Estimation of forest volume based on LM-BP neural network model

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Abstract

Since cost factors are of primary importance, continuously searching for more efficient and reliable estimation models that could integrate or, in some cases, substitute the traditional and expensive measuring techniques for forest investigation is necessary. The evaluation indexes set, which included 10 factors: elevation, slope, aspect, surface curvature, solar radiation index, topographic humidity index, tree ages, the depth of soil layer, the depth of soil A layer, and coarseness, was established. Then, using the integration data of the administrative map, Digital Elevation Model (DEM), and forest resource planning investigation data of the key forestry city of Longquan, Zhejiang Province, PRC, the membership of each factor was empirically fitted by polynomials, and the forest volume was estimated via an improved back propagation (BP) neural network(NN) model with Levenberg-Marquardt(LM) optimization algorithm(LM-BP). The results show that the individual average relative errors (IARE) were from 23.29% to 47.87% with an average value of 33.06%; The groups relative errors (GRE) were from 0.38% to 9.31% with an average value of 3.65%, this meant that groups estimation precision was more than 90% which is the highest standard of overall sampling accuracy about volume of forest resource inventory in china.

Keywords: LM-BP; Forest Volume; Estimation

1 Introduction

Forest inventories provide objective and scientifically reliable information on key forest ecosystem processes, and constitute an effective tool for forest management and forest resource monitoring. Forest inventory data define the extent, size distribution, and species composition of forested and non-forested lands and through periodical updating, they track the changes that occur in natural resources over time [1].

In China, the traditional large-scale survey of forest resources include forest inventory and forest resource planning investigation, where, forest inventory repeated once every 5 years, and the forest resource planning investigation conducted once every 10 years interval. Whether from an ecological viewpoint or from the perspective of the use of forest products, the traditional long cycle of forest resources survey has been unable to meet the actual demand.

Since cost factors are of primary importance, forest managers are continuously searching for more efficient and reliable estimation models that could integrate or, in some cases, substitute the traditional and expensive measuring techniques[1].

Many simulation models have been built to provide managers with predictions of forest growth and yield response to treatments. But, all developed models presented a very low R^2 implying that the variables explained a small portion of the growth processes. Traditional statistical methods are not always suited to solve unstructured problems occurring in natural resource assessment [2] mainly because statistical methods are based on some assumptions on the data distribution. Moreover, they have shown to have several limitations when variables that are involved interact in a complex manner and have difficulties in handling poor and noisy data. Such conditions are very frequent in forest data where classes may display a range of distributions, relationships between variables may be non-linear, and outliers and noise may exist in the data [1].

Thanks to their flexibility and adaptability, artificial neural networks (ANNs) constitute an alternative and valid approach for modelling non-linear and complex long-lived dynamic biological ecosystems such as forests. ANN models have become very popular because they can learn complex patterns and trends in the data, they are slightly affected by data quality problems and bias, and they are robust to data structures with highly interrelated relationships. Artificial neural networks were applied to develop models to predict aboveground forest carbon storage according to sample data and Land sat Thematic Mapper TM data. The results showed the BPNN algorithm could accurately generate the spatial distributions of forest carbon density and changes, where

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the mean estimate of carbon density for the whole study area was 0. 98mg (10. 89 mg/hm 2) which was smaller than the average from the sample plots with a relative error of only 13%[3]. Two BPNNs were constructed, and their performance in estimating the height of pure uneven-aged stands of common beech (Fagus sylvatica L.) in north-western Spain was compared with that of the models most commonly used to estimate tree height (nonlinear calibrated local and generalized mixed-effects models and generalized fixed-effects models). Comparison results showed that BPNNs require less sampling effort because no height measurements are required for their implementation [4].

Although ANNs have been showing potential for solving some difficult problems in forest resources management, research on ANNs applications has been very limited compared to other artificial intelligence techniques.

