Quality Assessment of Timber Forest at Sub-compartment Level: the Algorithm and its Accuracy

Ke Mo[1], Tianzhong Zhao[1,*], Wenbin Zhang[2], Shaohua Wang[1]

1 *School of Information Science and Technology*
Beijing Forestry University
Beijing, China
2 Department of Computer Science
Memorial University of Newfoundland
Newfoundland, Canada

Abstract **— With quantified data and factor analysis, a model of indicator system was established to study the quality of timber forest quantitatively. Cumulative Scores (CS), Matter-Element Analysis (MEA), Comprehensive Fuzzy Analysis (CFA) and Back Propagation Neural Network (BP-NN) were introduced and applied as four classic Quality Judgement Procedures (QJP). A benchmark of forest quality and the concepts of QJPs' accuracy and distance index (DI) were proposed for the first time to compare different QJPs' performance. A case study of a forest farm in Jiangle County is further used to illustrate these QJPs. The results indicate the MEA has the best accuracy (75.2%) and DI (0.108), which is much better than CS (47.5% and 0.308) and CFA (42.4% and 0.259). While the procedure of MEA is complex to demonstrate, the procedure of BP-NN is found to be easier to publicize and apply with an acceptable accuracy (64%) and DI (0.184).**

Keywords - forest quality; indicator system; cumulative scores; matter-element analysis; comprehensive fuzzy analysis; back propagation neural network

I. INTRODUCTION

Maintaining and conservation of our environment has become a global consensus, since the "sustainable development" theory was proposed by World Commission on Environment and Development (WCED) in 1987. As the largest land ecosystem, the forest deserves more extensive concern. After 1970s, various forest harmful problems arose in different areas of the world [1-3]. "Forest quality" was firstly suggested in a report for the World Wild Fund for Nature (WWF), which is defined as: the significance and value of all ecological, social and economic components of the forest landscape [4]. Ever since, this concept has been continually developed and improved [5-7].

Forest quality is usually studied at landscape level or stand level. By choosing a suite of quality-related indicators at first, the data of indicators will be normalized. Then according to the indicator system and the QJP, the Forest Quality Index (FQI) will be calculated in the forms of the accumulation, average or interaction of indicators' value [8]. And the grade of forest quality is classified based on FQI. At landscape level, a joint project of forest quality survey was completed in Dyfi valley of Wales by International Union for Conservation of Nature (IUCN), WWF and the École Polytechnique Fédérale de Lausanne (EPFL) [9]. Besides, in order to obtain the data of wide area quickly, Remote Sensing (RS) and Geographic Information System (GIS) are often applied [10-13]. At stand level, due to the limit of resolution, the normal RS image is not suitable, while the high-resolution image is expensive. Burger and Kelting studied the forest quality by a suite of soil quality-based indicators[14]. A model with sample-plot data was established by using Analytic Hierarchy Process (AHP) to assess a forest farm in Loess Plateau of China[15].

Considering the status quo of the present researches, there is still much to be improved in forest quality assessment: (1) The AHP-based model is highly subjective, and the indicators chosen by experience or theory are insufficiently researched in terms of correlations and validity. (2) Various procedures are applied to classify the forest quality grades, but the accuracy (suitability and reliability) of these procedures are still unknown.

In China, the basic unit of forest division and management is subcompartment, and every details of the subcompartment are listed in a forest resource inventory table (FRIT), which is updated annually, every 5 or 10 years a round. The FRIT is convenient and steady, it provides a possibility to assess the forest quality at subcompartment level quantitatively.

II. PROPOSED MODEL

A. Quantification and normalization of FRIT

Quantification is the basis of forest quality assessment. The FRIT contains more than 60 items, including the numerical data and the literal data. After removing uncorrelated data, the literal data should be converted into numerical data: taking fire risk as an example, there are three hierarchically statements: high risk, low risk and no

DOI 10.2013/IJSSST.a.17.06.08

ISSN: 1473-804x online, 1473-8031 print

risk. Each statement should be assigned as a sequence number (e.g. 3, 2, 1) and then could be applied to the quantitative assessment.

