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ORIGINAL ARTICLE

Application of artificial neural network approach and remotely sensed imagery for regional eco-environmental quality evaluation

Zhou Shi · Hongyi Li

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Abstract Eco-environment quality evaluation is an important research theme in environment management. In the present study, Fuzhou city in China was selected as a study area and a limited number of 222 sampling field sites were first investigated *in situ* with the help of a GPS device. Every sampling site was assessed by ecological experts and given an Eco-environment Background Value (EBV) based on a scoring and ranking system. The higher the EBV, the better the ecological environmental quality. Then, three types of eco-environmental attributes that are physically-based and easily-quantifiable at a grid level were extracted: (1) remote sensing derived attributes (vegetation index, wetness index, soil brightness index, surface land temperature index), (2) meteorological attributes (annual temperature and annual precipitation), and (3) terrain attribute (elevation). A Back Propagation (BP) Artificial Neural Network (ANN) model was proposed for the EBV validation and prediction. A three-layer BP ANN model was designed to automatically learn the internal relationship using a training set of known EBV and eco-environmental attributes, followed by the application of the model for predicting EBV values across the whole study area. It was found that the performance of the BP ANN model was satisfactory and capable of an overall prediction accuracy of 82.4%, with a Kappa coefficient of 0.801 in the validation. The evaluation results showed that the eco-environmental quality of Fuzhou city is considered as satisfactory. Through analyzing the spatial correlation between the eco-environmental quality and land uses, it was found that the best eco-environmental areas were related to forest lands, whereas the urban area had the relatively worst eco-environmental quality. Human activities are still considered as a major impact on the eco-environmental quality in this area.

Keywords Artificial neural network · Eco-environmental quality · Evaluation · Remote sensing · Land use

Z. Shi · H. Li
Institute of Agricultural Remote Sensing and Information Technology, College of Environmental and Resource Sciences, Zhejiang University, Hangzhou 310029, P R China

1 Introduction

Eco-environment problem is one of the most attention-getting issues in the new century. With the rapid acceleration of economic growth, widespread and severe environmental degradation in some developing countries occur with increasing pollution of air, water and land (Niu and Harris, 1996). Destruction of the forest vegetation has resulted in the deterioration of the ecological environment, such as increasing soil and water losses, and decreasing biodiversities (Qiao *et al*., 2004). Consequently, regional eco-environment protection and improvement are the urgent problems that need to be investigated now. We need to monitor the eco-environmental status and trends by developing methods and theoretical support for environmental planning and management. In the present study, a typical case area was selected from the most economically developed coastal regions in China facing the high pressure of eco-environmental issues.

Eco-environment quality index is a useful tool for environment assessment. With the recent development of geospatial technologies, such as remote sensing and geographic information systems (GIS), its assessment procedures can be significantly enhanced (Zhang *et al*., 2003; Li *et al*., 2005). For example, researchers use a series of eco-environmental attributes extracted from remotely sensed imagery and/or other auxiliary datasets, along with statistical methods such as Principal Component Analysis, the Analytic Hierarchy Process, or the Grey System assessment model, to synthetically evaluate the ecological and spatial distribution characteristics of eco-environment (Aspinall and Pearson, 2000; Petersen *et al*., 2001; Kang, 2002; Liu *et al*., 2003). A linear combination of original attributes with different weights is often used in previous studies for producing the eco-environment quality index. But because ecological systems are characterized by complexity and nonlinear interactions among a large number of system components (Wu and David, 2002), modeling eco-environmental quality index should account for such nonlinearities. Artificial neural network (ANN), which has excellent performance in modeling the nonlinear relationships involving a multitude of variables (Goh, 1995), can be a potentially useful tool to alleviate the problems mentioned above. Some applications of ANN in environmental protection, monitoring, and evaluation have been reported (Dzeroski, 2001; Park *et al*., 2004).

The objective of this study is to apply the ANN methodology for eco-environmental quality evaluation. A series of environmental attributes derived from remotely sensed data, meteorological observations and digital elevation model (DEM) at a spatially-continuous grid level are included and analysed during the evaluation. We first develop an ANN model with a training dataset containing those environmental attributes and referenced Eco-environment Background Values (EBVs) of observational sites, and then extended the model for assessing the eco-environmental quality across the whole study region.

2 Study area and data sources

Fuzhou city, the capital city of Fujian Province, is located in the southeast of China between 25°19′N–26°39′N and 118°08′E–120°31′E. With a total area of 12,140 km^2, it borders on the east by the Taiwan strait and East China Sea (Fig. 1). It spans the middle and south subtropical zones and belongs to the subtropical marine monsoon climate, with an average annual temperature of 19.6 °C and an average annual precipitation of 1342.5 mm. The city is part of a larger mountainous region and has extensive natural vegetation coverage. The topography of the area is characterized by the complex distribution of hills and valleys, with elevations ranging from sea level to 1798 m. Urban and towns are mainly concentrated in coastal and narrow river-valley areas with a population density of around 2330/km^2 (http://www.fuzhou.gov.cn). The complex topography, plentiful rainfalls and dense populations altogether result in the high vulnerability and sensitivity of eco-environmental systems in the area.

The basic data used in this study include: (1) Two scenes of Landsat7 Enhanced Thematic Mapper (ETM+) data which received on 04/03/2001 (Path 119, Row 42) and 13/03/2001 (Path 118, Row 42); (2) A freely available MODIS land surface temperature (LST) MOD11A1 imagery on 4 April 2001 downloaded from the Earth Observing System data gateway (USGS EOS, 2003); (3) A topographical map at the scale of 1:100 000 and a district map at a scale of 1:250 000, from the Bureau of Surveying and Mapping of Fujian Province; and (4) Meteorological observation data of 71 meteorological stations in Fujian province.