To facilitate the monitoring of forest resources by the forest managers, a simulation model based on the improved back propagation neural network (BPNN) with Levenberg-Marquardt(LM) algorithm(BP-LM) has been developed. In which, first, a comprehensive evaluated factor set were established to cost-effectively estimate forest volume, including 10 factors: elevation, slope, aspect, surface curvature, solar radiation index, topographic humidity index, tree ages, the depth of soil layer, the depth of soil A layer, and coarseness. Then, using the integration data of the administrative map, DEM, and forest resource planning investigation data of the key forestry city of Longquan, Zhejiang Province, PRC, the membership of each factor was empirically fitted by polynomials, and the forest volume was estimated via an improved BPNN model with LM optimization algorithm.

2 Study area

The key forestry city of Longquan, 3059 km^2 in extent, is a largely mountainous area located in the southwestern part of Zhejiang province in China, where the longitude is from 118°42′to 119°25′E, and latitude is between 27°42′to 28°20′N.

There are abundant forest resources with 3,985,000 mu of areas, forest volume reached 14.56 million cubic meters, and the forest coverage rate up to 84.2%.

3 Materials and methods

3.1 MATERIALS AND METHODS

Formation and development of forest resources is actually a forest cultivation process from tree seeds, seedlings, planting forest trees to mature, throughout the process of cultivating and nurturing, forest development must be carried out under certain site conditions which commonly evaluated by site factors including environmental factors, forestry vegetation factors and human activity factors[5].

Typically, in the natural state, the development of forest resources most affected by the environmental factors which include 3 classes:

- climate, mainly includes solar radiation and precipitation.
- topography, directly related to water potential and soil conditions, including elevation, aspect, slope, slope position, slope type, and small terrain, etc.
- soil, including soil type, soil depth, soil texture, soil structure, soil nutrients, soil humus, soil PH, soil erosion degrees, all levels of gravel reserves in the soil, soil salinity, soil-forming rock, and parent material type, etc.

In fact, site factors are not always suited to solve the monitoring of forest resources because the variety of site factors greatly increased the costs of data acquisition and greatly increased the complexity of research, which led to many experts and scholars try to select part of these factors involved in their experiment and have got some good results [6, 7]. Index system which monitor the forest resources changes should follow the basic principles of scientific, systematic, practicality and economy.

To estimate forest volume, a comprehensive evaluated index set including 10 factors: elevation, slope, aspect, surface curvature, solar radiation index, topographic humidity index, tree ages, the depth of soil layer, the depth of soil A layer, and coarseness, was established.

3.2 DATA SOURCES

There were data sources as following:

(1) Administrative map about Longquan city.

(2) The 2007 forest resource planning investigation data consisting of 83078 subplots, which composed a group of sub compartments with the size of 39377. In order to eliminate erroneous and incorrect data, a preliminary phase of the study comprised of severe data quality control. During preliminary processing, those samples, which were non-volume or located in non-forested land, were removed. Thus, the 2007 forest resource planning investigation data were remained with 28707 sub compartments and 40249 subplots.

(3) DEM with 30 meter resolution, which was generated by the first version data of ASTER GDEM (V1) in 2009, with a data type of IMG and a projection of UTM/WGS84.

3.3 IMPROVED BP NEURAL NETWORK MODEL BASED ON LM ALGORITHM

ANNs have received a great deal of attention over the last 3 decades as a valid alternative to traditional statistical methods to predict the behaviours of non-linear systems. The importance of neural networks is in their ability to learn very complex and correlated patterns.

As previously underlined, multilayer feed-forward neural networks trained by back, propagation algorithm has been the most prominent and well-researched class of ANNs in classification and pattern recognition. A back propagation system usually comprises three types of successive layers: input layer, hidden layer and output layer. During training, the input signal propagates through the network in a forward direction, from left to right on a layer-by-layer basis, generating a set of values on the output units and fixing all networks synaptic weights. Then, difference between the actual and desired output values is measured, and the network model connection strengths are changed so that the outputs produced by the network become closer to the desired outputs. A backward pass achieves this during which connection changes are propagated back through the network starting with the connections to the output layer and ending with those to the input layer [1].