Formulas listed in Table I are used to nondimensionalize the data (normalization). Now the FRIT is further divided into 3 types. 1) The positive type means the larger the value is, the higher the quality is, such as tree height or diameter at breast height (DBH). 2) The negative type means the smaller the value is, the higher the quality is, such as fire risk or slope gradient. 3) The extreme value type means the best value of quality is in the middle of a numerical interval, the farther the value is away from the best value, the poorer the quality is. For example, the sapling and seedling of a subcompartment with excessive canopy density will not function well in growing and updating. In fact, the best canopy density ranges from 0.5 ~ 0.85 [16]. According to a local forest management guideline, the best canopy density is defined as 0.8 in this study.

TABLE I NORMALIZATION FORMULA OF FRIT

Data type	Formula	Description
Positive type	$Z_i = \frac{x_i}{x_{\max}}$	x_i represents initial numerical data. x_{max} represents the largest value of x_i. x_{min} represents the smallest value of x_i. x_0 represents the value with the best quality. Z_i represents the normalized value.
Negative type	$Z_i = \frac{x_{\min}}{x_i}$	
Extreme value type	$Z_i = 1 - \frac{\lvert x_i - x_o \rvert}{x_o}$	

After the quantification and normalization, the scale of indicator value and FQI is transformed into [0,1]. The grade standard of indicator value and FQI is usually classified as 5 or 7 levels [15]. This study uses a 5 levels standard: poor =[0.0~0.2), low=[0.2~0.4), average=[0.4~0.6), good=[0.6~0.8), and excellent=[0.8~1.0].

B. *Build indicator system with factor analysis*

The criteria should be mutually independent while the indicators of certain criterion should be highly correlated in a reasonable indicator system. As a part of factor analysis, principal component analysis (PCA) is appropriate for calculating the correlations of indicators and constructing the indicator system [17, 18].

There are 3 basic steps of factor analysis: (1) Check the Kaiser-Meyer-Olkin (KMO) and Bartlett's test, to verify whether the data is suitable for factor analysis. (2) Check the components eigenvalues and the rotation sums of squared loadings, which expressed how much information is extracted from the initial data. The eigenvalues can be used in calculating the criteria's weights. (3) Check the rotated component matrix, and observe which indicators should be in a group. The values in component matrix will be used in calculating the indicators' weights. The details of factor analysis are fully explained in section "Indicator system and its weights".

C. *Quality Judgement Procedures*

(1) CS

CS is the most frequently used and simplest procedure in quality assessment. The formula of CS for forest quality assessment is listed below:

$$FQI_{cs} = \sum_{1}^{n} w_i \times v_i \tag{1}$$

represents the forest quality index of CS, represents the weights of indicators, represents the quantified value of each indicators, and *n* represents the total number of assessed indicators. The grade of forest quality is dependent on the interval where belongs to. (refer to section "Quantification and normalization of FRIT").

(2) MEA

Matter-element is a concept and model which is used to describe the relationship between the substance and its character. MEA has been proved to be effective in quality assessment problems. *R = (M, C, X)* is the fundamental model of matter-element theory [19], where *R* represents relationship, *M* represents the matter or substance, *C* represents its characteristics, and *X* represents the value of *C* (*C* and *X* could be a n-dimensional variable), so the forest quality of a subcompartment will be expressed as:

$$\begin{matrix} Forest \\ Quality \end{matrix} = \begin{pmatrix} subcompartment, & average\ tree\ height, & < s_{a1}(x), \cdots, s_{an}(x) > \\ & average\ DBH, & < s_{b1}(x), \cdots, s_{bn}(x) > \\ & \cdots, & \cdots \end{pmatrix} \tag{2}$$

Assume a subcompartment has *m* indicators, the grade standard is *n* levels, then the distance between every indicator value to *n* parts of the grade standard is defined as the "moment", which will make up a dependence matrix. The formulas of calculated by dependence matrix and its relationship function are listed below:

$$D = \begin{bmatrix} d_{11} & d_{12} & \cdots & d_{1n} \\ d_{21} & d_{22} & \cdots & d_{2n} \\ \cdots & \cdots & \cdots & \cdots \\ d_{m1} & d_{m2} & \cdots & d_{mn} \end{bmatrix} \tag{3}$$

$$d_{mn} = \begin{cases} \dfrac{-\rho(x, s_m)}{|q-p|}, & x \in s_m \\ \dfrac{\rho(x, s_m)}{\rho(x, s_x) - \rho(x, s_m)}, & x \notin s_m \end{cases} \tag{4}$$

$$\rho(x, s_i) = \left| x - 0.5(p+q) \right| - 0.5(q-p) \tag{5}$$

$$\begin{aligned} FQI_{mea} &= Max(FQI_1, \cdots, FQI_n) \\ &= Max(\sum_{i=0}^{i=m} w_1 \times d_{i1}, \cdots, \sum_{i=0}^{i=m} w_n \times d_{in} \end{aligned} \tag{6}$$