Ground reference data about various eco-environmental types and zones were collected by field investigation. First, a modified eco-environmental quality evaluation system was proposed with reference to the China Technical Criterion for Eco-environmental Quality Evaluation (SEPAC, 2005) (Table 1). Table 1 shows nine ranks of eco-environmental quality and their basic features about eco-environmental conditions. Each rank is given a score, which is also called Eco-environment Background Value (EBV); the higher EBV value means the better eco-environmental quality. Second, a total of 222 sites, which belong to different eco-environmental types and zones, were selected and positioned on the topographical base map before field investigation. For each site, a 200 by 200 m square was used as an investigation unit

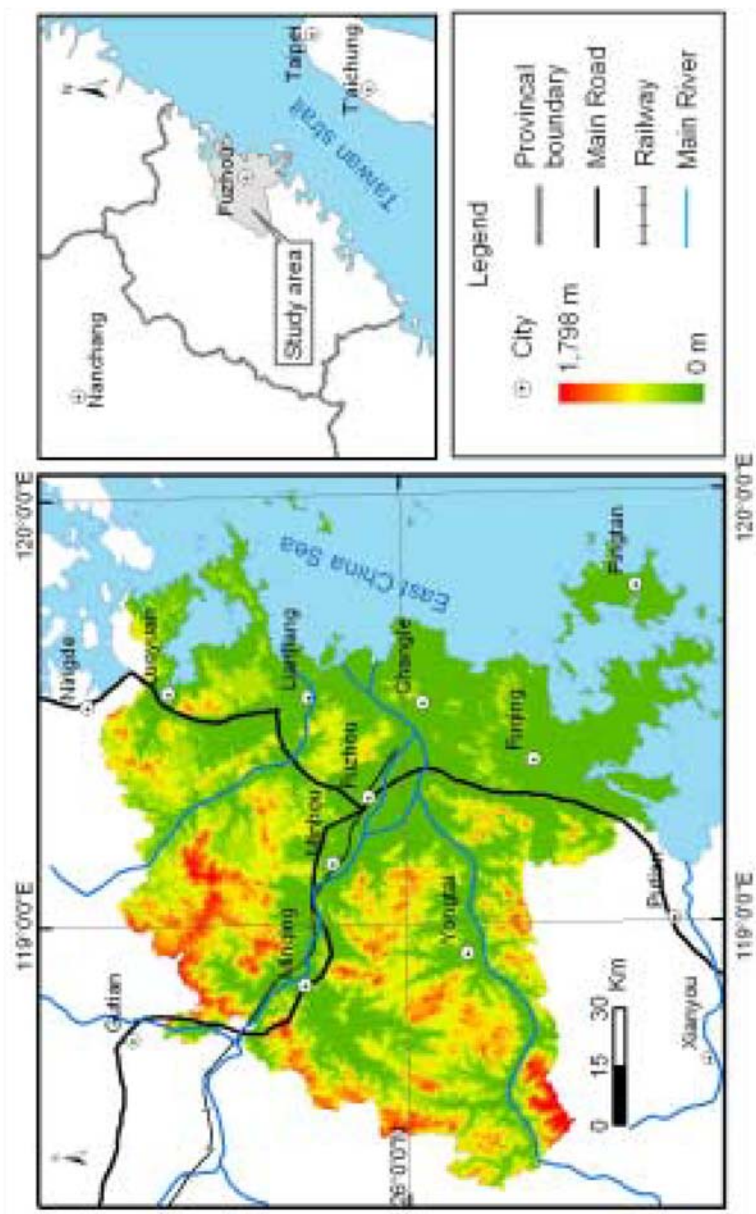

Fig. 1 Location of the study area

Table 1 The scoring and ranking system of the eco-environmental quality value

Rank	EBV range	Eco-environment type	Topographical condition	Vegetable cover/Land cover	Humidity & heat
I	500–450	High coverage ratio broadleaf, conifer & broadleaf mixed eco-environment type	Moderate mountains (1000–1200 m)	Evergreen broadleaf forest; Tree cover >90%	70–80% Shady and cool
II	450–400	Moderate coverage ratio conifer & broadleaf mixed eco-environment types	Low mountains (500–1000 m)	Subtropical conifer and broadleaf mixed forest, deciduous broadleaf forest; Tree cover is 80–90%	60–70% Shady and cool
III	400–350	Low coverage ratio conifer eco-environment type	Low mountains (500–1000 m)	Conifer forest: fir, horsetail forest	40% Shady
IV	350–300	Shrub eco-environment type	Various hilly and moutainous lands	Evergreen broadleaf forest, shrub	50–60% Warm
V	300–250	Meadow & brushwood eco-environment type	Top of moderate mountains (>1200 m)	Meadow, bunch grasses (gramineae)	30% Cool
VI	250–200	Economic forest eco-environment type	Costal low hills and uplands, valley	Orchard garden, tea garden, bamboo	30% Warm
VII	200–150	Wetland eco-environment type	Plain farmland	Irrigation farming	50% Dry and heat
VIII	150–100	Arid & barren land eco-environment type	Peninsula, sand beach	Dry farming	20% Dry and heat
IX	100–50	Artificial construction eco-environment type	Plain	Residential area, buildings	20% Dry and heat