However, the traditional BPNN has some shortcomings, such as slow convergence speed and easy to fall into local minimum, etc.

Fortunately, LM algorithm, which is actually a combination of gradient descent algorithm and newton algorithm, compare to the traditional BPNN, significantly reduce the number of iterations, accelerate the convergence speed, and get a higher accuracy. Especially, whose convergence speed is the fastest of all traditional and other improved BPNNs for medium-sized networks. In recent years, the improved BPNN by LM algorithm has been widely used in the fields of evaluation and forecasting and had some good effects [8-10].

In order to obtain a better result for the experiment, the improved BP neural network model based on LM algorithm was chosen to estimate the volume of forest resources.

3.4 Data preprocessing

3.4 .1 Data integration

The average volume per unit (m3/mu) of forest resources was the only estimated factor, whose data was stored in the database of forest resource planning investigation. The depth of soil layer, the depth of soil A layer, tree ages, coarseness were stored in the same database also.

However, the data about elevation, slope, aspect, surface curvature, solar radiation index, topographic humidity index were derived from DEM.

To take full advantage of the database management systems(DBMS) in the data storage and analysis, all data should be integrated into the same database of forest resource planning investigation.

3.4.2 Membership about evaluation indexes

Generally, membership is solved as follows:

- to group each evaluation index data according to the experience;
- to statistics its distribution area or the average volume per unit of forest resources by the each grouped evaluation index, and to obtain their polynomial fitting curves and fitting formulas;
- to get the fitted values for each evaluation index according the fitting formulas, and to get their membership with normalization through equation as shown in formula 1.

$$z_i = \left| y_i / \max\left(y_i\right) \right| , \quad (1)$$

where, y_i was the fitted value of each index of every monitoring unit, max(yi) was the maximum of all y_i, z_i was the membership of each index.

Exceptionally, in this article, the indexes of the depth of soil layer, the depth of soil A layer, the coarseness and the aspect, whose membership had its own special rules.

Specifically, the membership of each evaluation index was solved:

(1) Elevation: whose values were between 156 and 1806. Considering the distribution of species are usually within a certain elevation range, which is often hundreds of meters across, in order to speed up training, they first must be classified.

Step 1, to divide elevation values into 50 classes equidistantly.

Step 2, to statistics their distribution area of forest resources by the 50 classes.

Step 3, to obtain their polynomial fitting curves and the fitting formulas, in which the elevation was independent variable and the distribution area of forest resources was dependent variable.

Step 4, to get the membership of elevation according to formula 1.

(2) Slope: whose values were from 1 to 49. Considering the interval of slope values are relatively small, they were firstly rounded to the nearest integer and only classified into 47 classes. Correspondingly, the solution steps of slope membership should be a referring to the elevation.

(3) Aspect: firstly, according to their degree range, to divide aspect into 9 classes: flat, north, northeast, east, southeast, south, southwest, west, northwest, north; secondly, to statistics their distribution area of forest resources grouped by the 9 classes; finally, to get the membership of aspect according to formula 1. The classification and membership about aspect showed as table 1.

(4) Surface curvature: whose values were from -1.55555999279 to 1.46667003632 with an average value of 0.00703782594377091. Since the interval of curvature was too small, they were rounded to the nearest integer after amplification to 100 times of their original value and classified into 218 classes. Correspondingly, the solution steps of curvature membership should be a referring to the elevation.

(5) Solar radiation index: their values were firstly divided by 10000, then rounded to the nearest integer and classified into 95 classes. Other solution steps of

membership of solar radiation index should be a referring to the elevation.

(6) Topographic humidity index: their values were from 9.67430973053 to 34.2994995117. Considering the interval of the values were relatively small, they were rounded to the nearest integer after amplification to 10 times of their original value and classified into 228 classes. Correspondingly, the solution steps of membership of topographic humidity index should be a referring to the elevation.