D represents a dependence matrix with *m* rows and *n* columns, represents the moments, represents the interval that contains the value *x*, and its maximum number is *q*, minimum number is *p*. represents the interval [0,1], which means in formula (5), *q* will be 1 and *p* will be 0. represents the weight of each indicators. is the maximum value from to . The grade of forest quality is correspondingly judged as level 1 to *n* (*n*=5 in this study) by the 's subscript.

(3) Comprehensive Fuzzy Analysis

CFA is another method which is often used to assess the quality [20]. Similar to MEA, CFA uses matrix *R* and the membership function of *R* to describe and calculate the forest quality.

$$R = \begin{bmatrix} r_{11} & r_{12} & \cdots & r_{1n} \\ r_{21} & r_{22} & \cdots & r_{2n} \\ \cdots & \cdots & \cdots & \cdots \\ r_{m1} & r_{m2} & \cdots & r_{mn} \end{bmatrix} \tag{7}$$

Assume the grade standard is divided into *n* parts by a_1 to a_{n-1} . v_m represents the indicator's value. The membership funcion of *R* has 3 conditions:

① $v_m \le a_{m1}$

$$r_{m1} = 1, r_{m2} = r_{m3} = \cdots = r_{mn} = 0 \tag{8}$$

② $v_m \le a_{m1}$

$$r_{mn} = 1, r_{m1} = r_{m2} = \cdots = r_{m(n-1)} = 0 \tag{9}$$

③ $a_{ms} \le v_m \le a_{m(s+1)}$

$$\begin{aligned} r_{ms} &= \frac{a_{m(s+1)} - v_m}{a_{m(s+1)} - a_{ms}}, \\ r_{m(s+1)} &= \frac{v_m - a_{ms}}{a_{m(s+1)} - a_{ms}}, \\ r_{mk} &= 0, k < s \,||\, k > s+1 \end{aligned} \tag{10}$$

$$\begin{aligned} FQI_{cfa} &= Max(FQI_1, \cdots, FQI_n) \\ &= Max(\textstyle\sum_{i=0}^{i=m} w_1 \times r_{i1}, \cdots, \sum_{i=0}^{i=m} w_n \times r_{in}) \end{aligned} \tag{11}$$

FQI_{cfa} is the maximum value from FQI_1 to FQI_n. The grades of forest quality is correspondingly judged as level 1 to level (*s*+1) (*s*+1=*n*=5 in this study) by FQI_{cfa}'s subscript.

(4) BP-NN

Artificial neural network (ANN) is a computational model inspired by the structure and functions of animal's nervous system, which has been widely applied in resources assessment [21-23]. Figure 1 has illustrates the structure of neuron. It's input is from a_1 to a_n, and every input has a weight representing as w_1 to w_n. *b* represents the threshold, *f* represents the activation function, and *t* represents the output. Every output could be another neuron's input, except for the last one.

BP-NN is a layered feed-forward ANN which uses the back propagation algorithm. Figure 2 shows the structure of a BP-NN with 3 layers, including the input layer, hidden layer and output layer. The signals (data) of neuron will be sent forward from one layer to the next, then the outputs will be compared to the targets, after that the errors will be propagated backwards from the way it come.

The error's propagation is called the training of network, while the weight of every neuron will be adjusted by some specific algorithms. The training will stop when the errors have been effectively reduced or the training time is over, after that the pattern of assessment is stored in the weights and threshold of every neuron and this BP-NN will be capable of simulating the process of forest quality assessment.