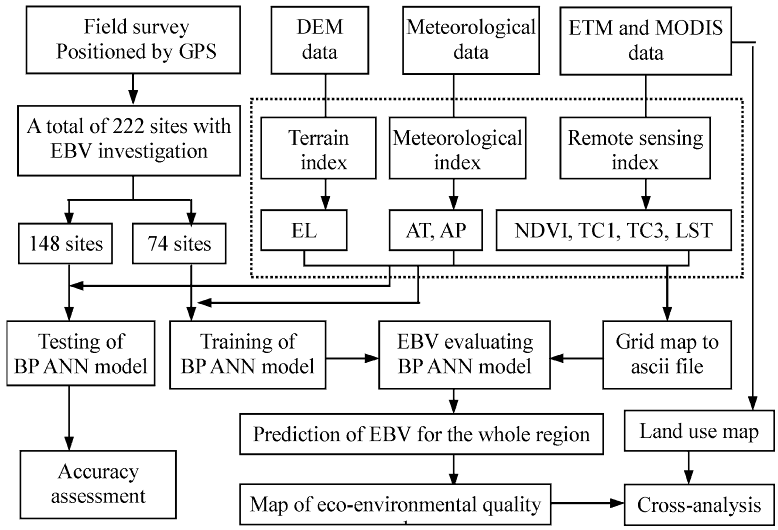

Fig. 2 Flowchart illustrating the research methodology.

and its position was recorded by a 'Trimble' Global Positioning System (GPS) device. Environmental attributes including topographical conditions, soil types, vegetation covers were documented. Ranking eco-environmental quality and corresponding EBV value for every site was subsequently manually conducted by ecological experts with reference to the evaluation system (Table 1).

3 Methodology

3.1 Evaluation framework

The conceptual framework for assessing eco-environmental quality in Fuzhou city includes the following four major steps: (1) acquisition of environmental attributes as inputs; (2) training and testing an ANN model; (3) accuracy assessment; (4) prediction and mapping for the whole region by the ANN model (Fig. 2). Imagine 8.6 (ERADS, 1999) and ArcInfo 8.3 (ESRI, 2004) were used to analyze remotely sensed images and GIS data layers, and the ANN model was performed in MATLAB 6.5 software (The MathWorks, Inc., 1998).

All geospatial inputs were geo-referenced and used the Gauss–Krueger Projection with central longitude 117°E, original latitude 0°, Beijing1954 geodetic datum and *Krassovsky* ellipsoid. In imagery geometrical correction, a third order polynomial method was applied. A total of 12 distinguishable ground control points (e.g., intersections of railway and/or roads) were selected from a detailed topographical map. After correction, a satisfactory mean squared error (MSE) of 10.6 m was obtained.

3.2 Input attributes

Precipitation, temperature, vegetation status and structure, terrain, and their spatial patterns are important for the stability and natural balance of regional eco-environment. Water and heat are determining factors of the distribution and structure of ecosystem (Zhang *et al.*, 2003). In our evaluation, three types of eco-environmental attributes were considered: (1) remote sensing image derived indices (based on vegetation index, soil brightness index, wetness index, land surface temperature index); (2) meteorological indices (annual temperature and annual precipitation); and (3) terrain indices (elevation).

Firstly, the remote sensing image derived indices include Normalized Difference Vegetation Index (NDVI), soil brightness index (TC1), wetness index (TC3), and Land Surface Temperature (LST). With the Landsat ETM + imagery, NDVI is calculated by $(NIR_{TM4} - R_{TM3})/(NIR_{TM4} + R_{TM3})$, where NIR_{TM4} and R_{TM3} are the digital number (DN) of ETM + Band 4 (near-infrared band) and Band 3 (red band), respectively. Because these two bands are closely related to the amount of vegetation biomass, vegetation index is very useful for vegetation cover discrimination. Soil brightness index (TC1) and wetness index (TC3) were derived from the ETM+ imagery by the Tasseled Cap approach. The Tasseled Cap approach is a linear transformation and the first three features derived from the Landsat ETM+ imagery are known as brightness, greenness, and wetness. These three features, which have physical significance, can typically express 95% or more of the total variability of the original images (Crist and Kauth, 1986). Because the greenness index here is similar to NDVI to some extent, we selected brightness index and wetness index for the eco-environmental quality evaluation. The Land Surface Temperature (LST) is one of the key parameters in the physics of land surface processes, combining surface-atmosphere interactions and the energy fluxes between the atmosphere and the ground. In the present study, LST was derived from the MODIS MOD11A1 product.

Secondly, annual temperature (AT) and annual precipitation (AP) were selected as the meteorological indices. These two attributes were estimated and interpolated using the multi-linear regression model (Shi *et al.*, 1997). Based on meteorological observation data of 71 stations, a multi-linear regression model between AT (or AP) and three geo-referenced parameters (i.e. longitude, latitude, and altitude) were established (Equations (1) and (2)).

$$\mathrm{AT} = 57.2545 - 0.151 \times \phi - 0.7502 \times \lambda - 0.0046 \times h, \quad R^2 = 0.948 \tag{1}$$

$$\mathrm{AP} = 11555.1102 - 113.3411 \times \phi + 128.9795 \times \lambda + 0.2885 \times h, \quad R^2 = 0.639 \tag{2}$$

where ϕ and λ represent longitude and latitude (degree), and h altitude (m).

Thirdly, elevation information (EL) extracted from the digital elevation model (DEM) was selected as the terrain index. Together, all seven eco-environmental indices above were re-sampled at a grid level with the cell size of 100 m.

3.3 Neural network model

ANN is a computer model whose architecture essentially mimics the knowledge acquisition and organizational skills of the human brain (Goh, 1995). ANN is often applied in the field of regression or classification. Although there are a variety of ways to construct these models, Back-Propagated (BP) neural networks has become one of the most widely used ANNs in practice (Moisen and Frescino, 2002). BP neural networks with a single hidden layer have been proved to be capable of providing an accurate approximation of any continuous functions (Hornik, 1991). In the present study, therefore, a three-layer ANN model with a single hidden layer was designed (Fig. 3) and introduced briefly here (Zhang *et al.*, 2005).