(7) Tree ages: tree ages did not directly affect forest distribution area, but would affect forest volume, and thus the membership of the index should be based on the relationship between tree ages and the average volume per unit rather than the distribution area of forest resources. In addition, the solution steps of membership of tree ages should be a referring to the elevation.

(8) The depth of soil layer: a positive correlation between soil thickness and plant height has been presented [11]. Similarly, in this research, the experimental data also reflected a generally positive linear correlation between the depth of soil layer and the volume of forest resources. So, the membership of this index was calculated by formula 1 directly.

(9) The depth of soil A layer: according to the data from forest resource planning investigation, the depth of soil A layer qualitatively recorded as thick, medium, thin or null. Accordance with experts' experience, the membership of the depth of soil A layer were quantified as: thick to 1; medium to 0.7; thin to 0.4 and null to 0.

(10) Coarseness: Similarly, with tree ages, the creating membership of this index should be based on the relationship between the coarseness and the average volume per unit of forest resources. In addition, other solution steps of coarseness membership should be a referring to the elevation.

The polynomial fitting curves about those evaluation indexes, which included elevation, slope, surface curvature, solar radiation index, topographic humidity index and Coarseness, were showed as figure 1-figure 7. Correspondingly, their polynomial fitting formulas were showed as table 2.

TABLE 1 Classification and membership of aspect

Aspect classification	Degrees range	Actual distribution area of forest	Membership
Flat	<=0	-	-
North	(>0 and <=22.5) or (>337.5 and <=360)	4501	0.006683138
Northeast	>22.5 and <=67.5	139973	0.20783357
East	>67.5 and <=112.5	360173	0.534789142
Southeast	>112.5 and <=157.5	534362	0.793427035
South	>157.5 and <=202.5	652845	0.969351998
Southwest	>202.5 and <=247.5	673486	1
West	>247.5 and <=292.5	473574	0.703168292
Northwest	>292.5 and <=337.5	172661	0.2563691

TABLE 2 The polynomial fitting formulas for the 7 evaluation indexes

Index name	Polynomial fitting formula
Elevation	$y=-6.78e^{-08}x^4+0.00042981\,x^3-0.941288539x^2+738.4373822x-79871.40674$
Slope	$y=-6.78e^{-15}x^{15}+2.63e^{-12}x^{14}-4.63e^{-10}x^{13}+4.85e^{-08}x^{12}-3.38e^{-06}x^{11}+0.000165019x^{10}-.005798663x^9+0.148429674x^8-2.770327014x^7+37.376799x^6-357.7547367x^5+2353.107885x^4-0098.0831x^3+26373.10656x^2-34728.49104x+16580.03954$
Surface Curvature	$y=3.72e^{-36}x^{20}-1.91e^{-34}x^{19}-4.81e^{-31}x^{18}+1.69e^{-29}x^{17}+2.59e^{-26}x^{16}-6.58e^{-25}x^{15}-7.70e^{-22}x^{14}+1.52e^{-0}x^{13}+1.40e^{-17}x^{12}-2.31e^{-16}x^{11}-1.63e^{-13}x^{10}+2.40e^{-12}x^9+1.25e^{-09}x^8-1.68e^{-08}x^7-6.32e^{-06}x^6+7.37e^{-05}x^5+0.02123x^4-0.1805x^3-45.6071x^2+189.1521x+50263.14$
Solar Radiation Index	$y=-6.16e^{-20}x^{15}+1.07e^{-16}x^{14}-8.42e^{-14}x^{13}+3.91e^{-11}x^{12}-1.18e^{-08}x^{11}+2.30e^{-06}x^{10}-0.000260073x^9+0.002569461x^8+5.022223928x^7-1044.693319x^6+122333.9409x^5-9544261.604x^4+508159595.3x^3-17869026938x^2+3.75995e^{+11}x-3.59689e^{+12}$
Topographic Humidity Index	$y=-5.072435697e^{-26}x^{16}+1.816994302e^{-22}x^{15}-3.022650299e^{-19}x^{14}+3.098679650e^{-16}x^{13}-2.190274111e^{-13}x^{12}+1.131479979e^{-10}x^{11}-4.417347193e^{-8}x^{10}+1.328940533e\text{-}05e^{-05}x^9-0.003112417x^8+0.569125647x^7-80.949868992\,x^6+8858.396346998x^5-730836.145378965x^4+43927720.9766960x^3-1813419841.016x^2+45921882977.516x-537240051906.498$
Tree Ages	$y=2.34e^{-05}x^3-0.003269209x^2+0.220835719x+0.84902787$
Coarseness	$y=-0.007507773x^3+0.18633539x^2-0.027133501x+0.195631142$