Compared with other three QJMs, a simpler and faster method of BP-NN is represented as the following formulas:

$$Grade_{BP} = \left\lfloor \sum f_2(W_2 * K_i) + b_2^2 + 0.5 \right\rfloor \tag{12}$$

$$K_i = f_1(W_1 * A_i + b_1) \tag{13}$$

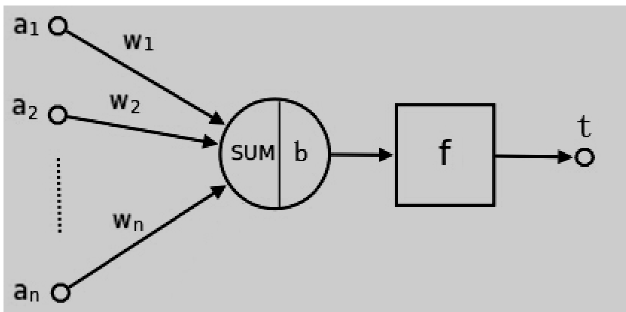

Figure 1. The structure of neuron

DOI 10.2013/IJSSST.a.17.06.08

ISSN: 1473-804x online, 1473-8031 print

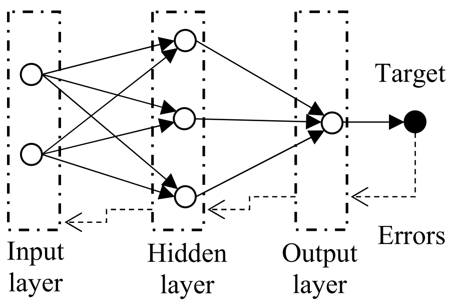

Figure 2. A 3-layers back propagation neural network

W_2 and W_1 represent the weights matrix of neurons in output layer and input layer respectively; b_2 and b_1 represent the threshold vector quantities of neurons in output layer and input layer respectively; f_2 and f_1 represent the activation function in output layer and input layer respectively, A_i represents the matrix of indicators' value. The symbol "$\lfloor\rfloor$" means the value should be rounded down. Due to the space limit, the weights and threshold are skipped in this paper but can be easily obtained in Matlab.

D. Benchmark of Forest Quality

In terms of the evaluation of QJMs' suitability and reliability, there does not exist a workable and widely-accepted benchmark. Therefore, the benchmark should be studied and established as soon as possible. In the previous study, sometimes the grades of different QJM are inconsistent with each other (e.g. the grade of CS | MEA | CFA are poor | good | excellent), but in most instances, the grades are near or the same (e.g. good | good | excellent). Therefore, the benchmark proposed in this study uses the approach of approximation. Assume the quality of forest is an objective value and could be classified by QJM, its' grade of certain QJM may be inconsistent with other QJM's, but the average grade should approximate the benchmark when sufficient QJMs are applied.

Since the quality of forest is classified as 5 equidistance grades, by reassigning these 5 quality grades as very poor=1, low=2, average=3, good=4 and excellent=5 will easily calculate the benchmark with the following formula:

$$Grade_B = \left\lfloor \sum_{i=1}^{n} \frac{Grade_i}{n} + 0.5 \right\rfloor \tag{14}$$

$Grade_B$ represents the benchmark, $Grade_i$ represents every result of the QJM, n represents the number of methods, the symbol "$\lfloor\rfloor$" means the value inside will be rounded down. In this study, BP-NN is a supervised model which needs the benchmarks to train the network, so the benchmarks are calculated by the results of CS, MEA, CFA.

Finding the benchmark is important. The accuracy of QJM is easily defined in the following formula:

$$A_q = \frac{n}{N} \tag{15}$$

A_q represents the accuracy of QJM, N represents the total number of assessed cases, n represents the number of quality grade which matches its benchmark. If all the grades of a QJM can match its corresponding benchmark, its A_q is 100%.

To further study the deviation of different QJMs, the concept of distance index (DI) is introduced: assume the grade of benchmark is excellent, the grade of method A is good, the grade of method B is low. Both of the results can not match the benchmark, but the grade of method A is closer to the benchmark and is more acceptable than grade of method B. The DI of QJM is defined in the following formulas:

$$\mathrm{DI} = \sum \frac{|\ Grade_B - Grade_i\ |}{Grade_B \times N} \tag{16}$$

DI represents the distance index of QJM, N represents the total number of assessed cases. When two QJMs' accuracy are close or the same, the method with lower DI is more accurate.

III. Results

A. Site and Data Description

This study was conducted in Jiangle national forest farm, located in the Mingtoushan area and Yufang area of Jiangle county, Fujian province, China. Jiangle is a main timber-production area in the south of China. The landform is a typical hilly and lower mountainous landscape with altitude from 400 to 800 m above the sea level. In a climate of subtropical monsoon, the frost-free days are around 287. The annual average precipitation is 1670 mm, and annual average temperature is 19.8 ℃. The overall area of Jiangle County is approximately 2246 km^2, with a forest coverage of 85.2%. The total standing forest stock of Jiangle national forest farm is about 114,000 m^3. The main forest type contains masson pine (*Cunninghamia lanceolata*), Chinese-fir (*Pinus massoniana*) and some other broad-leaf species with the percentages being 46.9%, 40% and 13.1% respectively.