The three layers are called the input layer, hidden layer and output layer, respectively. Each layer consists of logic units or neurons, as the basic information-processing units in ANN. The relationship of the input value of the unit i in input layer and that of unit h in hidden layer is:

$$\varphi_h = \sum_{i=1}^{m} s_i \omega_{ih} + \theta_h \tag{3}$$

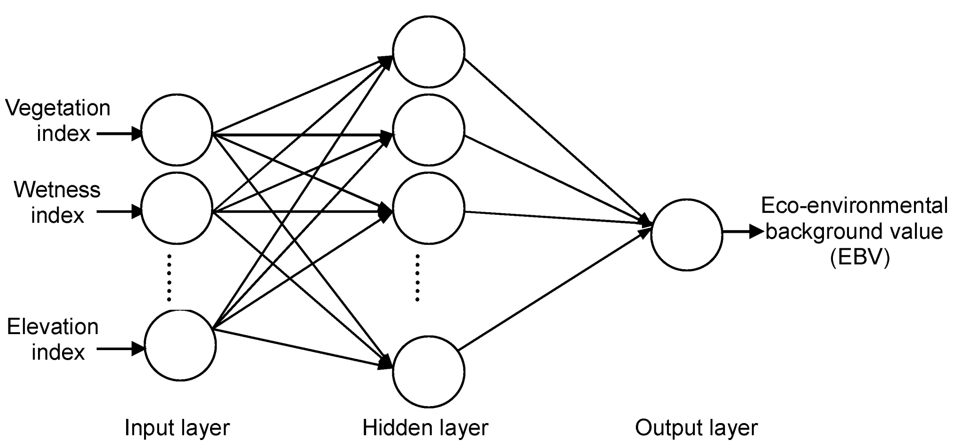

Fig. 3 Diagram of the BP neural network model

Table 2 Assessment of the predicted accuracy of eco-environment quality ranks

Rank	I	II	III	IV	V	VI	VII	VIII	IX	UA[a] (%)
	Reference data									
	Predicted data									
I	5	1	0	0	0	0	0	0	0	83.3
II	0	6	1	1	0	0	0	0	0	75.0
III	0	0	9	0	1	0	0	0	0	90.0
IV	0	0	1	9	1	0	0	0	0	81.8
V	0	0	0	2	8	0	0	0	0	80.0
VI	0	0	0	0	1	6	1	0	0	75.0
VII	0	0	0	0	0	0	6	1	0	85.7
VIII	0	0	0	0	0	0	0	7	0	100.0
IX	0	0	0	0	0	0	0	2	5	71.4
PA[b] (%)	100.0	85.7	81.8	75.0	72.7	100.0	85.7	70.0	100.0	Kappa = 0.801, OA[c] = 82.4%

[a]User's accuracy
[b]Producer's accuracy
[c]Overall accuracy

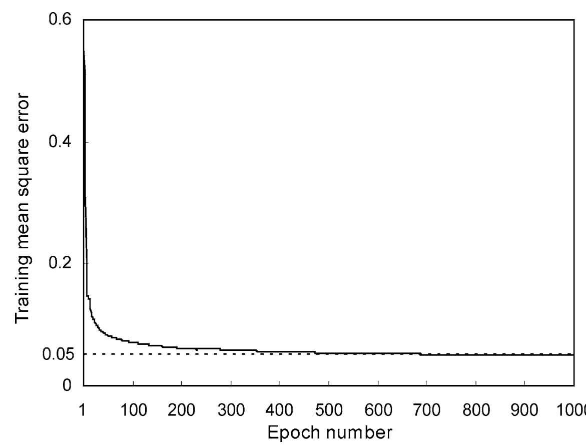

Fig. 4 Training performance of the BP ANN model

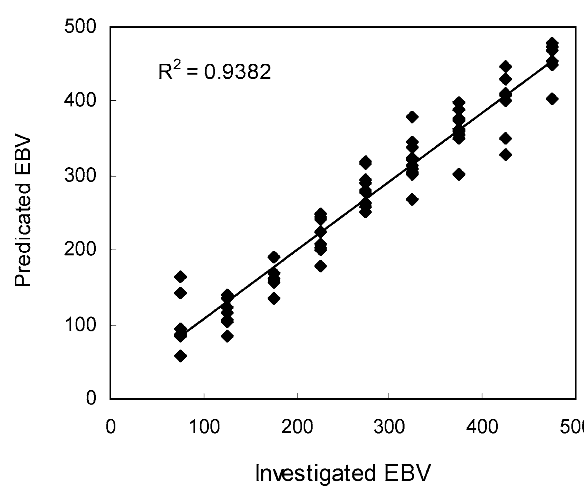

Fig. 5 Comparison of the investigated EBV and predicted EBV using the BP ANN model