3.4.3 Volume normalization

In order to unify the dimension for all variables, the volume of forest resources should also be normalized according to formula 1 before they were input into BPNN. In which, the volume referred to the average volume per unit(m^3/mu).

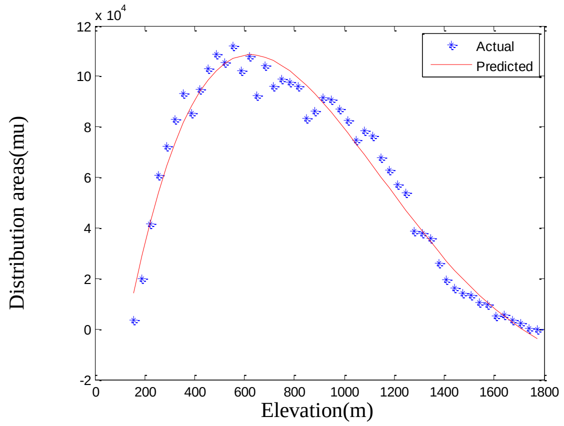

FIGURE 1 Polynomial fitting curves of elevation

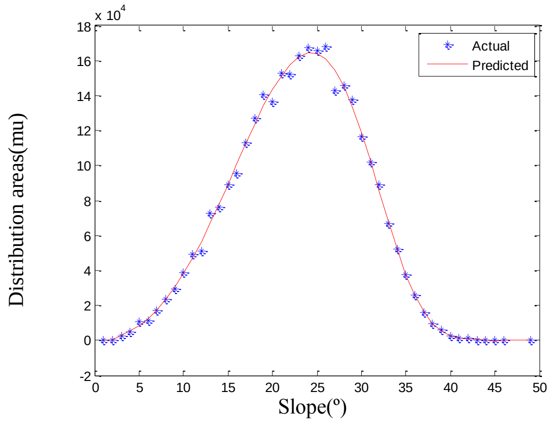

FIGURE 2 Polynomial fitting curves of slope

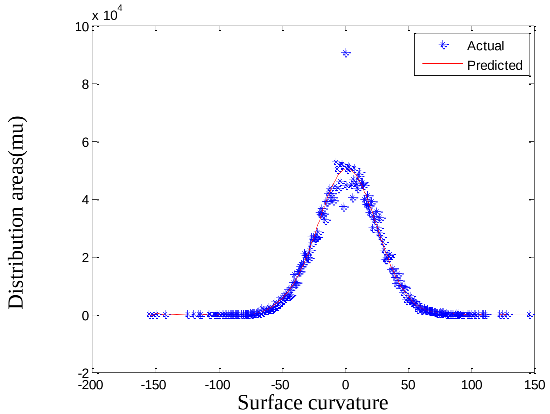

FIGURE 3 Polynomial fitting curves of surface curvature

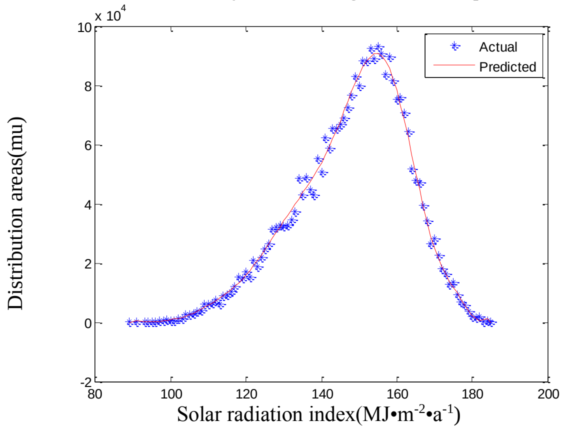

FIGURE 4 Polynomial fitting curves of solar radiation index

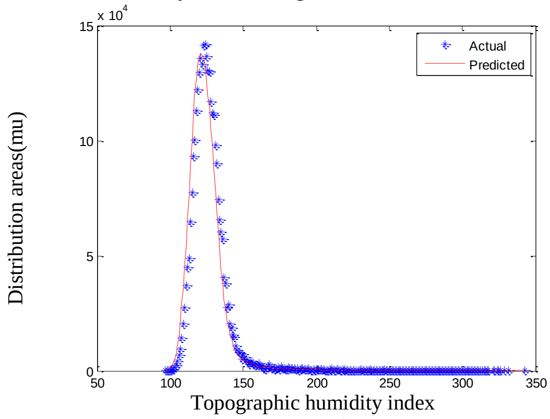

FIGURE 5 Polynomial fitting curves of topographic humidity index

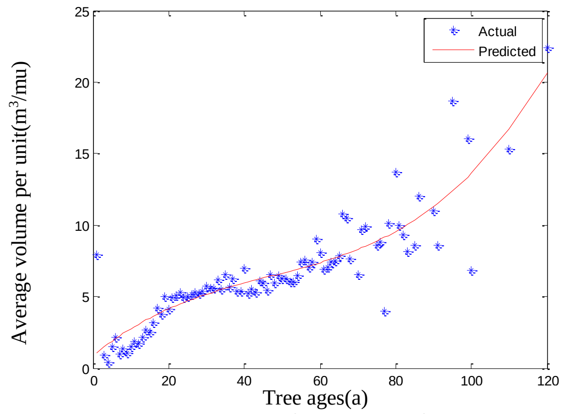

FIGURE 6 Polynomial fitting curves of tree ages

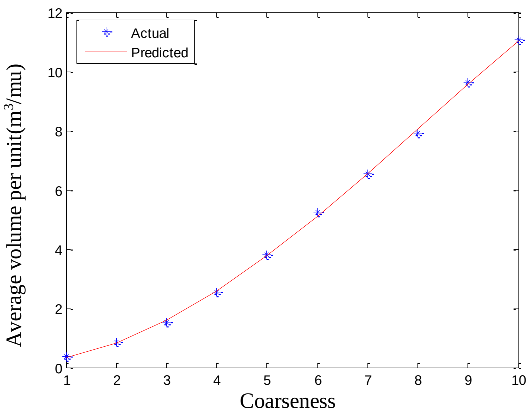

FIGURE 7 Polynomial fitting curves of coarseness

3.5 ESTIMATION FOR FOREST VOLUME BASED ON BP-LM NEURAL NETWORK MODEL

3.5.1 Determining of modelling sample set and simulating sample set

The pre-processed data were divided by administrative unit into 22 groups including 3 streets, 8 towns, 8 townships, a scenic spot and two forest farms. After removing a forest farm(city forest farm) for its too small sample size with only 13, the other 21 groups of samples were independently divided into 2 sets: a modelling sample set and a simulating sample set.

3.5.2 Setting model parameters

The improved BPNN based on LM algorithm comprised three successive layers: input layer, hidden layer and output layer. In which, the nodes of hidden layer were calculated by formula 2.

$$Hidden\_Num = 2 * Input\_Num + Output\_Num\,, \qquad (2)$$

where, Hidden_Num was the number of nodes about the hidden layer, Input_Num was the number of nodes of the input layer, and Output_Num was the number of nodes of the output layer.