314 FRIT records were used in this study, which derived from the FRIT of Jiangle national forest farm in 2013. A sample of FRIT(after quantification) was listed in Table 2.

B. Indicator System and its Weights

Table 2. A SAMPLE OF FRIT(AFTER QUANTIFICATION)

Item	Value (Unit)	Item	Value (Unit)
Subcompartment No.	10020306104010	Area	Mingtoushan
Forest type	Masson pine	Sum of timber/ unit area	74
Canopy density	80(%)	Average DHB	23.1(cm)
Average tree height	14.3(m)	Stock volume/ unit area	24.6(m^3)
Soil layer depth	53 (cm)	Humus layer depth	18 (cm）
Shrubs height	80 (cm)	Shrubs density	80 (%)
Herbs height	40(cm)	Herbs density	80 (%)
Slope gradient	24 (°)	Slope position	2-top slope
Slope direction	4-Southeast		

Table 1. KMO AND BARTLETT'S TEST

Test item		Value
KMO measure of sampling adequacy		0.684
Bartlett's test of sphericity	Approx.Chi-square	691.547
Bartlett's test of sphericity	df	78
Bartlett's test of sphericity	Sig	0.000

Table 2. COMPONENTS EIGENVALUES

Component	Rotation sums of squared loadings		
	Eigenvalue	% of variance	Cumulative %
1 (Timber)	3.051	23.473	23.473
2 (Shrubs)	2.009	15.454	38.926
3 (Herbs)	1.575	12.112	51.038
4 (Soil)	1.285	9.887	60.925
5 (Terrain)	1.279	9.842	70.767

The eigenvalues which below 1.0 were skipped.
The initial eigenvalues and the extraction sums of squared loadings were skipped.

Table 3. ROTATED COMPONENT MATRIX

Indicators	Component				
	1-Timber	2-Shrubs	3-Herbs	4-Soil	5-Terrain
Average tree height	0.905	0.244	0.081	0.079	0.039
Average DBH	0.850	0.349	0.053	-0.018	0.104
Stock volume / unit area	0.845	0.164	0.005	0.122	-0.092
Canopy density	0.781	-0.126	0.138	-0.030	-0.061
Shrubs density	0.229	0.843	-0.018	0.013	0.014
Shrubs height	0.133	0.841	0.262	-0.027	0.166
Herbs height	0.099	0.092	0.839	-0.087	0.064
Herbs density	0.101	-0.015	0.789	0.044	-0.090
Humus layer depth	0.031	0.037	-0.122	0.792	0.000
Soil layer depth	0.060	-0.071	0.092	0.788	-0.013
Slope direction	0.187	-0.154	-0.144	-0.001	0.797
Slope gradient	-0.212	0.236	0.098	-0.025	0.680
Slope position	-0.105	-0.521	0.312	0.065	0.342

To discover the correlations among the indicators, the data were analysed with the help of Predictive Analytics Suite Workstation (PASW) Statistics 18.0. In the module of Factor Analysis, the factor extraction chose the method of Principal Components. The step of rotation chose the method of Varimax, the rest options and parameters were set as default. Different combination of quality-related indicators were picked and tested to find the best results.

DOI 10.2013/IJSSST.a.17.06.08

ISSN: 1473-804x online, 1473-8031 print

Table 4. INDICATORS SYSTEM OF FOREST QUALITY AT SUBCOMPARTMENT LEVEL

System	**Attributes**	**Criteria**	W_c	**Indicators**	W_i	W_g
Indicators system of forest quality at subcompa-rtment level	Timber quality	Timber	0.392	Average tree height	0.268	0.105
				Average DBH	0.251	0.098
				Stock volume / unit area	0.250	0.098
				Canopy density	0.231	0.090
		Undergrowth vegetation (Shrub and Herbs)	0.343	Shrubs density	0.255	0.087
				Shrubs height	0.254	0.087
				Herbs height	0.253	0.087
				Herbs density	0.238	0.082
	Forest land quality	Soil	0.136	Humus layer depth	0.501	0.068
				Soil layer depth	0.499	0.068
		Terrain	0.129	Slope direction	0.438	0.057
				Slope gradient	0.374	0.048
				Slope position	0.188	0.024

W_c represents the criteria's weight; W_i represents the indicators' weight; W_g represents the global weight.