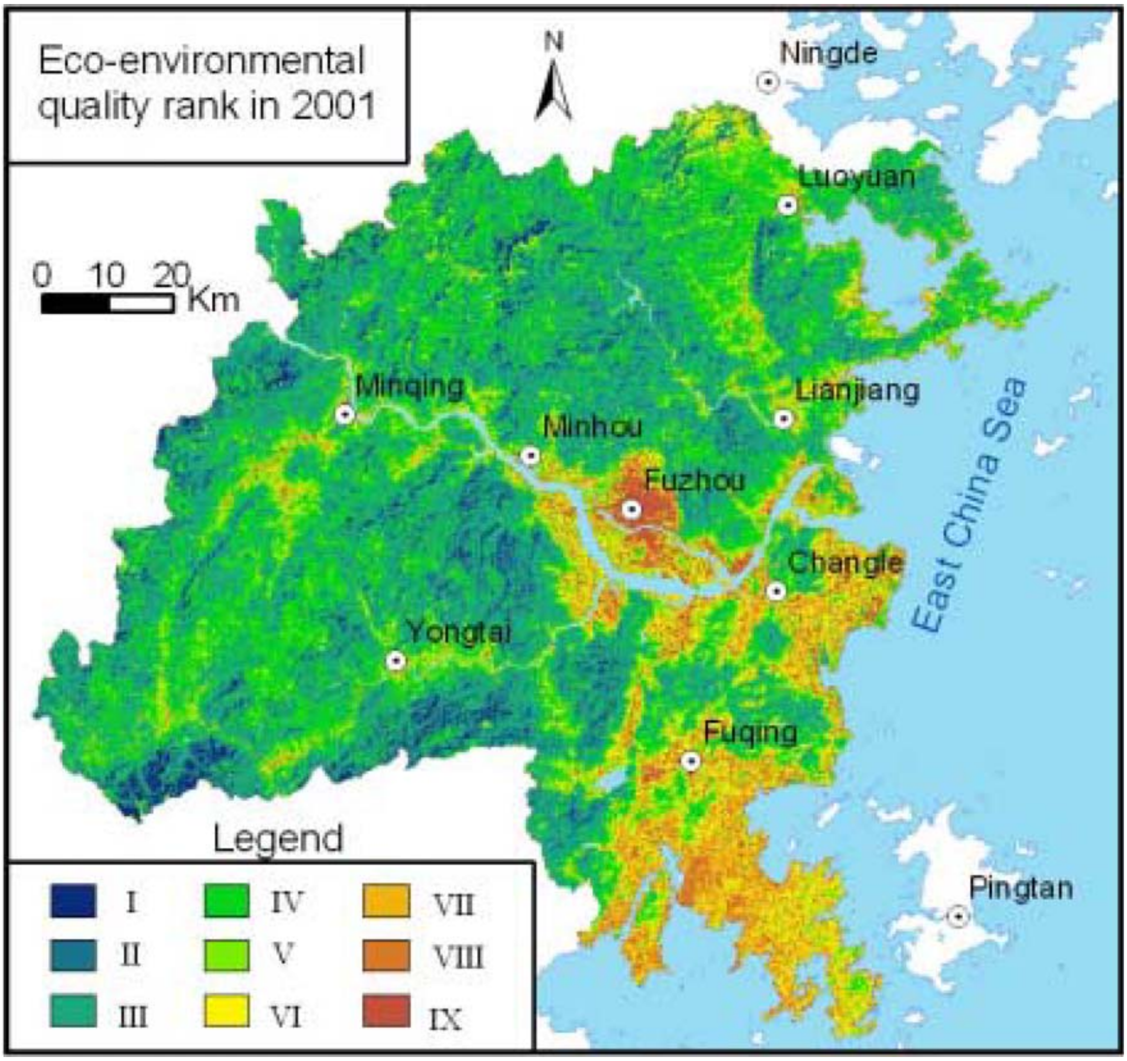

Fig. 6 Spatial distribution map of eco-environmental quality ranks in Fuzhou city

where s_i is an input value of the logic unit i in the input layer, ϕ_h an initial output value of the logic unit h in the hidden layer, ω_{ih} connection weights between unit h and i, θ_h input bias of the unit h, m the number of logic units in the input layer and adjustable according to the modeling task.

The initial output value ϕ_h is further transformed with the common transfer function in a sigmoidal form:

$$O_h = \frac{1}{1 + e^{-\varphi_h}} \tag{4}$$

where O_h is the final output value of the logic unit h.

The goal of the training of ANN is to minimize the error between predicted and target values by adjusting the connection weights and biases. The error is given by Equation (5):

$$E = \sum_{p=1}^{P} \sum_{m=1}^{M} (a_{pm} - o_{pm})^2 \tag{5}$$

where M is the number of logic units in output layer, and P is the number of training samples. a_{pm} and o_{pm} are the predicted and target values, respectively.

The whole 222 investigated sites were divided into two parts. For the model training purpose, two-thirds

Table 3 Area of the different land uses in each eco-environment quality rank (ha)

	I	II	III	IV	V	VI	VII	VIII	IX
Arable	764	5568	46896	118055	66015	50640	37324	20596	9376
Orchard	24	342	4977	21205	9433	2390	960	588	556
Forest	24504	83256	319054	163710	36659	8742	3237	1670	2709
Urban/Town	2	41	305	2387	7646	9094	9205	10165	15623
Barren	0	0	0	35	140	185	245	300	675

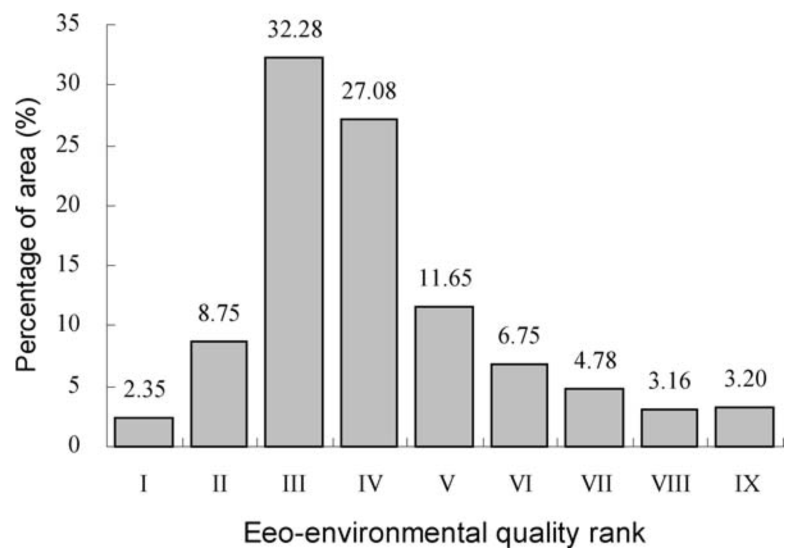

Fig. 7 Area proportion histogram of eco-environment quality ranks

of the sites in each EBV rank were used, resulting in a total of 148 samples in a training set to construct the ANN model. Testing was made by the data from the rest 74 samples. To examine the reliability and accuracy of the ANN model, predicted results were compared with the EBV value produced in the field investigation.