Specifically, those model parameters were set as follows:

Epochs = 1000; % the maximum of epochs was 1000.

Input_Num=10; %the nodes of input layer was 10.

Output_Num=1; %the nodes of output layer was 1.

Hidden_Num=2*Input_Num+ Output_Num; %the nodes of the hidden layer

TransferFcn= {'tansig' 'purelin'}; %tansig was the transfer function transferring values from the input layer to the hidden layer, and purelin was the transfer function transferring values from the hidden layer to the output layer.

TrainFcn = 'trainlm'; % training function was trainlm corresponding to LM algorithm.

LearnFcn = 'learngdm'; %learning function was learngdm.

PerformFcn = 'mse'; % performing function was mse(mean square error).

3.5.3 Creating net

Net =newff(P,T, Hidden_Num), where P was the input vector and T was the output vector.

3.5.4 Training net

[Net TR] = train(Net,P,T);%training net

3.5.5 Simulation

y =sim(Net,P_test), where, Net was the trained net, P_test was the input vector of simulating samples and y was the estimation result.

4 Results and discussion

Estimation results of forest volume based on improved BPNN with LM algorithm were showed as table 3.

TABLE 3 Estimation results of forest volume

Administrative unit name	Total samples	Modelling samples	Simulating samples	Observed value(m^3/mu)	Calculated value(m^3/mu)	*IARE* (%)	*GRE* (%)
Longyuan street	1498	1200	298	0.307747	0.317165	25.90	3.06
Jianchi street	421	221	200	0.272585	0.274099	47.87	0.56
Xijie street	634	434	200	0.329917	0.354546	43.98	7.47
Zhulong town	3155	2500	655	0.324390	0.308923	28.77	4.77
Badu town	2457	2000	457	0.368117	0.353936	29.18	3.85
Pingnan town	3264	2500	764	0.144387	0.148159	29.46	2.61
Jinxi town	2111	900	211	0.297376	0.290909	26.75	2.17
Xiaomei town	1358	1000	358	0.280108	0.276572	25.50	1.26
Chatian town	1144	900	244	0.319118	0.323485	28.95	1.37
Shangyang town	1906	1500	406	0.251733	0.240635	24.95	4.41
Anren town	2870	2000	870	0.268594	0.253586	31.74	5.59
Daotai township	5507	4500	1007	0.111731	0.112151	27.27	0.38
Chengbei township	4054	3000	1054	0.161777	0.153023	35.23	5.41
Zhuyang township	1553	1200	353	0.300755	0.313140	42.75	4.12
Tashi township	1165	900	265	0.379292	0.343975	35.00	9.31
Baoxi township	1696	1400	296	0.227732	0.225360	35.11	1.04
Yanzhang township	826	600	226	0.230112	0.238182	46.82	3.51
Lanju township	1240	1000	240	0.229669	0.219144	25.12	4.58
Longnan township	2723	2400	323	0.139618	0.146168	23.29	4.69
Fengyang mountain	550	400	150	0.247506	0.251961	35.43	1.8
Forest farm of shankeng	104	70	34	0.325962	0.310383	45.29	4.78
Average value				0.262773	0.259786	33.06	3.65

Note: *IARE* was the individual average relative error which calculated by formula 3, and *GRE* was the group relative error which calculated by formula 4.

$$IARE = \frac{1}{n}\sum_{i=1}^{n}\left|\frac{t_i - y_i}{t_i}\right|, \qquad (3)$$

$$GRE = \frac{1}{n}\left|\frac{\sum_{i=1}^{n}(t_i - y_i)}{\sum_{i=1}^{n}(t_i)}\right|, \tag{4}$$

where, n was the number of simulating samples, t_i was the observed value of the i-th sample, y_i was the calculated value of the i-th sample.