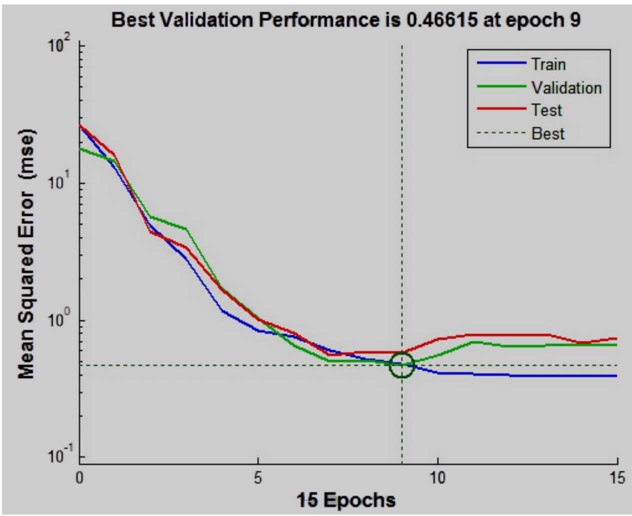

Figure 3. The MSE in training process

Table 5. THE SAMPLE RESUTLS, AQ AND DI OF DIFFERENT QJMS

Sample No.	**Area**	**Forest type**	**Grade**$_{cs}$	**Grade**$_{mea}$	**Grade**$_{cfa}$	**Grade**$_{bp}$	**Benchmark**
1	M	Masson pine	Excellent (5)	Good (4)	Average (3)	Good (4)	Good (4)
10	M	Chinese-fir	Low (2)	Poor (1)	Poor (1)	Poor (1)	Poor (1)
18	M	Masson pine	Good (4)	Average (3)	Excellent (5)	Good (4)	Good (4)
34	M	Masson pine	Good (4)	Low (2)	Average (3)	Good (4)	Average (3)
86	M	Broad leaf	Average (3)	Poor (1)	Good (4)	Low (2)	Average (3)
147	Y	Chinese-fir	Average (3)	Good (4)	Good (4)	Average (3)	Good (4)
170	Y	Chinese-fir	Low (2)	Poor (1)	Poor (1)	Low (2)	Poor (1)
251	Y	Masson pine	Average (3)	Good (4)	Average (3)	Average (3)	Average (3)
252	Y	Chinese-fir	Average (3)	Low (2)	Low (2)	Low (2)	Low (2)
259	Y	Masson	Average (3)	Low (2)	Low (2)	Average (3)	Low (2)
…	…	…	…	…	…	…	…
Total A_q			0.475	0.752	0.424	0.640	—
Total DI			0.308	0.108	0.259	0.184	—

M represents Mingtoushan area; Y represents Yufang area.

According to Table 3, the observed significance level of Bartlett's test of sphericity is 0.000, and the KMO values is 0.684> 0.5, which means the data is satisfied to proceed in factor analysis [24].

Based on Table 4, the cumulative rotation sums of squared loadings means there is about 70.767% information has been extracted to 5 components from the initial data, which indicates 5 aspects (criteria) of the forest quality can be reflected. As was mentioned above, the components' eigenvalues in Table 4 show the amount of the information that has been extracted to each component from the initial data, so the weights of each component (criteria) can be obtained by dividing its eigenvalue with their sums.

The values in Table 5 (named as factor loadings) are derived from the rotated component matrix, which could describe the correlation between the indicator and the component: the larger the value is, the higher the correlation exists, and the more information of indicator is contained in this component. According to Table 5, the factor loadings of average tree height, average DBH, stock volume per unit area and canopy density are much higher than the others in column 1, which means these 4 indicators have high correlations with component 1 and should be grouped in one. Based on the comprehensive meaning of the 4 indicators, this group is named as Timber. Similarly, the shrubs density and shrubs height should be in a group named as Shrubs. The indicators of group Herbs include herbs height and herbs density. Group Soil includes humus layer depth and soil layer depth. The last group Terrain includes slope direction, slope gradient and slope position. The factor loadings are related to the correlations between the indicators and components, so the weights of indicators in each group could be calculated in the same way as the weight of criteria. Multiply the weights of the criteria and the corresponding indicators will get the global weight of indicators.

