RBF neural network model

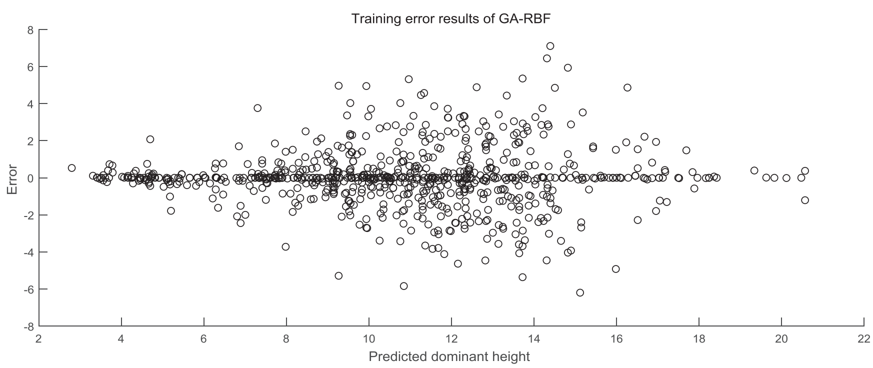

Fig. 4: Training error results of GA-RBF neural network.

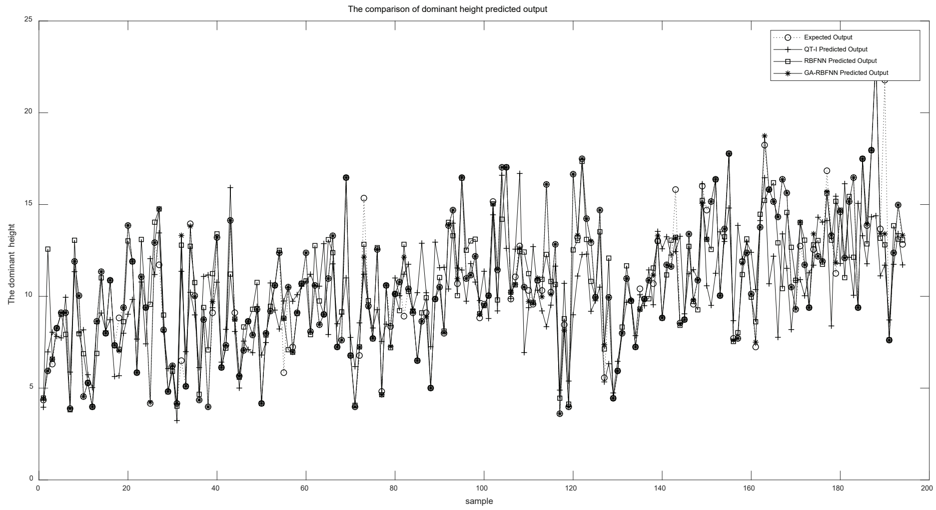

Fig. 5: The predicted results of different models.

Table 5: The evaluation indexes of three models.

Statistical indicator	QT-I Model	RBFNN Model	GA-RBFNN Model
MEP	0.3623	-3.6083E-11	2.57732E-11
MAEP	2.15783	1.50993	0.26643
MSEP	8.13933	4.69731	0.93643

Table 6: The SI evaluation results of different models.

Model	Total plot	Consistency	Inconsistency	Consistency rate
QT-I	194	89	105	45.88%
RBFNN	194	100	94	51.55%
GA-RBFNN	194	142	52	73.20%

had the smallest MEP, MSEP and MAEP and performed best.

Site Quality Assessment Result of Afforestation Land

The site quality of 194 sample plots in the testing dataset was evaluated. Firstly, the site evaluation results obtained by the standard index table of Chinese fir were used to compare the QT-I model and the RBF neural network model. The results shown in Table 6 indicated that the GA-RBF neural network model had the highest consistency of 73.20%. The GA-RBF model provided a feasible site quality evaluation strategy for afforestation land when tree species was without SI table.

DISCUSSION AND CONCLUSIONS

In this study, the dominant model of afforestation land for Chinese fir plantations was developed by three strategies such as QT-I, RBF neural network and GA-RBF model. It was shown that the GA-RBF had a high consistency with SI table and proposed to predict stand dominant height. Because of the nonlinear and complex relationships between site factors, machine learning of nonlinear branches was used to simulate the non-linear relationship with strong adaptability and flexibility. BP neural network algorithm was used to achieve site quality evaluation (Huang 2006, Gong 2013). However, because of the instability of SI prediction model based on BP neural network, traditional QT-I method has been used in afforestation practice, and the RBF neural network model developed in this paper overcame the defect of the BP neural network. Furthermore, aiming at the problem that RBF was prone to fall into the local optimal solution, the model of RBF neural network was improved by genetic algorithm with better global search ability. The study showed that GA-RBF neural network model was better to evaluate the site quality of forestland.

It should be pointed out that the optimization of GA-RBF in this paper only showed the centre value of the hidden layer, the width of the base function and the connection weight of the hidden layer to the output layer. The optimization of the number of neurons in the hidden layer will be studied for further study. And other intelligent optimization algorithms such as simulated annealing algorithm (SA), particle swarm optimization (PSO) could also prevent falling into the local optimal solution. Whether these algorithms can further improve the prediction accuracy of the model to improve the applicability of machine learning methods in the evaluation of site quality of afforestation land will be explored.

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