Prior to the model training, all input attributes were normalized in order to reduce the effect of different input units and boost the speed of convergence of a BP ANN model (Equation (6)):

$$S_{ij} = 10 \times (X_{ij} - X \min_i)/(X \max_i - X \min_i),$$
$$i = 1, 2, \ldots, n; \quad j = 1, 2, \ldots, m \tag{6}$$

where S_{ij} and X_{ij} are the normalized score and original value the *i*th attribute at the *j*th site, respectively; $X \max_i$ and $X \min_i$ are the maximum and minimum value of *i*th attribute; *n* and *m* are the total numbers of attributes and sites ($n = 7$ and $m = 222$).

The MATLAB Toolbox was used to create the BP model. In the training phase, step size and momentum were initialized as 0.1 and 0.7, respectively. A minimum of the total error of the system was set to 0.05.

4 Results

4.1 Training and testing of an ANN model

Seven input attributes as logic units in the input layer and the EBV value as the single logic unit in the output layer were adopted, and the number of logic units in the hidden layer was set to 10. Therefore, the optimized ANN model structure was 7:10:1. During the training phase, associated trained weights of the logic units or neurons were stored in the neural network memory. In testing, prediction values from the neural network were compared and validated with the observed EBV values. If the predictions are still in their original EBV range, we then consider the prediction is acceptable. Mean square errors (MSEs) of the trained model in

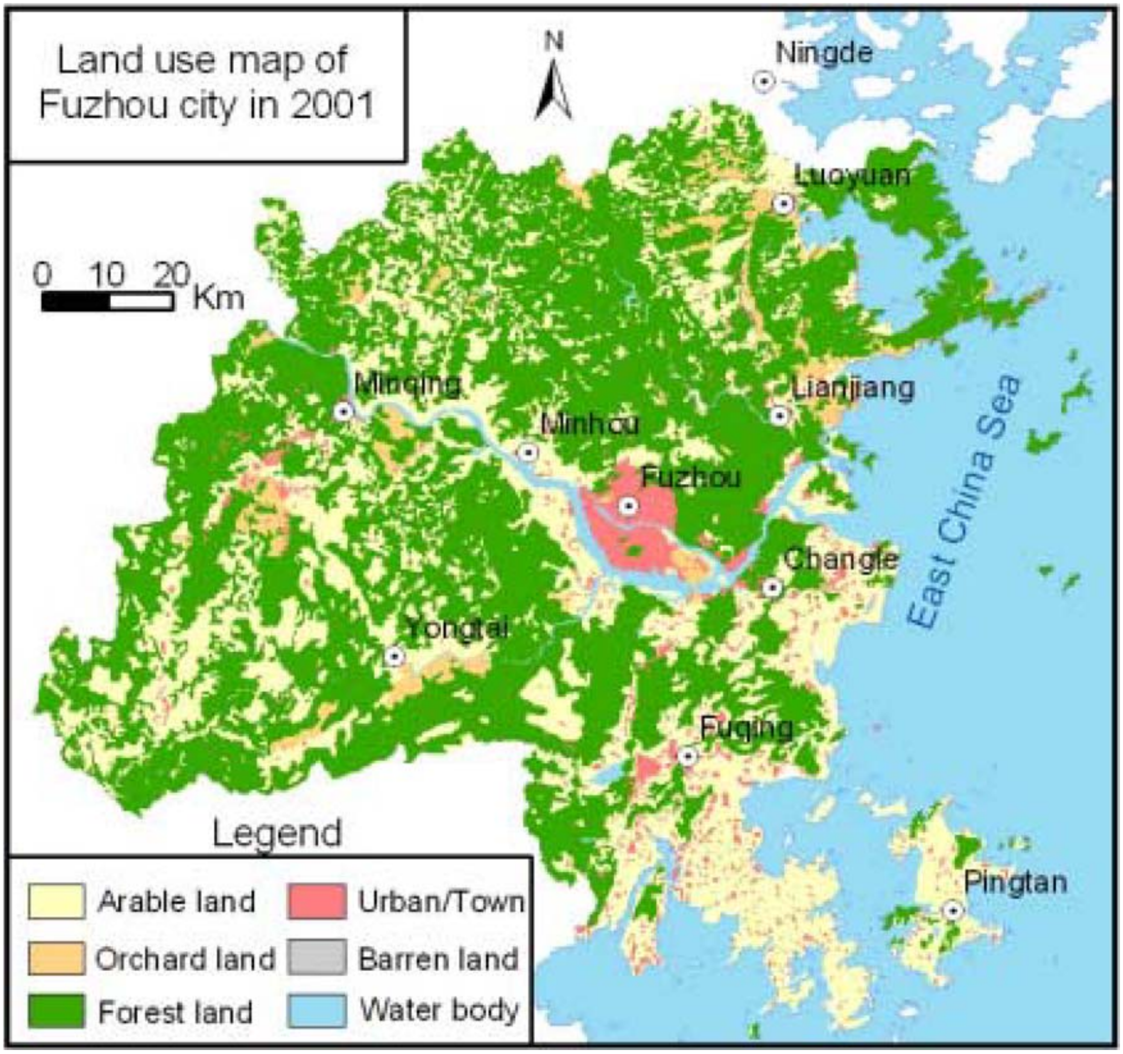

Fig. 8 A remotely sensed classified land use map of Fuzhou city in 2001

the first 1,000 iterative epochs are shown in Fig. 4. The MSEs dropped dramatically from 0.5488 to 0.144 in the initial training period of the first ten epochs, and then decreased slowly and reached a flat threshold (MSE = 0.05).