The indicator system of forest quality at subcompartment level (including 2 attributes, 4 criteria and 13 indicators) is listed in Table 6. Group Shrubs and group Herbs is combined into group Undergrowth Vegetation to make the indicator system more concise.

C. Construction of BP-NN

The module of neural network in Matlab R2014 provides a convenient and visible approach to study the BP-NN. 156 records of FRIT and its corresponding benchmark were imported as the input data and target data respectively.

A 3-layer BP-NN is usually considered to be capable of simulating most nonlinear problems [25,26], so the training function and the numbers of neurons in hidden layer will be directly related to the performance of neural network.

After many trials, the Quasi-Newton algorithms (marked as trainbfg in Matlab) was chosen as the training function, the best numbers of neurons in hidden layer was proven to be 14, the transfer function was purelin. The rest parameters were set as default. Mean Squared Error (MSE) were used as the training target. Fig. (3) shows the MSE curve of the neural network's training process. The MSE reaches its lowest value of 0.46615 at the 9th iteration, after that the validation curve even rises a little bit, which means the neural network can not be improved anymore and the training is finished.

D. Grades and Accuracy of Different QJMs

Using the models and methods proposed in the paper, the results of forest quality assessment were finally calculated and analysed. Since the space is limited to list the whole 314 cases, there are 10 samples of cases listed in

Table 5 with its forest quality grades of different QJMs. The accuracy (A_q) and DI are also listed.

The results indicates that, in terms of forest quality assessment, compared to other QJMs, the accuracy of CS is not good enough (A_q =47.5% and DI= 0.308); the A_q of CFA (42.4%) is even worse, but since the algorithm of CFA considered the membership between the indicator value and its grade standard, the DI (0.259) is more steady and lower than CS; as a matter of fact, MEA has the best accuracy (75.2%) and DI (0.108), which proves the relationship function of MEA is more suitable and reliable for forest quality assessment at subcompartment level. Since MEA is complex to demonstrate and hard for ordinary forest owners to understand, a simpler and faster method of BP-NN is put forward to extend the application of this study with an acceptable accuracy (64%) and DI (0.184).

IV. CONCLUSION

In this study we proposed a model to assess the forest quality at subcompartment level. The FRIT after quantification and normalization were proven to be a convenient and steady data source of forest quality assessment, and provided a possibility to assess the forest quality quantitatively. By using factor analysis, groups of highly correlated indicators were chosen to construct the indicator system with more objective weights. Different QJMs were introduced and applied to assess the forest quality at subcompartment level. To our knowledge, for the first time, a benchmark was proposed to evaluate the accuracy of different QJMs.

As far as we know the proposed model is tested in Jiangle national forest farm, it should be further used in other places to refine the indicator system. For further development of this study, additional work is needed to choose more indicators of ecology and economics, and more QJMs should be applied for the benchmark, such as the grey relational analysis and set-pair analysis.

ACKNOWLEDGMENT

This study is a part of the results of "Forestry Commonweal Special Project of the State Forestry Administration P.R.China" (No.200904003). The support of Jiangle national forest farm in Fujian province, China is greatly acknowledged.

REFERENCES

[1] Cheng L., McDonald K. M., Angle R. P., et al., "Forest fire enhanced photochemical air pollution. A case study". Atmospheric Environment, vol. 32, No. 4, pp. 673-681, 1998

[2] Coulston John W., Koch Frank H., Smith William D., et al., "Invasive forest pest surveillance: Survey development and reliability". Canadian Journal of Forest Research, vol. 38, No. 9, pp. 2422-2433, 2008

[3] de Vries W., Dobbertin M. H., Solberg S., et al., "Impacts of acid deposition, ozone exposure and weather conditions on forest ecosystems in Europe: an overview". Plant And Soil, vol. 380, No. 1-2, pp. 1-45, 2014

[4] Dudley Nigel, Forest quality: Assessing forests at a landscape scale. 2006, UK: Earthscan.