As shown in table 3, *IARE* were from 23.29 to 47.87 with an average value of 33.06, and *GRE* were from 0.38 to 9.31 with an average value of 3.65. There was a considerable reason why those 4 groups *GRE* were more than 5%, that is, most of their tree ages were between 18 years and 30 years that almost all observed points were located above the fitting curve(figure 6), respectively, there were 75% in Tashi township(*GRE* 9.31), 80% in Xijie street(*GRE* 7.47), 54% in Anren town t(*GRE* 5.59), and 55% in Chengbei township(*GRE* 5.41).

5 Conclusions

In this study, the forest volume of the key forestry city, Longquan in Zhejiang province of China, was estimated dynamically. First, the evaluation index set was established, which included 10 factors: elevation, slope, aspect, surface curvature, solar radiation index, topographic humidity index, tree ages, the depth of soil layer, the depth of soil A layer, and coarseness. Then, the membership of each evaluation set was empirically fitted by polynomials, and the forest volume was estimated via an improved BPNN model with LM optimization algorithm. The results showed that the average individual relative errors(IARE) were from 23.29% to 47.87% with an average value of 33.06%; the groups relative errors (GRE) were from 0.38% to 9.31% with an average value of 3.65%, this meant that groups estimation precision was more than 90% which is the highest standard of overall sampling accuracy about volume of forest resource inventory in china.

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References

[1] Scrinzi G, Marzullo L, Galvagni D 2007 Development of a neural network model to update forest distribution data for managed alpine stands *Ecological Modelling* **206** 333-46

[2] Gimblett R H, Ball G L 1995 Neural network architectures for monitoring and simulating changes in forest resources management *AI Appl.* **9**(2) 103-23

[3] Wang Shaohua, Zhang Maozhen, Zhao Pingan, Chen Jinxing 2011 Modelling the spatial distribution of forest carbon stocks with artificial neural network based on TM images and forest inventory data *Acta Ecologica Sinica* **31**(4) 998-1008

[4] Castaño-Santamaría J, Crecente-Campo F, Fernández-Martínez J L, Barrio-Anta M, Obeso J R 2013 Tree height prediction approaches for uneven-aged beech forests in north-western Spain *Forest Ecology and Management* **307** 63-73

[5] Shen Guofang 2001 *Silviculture* China Forestry Press: Bei Jing

[6] Xie Huiqin 2004 Establishment on growth model of Chinese fir and application of multilinear regression *Journal of Fujian Forestry Science and Technology* **1** 34-7

[7] Xu Weimin, Chen Youfei1, Lin Guangfa, Chen Minghua 2011 Dynamic visualization of Chinese fir volume driven by site condition and growth model *Journal of Fujian College of Forestry* **31**(2) 151-5

[8] Miao Xinying, Chu Jinkui, Du Xiaowen 2011 Application of LM-BP neural network in predicting dam deformation *Computer Engineering and Applications* **47**(1) 220-2

[9] Jian Xiaochun, Wang Liwei, Min Feng 2012 BP Neural Network Based on LM Algorithm for the Forecasting of Vehicle Emission *Journal of Chongqing University of Technology (Natural Science)* **26**(7) 11-6

[10] Wang Zeping 2013 Application of LM - BP Neural Network in Lake Trophic Evaluation *Environmental Science Survey* **32**(3) 98-101

[11] Li Chengcheng, Cheng Xing, Yang Shichao 2012 Study on The Soil Thickness Factor of Plant Growth in Karst Mountains - Take The Guizhou Xiangbao Mountain as An Example *Journal of Guizhou Normal College* **28**(9) 38-41

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- **Education:** September 2008 to present, Zhejiang University, majored in remote sensing and information system application; September 2000 to December 2003, Beijin Forestry University, majored in information system, got master's degree; September 1990 to July 1994, Zhejiang Forestry College, majored in forestry, got bachelor's degree.
- **Work experience:** August 1994 to present, Zhejiang A&F University.