Figure 5 shows the the predicted EBV values and their corresponding investigated EBV values for the entire 74 testing sites. Clearly, there is a remarkable agreement.

From the predicted EBVs, all testing sites were given corresponding ranks according to the EBV evaluation system in Table 1. Table 2 summarizes the error matrix in accuracy assessment. Reference data are in columns representing ground-truths collected by field investigation, and predicted data are in rows. Both user's accuracy and product's accuracy for each EBV rank can be calculated. An overall accuracy is expressed as the percentage of the testing sites successfully assigned to the correct ranks. Kappa coefficient was also calculated. The higher overall accuracy or Kappa coefficient indicates better prediction accuracy. In this study, an overall prediction accuracy of 82.4% was achieved, with a Kappa coefficient of 0.801. These results suggest that the ANN model is indeed promising in the eco-environmental quality evaluation. In contrast to the conventional evaluation approach, an ANN approach is more easily-operational and practical because the complex relationship among the input attributes in

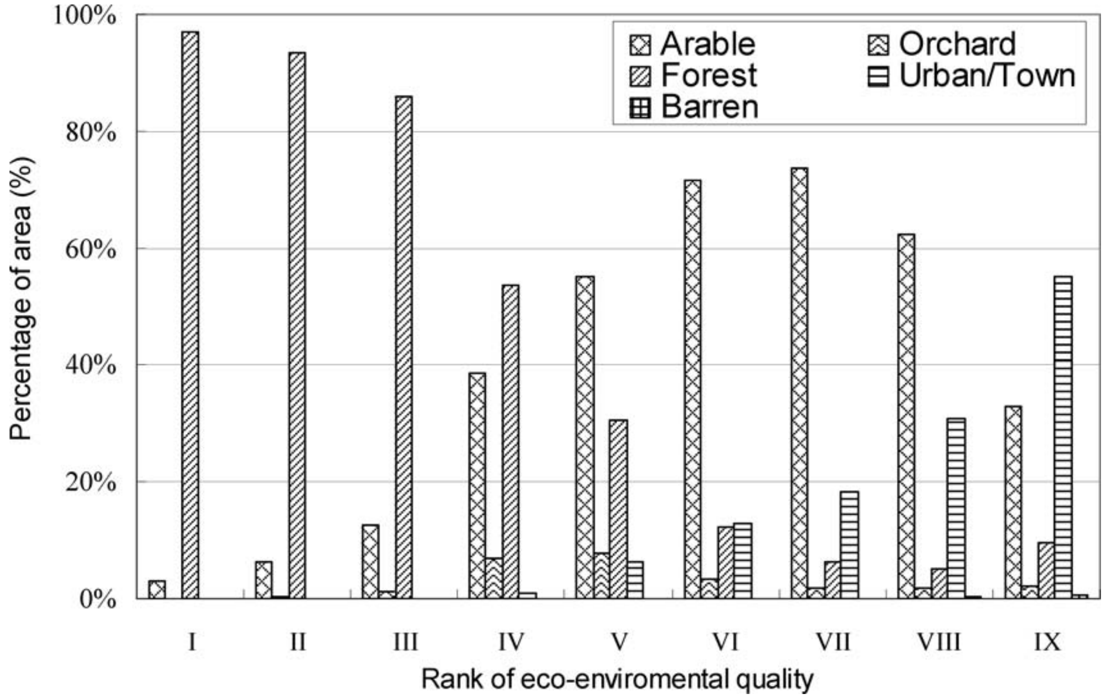

Fig. 9 Percentages of different land uses in each eco-environmental quality rank

relation to EBVs is handled automatically by the model itself.

4.2 Predicting EBV distributions for the whole study area

Seven grid-based input attributes were first converted to an ASCII format by ArcGIS software, and then inputted into the MATLAB software for the BP ANN modeling. Fig. 6 shows the predicted EBV results and ranks, and Fig. 7 area proportions of individual ranks. Rank III has the largest areal proportion (32.28%), followed by Rank IV (27.08%). The upper ranks (from Rank I to Rank IV), which means relatively better eco-environmental quality, covered 70.46% of the whole study area. Only 11.14% of the study area belongs to the last three ranks (from VII to IX). These indicate that the overall eco-environmental quality of the Fuzhou city is relatively satisfactory.

As far as the spatial distribution of the eco-environmental quality ranks is concerned (Fig. 6), the majority areas with the better EBV ranks are located in mountain areas of the west and north of Fuzhou city. The worse EBV ranks are located mainly at built-up areas, eroded/deforested hills, and coastal stretches (compare Fig. 1).

4.3 Relationship between land use and eco-environmental quality ranks

A land use map of Fuzhou city in 2001 was produced by visual interpretation with the Landsat ETM+ images and field investigation (Fig. 8). Table 3 summarizes areas of various land use categories with different eco-environmental ranks. In Fuzhou city, the majority of region is covered by forest lands (56.6%) and arable lands (32.8%), and urban and town areas occupy 4.9% of the whole region only.