[5] Lees Alexander C and Peres Carlos A, "Conservation value of remnant riparian forest corridors of varying quality for Amazonian birds and mammals". Conservation biology, vol. 22, No. 2, pp. 439-449, 2008

[6] Magdaleno F. and Martinez R., "Evaluating the quality of riparian forest vegetation: the Riparian Forest Evaluation (RFV) index". Forest Systems, vol. 23, No. 2, pp. 259-272, 2014

[7] Valero E., Picos J., and Alvarez X., "Characterization of riparian forest quality of the Umia River for a proposed restoration". Ecological Engineering, vol. 67, No. 216-222, 2014

[8] McElhinny Chris, Gibbons Phillip, Brack Cris, et al., "Forest and woodland stand structural complexity: its definition and measurement". Forest Ecology and Management, vol. 218, No. 1, pp. 1-24, 2005

[9] Dudley N and Stolton S, "Forest Quality in the Dyfi Valley Rapid Assessment on a Landscape Scale and Development of a Vision of Forests in the Catchment". Monograph, No. 8-9, 2000

[10] Bochenek Zbigniew; Ciolkosz, Andrzej; Iracka, Maria, "Assessment of forest quality in southwestern Poland with the use of remotely sensed data". No. 1998

[11] Singh I. J., Jugran D. K., Thanruma Samson, et al., "Forest resource assessment in mohand forest range, Uttar Pradesh using remote sensing and GIS". Journal of the Indian Society of Remote Sensing, vol. 33, No. 4, pp. 565-574, 2005

[12] Yu Deyong, Hao Zhanqing, Xiong Zanqing, et al., "Quality and change analysis of forest resource in typical Changbai Mountain forest region". Journal of Forestry Research, vol. 15, No. 3, pp. 171-176, 2004

[13] Brower Lincoln P, Castilleja Guillermo, Peralta Armando, et al., "Quantitative changes in forest quality in a principal overwintering area of the monarch butterfly in Mexico, 1971–1999". Conservation Biology, vol. 16, No. 2, pp. 346-359, 2002

[14] Burger James A. and Kelting Daniel L., "Using soil quality indicators to assess forest stand management". Forest Ecology and Management, vol. 122, No. 1–2, pp. 155-166, 1999

[15] Wang Naijiang and Bao Yeqing, "Modeling forest quality at stand level: A case study of loess plateau in China". Forest Policy and Economics, vol. 13, No. 6, pp. 488-495, 2011

[16] Zhang Huan, "Study on Forest Health Assessment for Nature Reserve in Northern China ", M.Sc., Beijing Forestry University, 2010.

[17] Dalal S. G., Shirodkar P. V., Jagtap T. G., et al., "Evaluation of significant sources influencing the variation of water quality of Kandla creek, Gulf of Katchchh, using PCA". Environmental Monitoring And Assessment, vol. 163, No. 1-4, pp. 49-56, 2010

[18] Shirali G. A., Mohammadfam I., and Ebrahimipour V., "A new method for quantitative assessment of resilience engineering by PCA and NT approach: A case study in a process industry". Reliability Engineering & System Safety, vol. 119, No. 88-94, 2013

[19] Feng L. H. and Hong W. H., "Application of matter element analysis in weather forecasting". Meteorological Applications, vol. 21, No. 2, pp. 398-402, 2014

[20] Nie Hongfeng, Diao Shujuan, Liu Jixuan, et al., "The application of remote sensing technique and AHP-fuzzy method in comprehensive analysis and assessment for regional stability of Chongqing City, China", in Paper presented at the 22nd Asian Conference on Remote Sensing: Citeseer, 2001.

[21] Lek Sovan, Delacoste Marc, Baran Philippe, et al., "Application of neural networks to modelling nonlinear relationships in ecology". Ecological Modelling, vol. 90, No. 1, pp. 39-52, 1996

[22] Chen Wangxiong, "The Research on Forest Ecosystem Health Envaluation and Early Warning in East Dongting Lake Area", PhD., Central South University of Forestry and Technology, 2012.

[23] Wu Gaojie and Zhao Tianzhong, "Study on the Forest resources quality evaluation based on BP neural network", in Information and Computing (ICIC), 2010 Third International Conference on: IEEE, 2010.

[24] Raschka Sebastian, "Implementing a Principal Component Analysis (PCA) in Python step by step". No. 2014

[25] Sirat Manhal, "Neural network assessment of groundwater contamination of US Mid-continent". Arabian Journal Of Geosciences, vol. 6, No. 8, pp. 3149-3160, 2013

[26] Ma Zhen, Song Xiefa, Wan Rong, et al., "Artificial neural network modeling of the water quality in intensive Litopenaeus vannamei shrimp tanks". Aquaculture, vol. 433, No. 307-312, 2014