Figure 9 shows the percentages of arable lands, orchards, forest lands, urban and town areas, and barren lands with individual eco-environmental quality ranks. The first three EBV ranks – Rank I, Rank II and Rank III are dominated by forest lands (96.9, 93.3 and 85.9%, respectively), whereas the last (worst) three ranks mainly consist of arable lands and urban and town areas. The composition of arable lands and orchards in each rank are almost similar to a normal frequency distribution, suggesting the moderate ranks of the eco-environmental quality. It should be noted that the proportion of urban areas is on the increase in recent years yet with the descending ranks of eco-environmental quality. Human activity can be regarded as the main factor worsening the overall eco-environmental quality in the study area.

5 Summary and discussion

Population growth, rapid urbanization and intensifying economic development have placed tremendous pressures on the natural environment in the coastal developed region of China. Monitoring and assessing the eco-environmental quality is required by different levels of government agencies when formulating any development policies, plans and programs. This paper demonstrates an integrated approach for combining an ANN model with GIS databases to evaluate and map the regional eco-environmental quality. Starting from the field observations and after absorbing the knowledge gleaned from conventional expert assessment, our investigation with an overall high prediction accuracy shows the ANN approach practical and capable.

Our assessment results show that the eco-environmental quality of Fuzhou city is satisfactory. Through analyzing the spatial correlations between eco-environmental quality values and land uses, it was found that the majority of the city with a better eco-environmental quality is related to forest lands, whereas urban areas were assessed to have the worst. Human activities are still considered as the main driver impacting the eco-environmental quality in this area.

An ANN model can be easily revised and updated by new training samples. In this sense, it also has the potential for evaluating the dynamic changes of the eco-environmental quality in the area. Future research on this with more up-to-date remotely sensed images and field investigations will be pursued. Moreover, because the methodology developed in this study is largely data-driven and generic, it can be readily applied for assessing the similar eco-environment quality of other regions.

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References

Aspinall, R., & Pearson, D. (2000). Integrated geographical assessment of environmental condition in water catchments: linking landscape ecology, environmental modeling and GIS. *Journal of Environmental Management, 59*(4), 299–319.

Crist, E.P., & Kauth, R.J. (1986). The Tasseled Cap de-mystified. *Photogrammetric Engineering and Remote Sensing, 52*(1), 81–86.

Dzeroski, S. (2001). Application of symbolic machine learning to ecological modelling. *Ecological Modeling, 146*(1–3), 263–273.

EOS. (2004). NASA Earth Observing System data gateway. Available at: http://edcimswww.cr.usgs.gov/pub /imswelcome/.

ERDAS, Inc. (1999). *ERADS field guide*. Atlanta: Georgia.

ESRI, Inc. (2005). ArcInfo. ESRI, CA, USA.

Goh, A.T.C. (1995). Back-propagation neural networks for modeling complex-systems. *Artificial Intelligence in Engineering, 9*(3), 143–151.

Hao, Y.H., & Zhou, H.C. (2002). A grey assessment model of regional eco-environment quality and its application. *Environmental Engineering, 20*(4), 66–68. (in Chinese)

Hornik, K. (1991). Approximation capabilities of multilayer feedforward networks. *Neural Network, 4*(2), 251–257.

Kang, S.M. (2002). A sensitivity analysis of the Korean composite environmental index. *Ecological Economics, 43*(2–3), 159–174.

Li, A.N., Wang, A.S., Liang, S.L., & Zhou, W.C. (2005). Eco-environmental vulnerability evaluation in mountainous region using remote sensing and GIS – A case study in the upper reaches of Mining river, China. *Ecological Modeling* (in press).

Liu, Z., Xie, Z.R., & Shen, W.S. (2003). A new method that can improve regional eco-environmental evaluation–combining GIS with AHP. *Resources and Environment in the Yangtze Basin, 12*(2), 163–168. (in Chinese)

Moisen, G.G., & Frescino, T.S. (2002). Comparing five modelling techniques for predicting forest characteristics. *Ecological Modelling, 157*(2–3), 209–225.

Niu, W.Y., & Harris, W.M. (1996). China: the forecast of its environmental situation in the 21st century. *Journal of Environmental Management, 47*(2), 101–114.

Park, Y.S., Chon, T.S., Kwak, I.S., & Sovan, L. (2004). Hierarchical community classification and assessment of aquatic ecosystems using artificial neural networks. *Science of Total Environment, 327*(1–3), 105–122.

Petersen, W.L. Bertino, Callies, U., & Zorita, E. (2001). Process identification by principal component analysis of river water-quality data. *Ecological Modelling, 138*(1–3), 193–213.

Qiao, Y.L., Wang, Y., & Tang, J.Y. (2004). Study of remote sensing monitoring of dynamic change of the Loess Plateau forest resources. *Advances in Space Research, 33*(3), 302–306.

SEPAC. (2005). State Environmental Protection Administration of China. Technical Criterion for Eco-environmental Quality Evaluation.

Shi, Z., Wang, R.C., & Wu, H.H. (1997). GIS-based simulating and mapping of annual mean temperature in mountain area. *Mountain Research, 15*, 264–268. (in Chinese)

The MathWorks Inc. (1998). *User's Guide, Version 3, Neural Network Toolbox for Use with MATLAB*.

Wu, J.G., & David, J.L. (2002). A spatially explicit hierarchical approach to modeling complex ecological systems: theory and applications. *Ecological Modelling, 153*(1–2), 7–26.

Zhang, X.L., You, X.X., Liu, X.S., & Huang, H.G. (2003). A study on forest ecological environment gradient with remote sensing, GIS and expert system. Proceedings of the Second International Conference on Machine Learning and Cybernetics. Xi'an China, 2374–2378.

Zhang, Y.X., Li, H., & Havel, J. (2005). Modeling of the relationship between electroosmotic flow and separation parameters in capillary zone electrophoresis using artificial neural networks and experimental design. *Talanta, 65*(4), 853–860.