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RESEARCH ARTICLE

An artificial neural network model of the landscape pattern in Shanghai metropolitan region, China

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Abstract To characterize the urbanization pattern quantitatively, a study on the mechanisms of the landscape pattern formation could facilitate the understanding on urban landscape patterns and processes, the ecological and socioeconomic consequences of urbanization, as well as the establishment of more effective strategies for landscape management. In this study, we integrated a Geographic Information System (GIS)-based analysis on landscape pattern with an artificial neural network (ANN) to quantitatively characterize the urbanization pattern of the metropolitan area of Shanghai, China, and to establish an ANN model that could preferably simulate the responses of urban landscape pattern to the natural and socioeconomic factors such as residence area, road density, population density, urban development history and the Huangpu River as an element of economic change. Our results showed that the ANN model seems appropriate for studying the nonlinear relationship among the forcing factors of urbanization and the urban landscape patterns, which provided an effective and practical approach for further understanding the mechanisms of the landscape formation pattern and the reciprocal relationship between landscape spatial pattern and ecological process.

Keywords Shanghai, urbanization, landscape pattern, artificial neural network (ANN), forcing mechanism

1 Introduction

Shanghai, the most powerful and active core area for Chinese economic development, is accelerating its process of promising modernization. Together with this acceleration are high-density investment, population boom, assemblage of industry, drastic urbanization and a sharp increase in construction density, which has brought great challenge to Shanghai's sustainable development (Zhang et al., 2004). By its very nature, a city is a human-dominated ecosystem woven by nature, society and economy. Studies on urban ecology have great significance in solving problems such as population increase, lack of natural resource, change of urban pattern and environmental pollution, all of which are trigged by the acceleration of urban development (Zipperer et al., 2000; Zhu et al., 2002; Berling-Wolff; Wu, 2004).

Interaction between landscape's spatial pattern and its ecological process is the most important issue in landscape ecology (Wu, 2000). Urban landscape ecology concern includes describing pattern and dynamics of city, identifying and determining the driving forces. Quantity analysis on spatial pattern in urban area and its forming mechanism can help us understand the relationship between landscape pattern and ecological process and predict consequences of society, economy and ecology. Accordingly, counter measures will be made for urban administration (Pickett et al., 2001; Whitford et al., 2001; Zhang et al., 2004).

The artificial neural network (ANN), which is composed of numerous units (neurons), is a highly non-liner mass time-connected system. It is developed on the basis of modern neurology, acting like the human brain. It's human brain's abstract, predigesting and simulation rather than a description for real brain (Xu, 2002). Self-organization, associative memory and speedy optimization are the three most sophisticated functions. ANN, one of the most important methods in modern geography, is usually applied to geographical pattern identification, geographical process simulation and prediction and optimization of complex geographical system. Meanwhile, the advantages of ANN is making itself more widely used in simulation, assessment and prediction of environment protection, ecology and urban planning (Jin and Li, 1998; Lek and Guégan, 1999). Nevertheless, few ANN models has been found among the researches with regard to urban landscape pattern, landscape

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dynamics and driving forces (Zhang et al., 2003).

With a viewpoint of landscape ecology, this study tries to discover the mechanism of urban landscape formation with the aid of ANN modeling and landscape pattern analysis (Zhang et al., 2004). The results should interpret the interaction between the urban patterns and its process, and consequently to monitor and evaluate the urbanization process of the Shanghai metropolitan area.

2 Study area and methods

2.1 Study area

Shanghai lies on an area between 30°23′ to 31°37′N, 120°50′ to 121°45′E. This metropolitan area (6 340 km^2), by administrative division in 1994, is divided into 20 parts, including 14 districts (Huang Pu, Nan Shi, Lu Wan, Xu Hui, Chang Ning, Jing An, Pu Tuo, Zha Bei, Hong Kou, Yang Pu, Min Hang, Bao Shan, Jia Ding and Pu Dong) and 6 counties (Nan Hui, Song Jiang, Feng Xian, Jin Shan, Qingpu and Chong Ming). Shanghai has a population of 12 988 100, including 9 530 400 downtown area population. The average population density of the whole metropolitan and downtown areas went up to 2 048 / km^2 and 4 633 / km^2, respectively (Shanghai Statistics Bureau, 1999).

This research takes advantage of land use map of Shanghai metropolitan area extracted from 154 IR/Color remote sense data set of 1:6 000 provided by Shanghai Remote Sensing Comprehensive Survey Office. This data set was interpreted in accordance to the “urban land use classification” frame in Urban Land Use and Planning Land Use Standard (GBJ137-90) issued by the Ministry of Construction of China in 1991. Land use data set (1994) for analysis was finished through base-map dealing and field validation. Vectorization was completed using PC ARC/INFO, and all the vector map and land use data set were compiled in PC ArcView Geographic Information System (GIS) (Zhang et al., 2004).

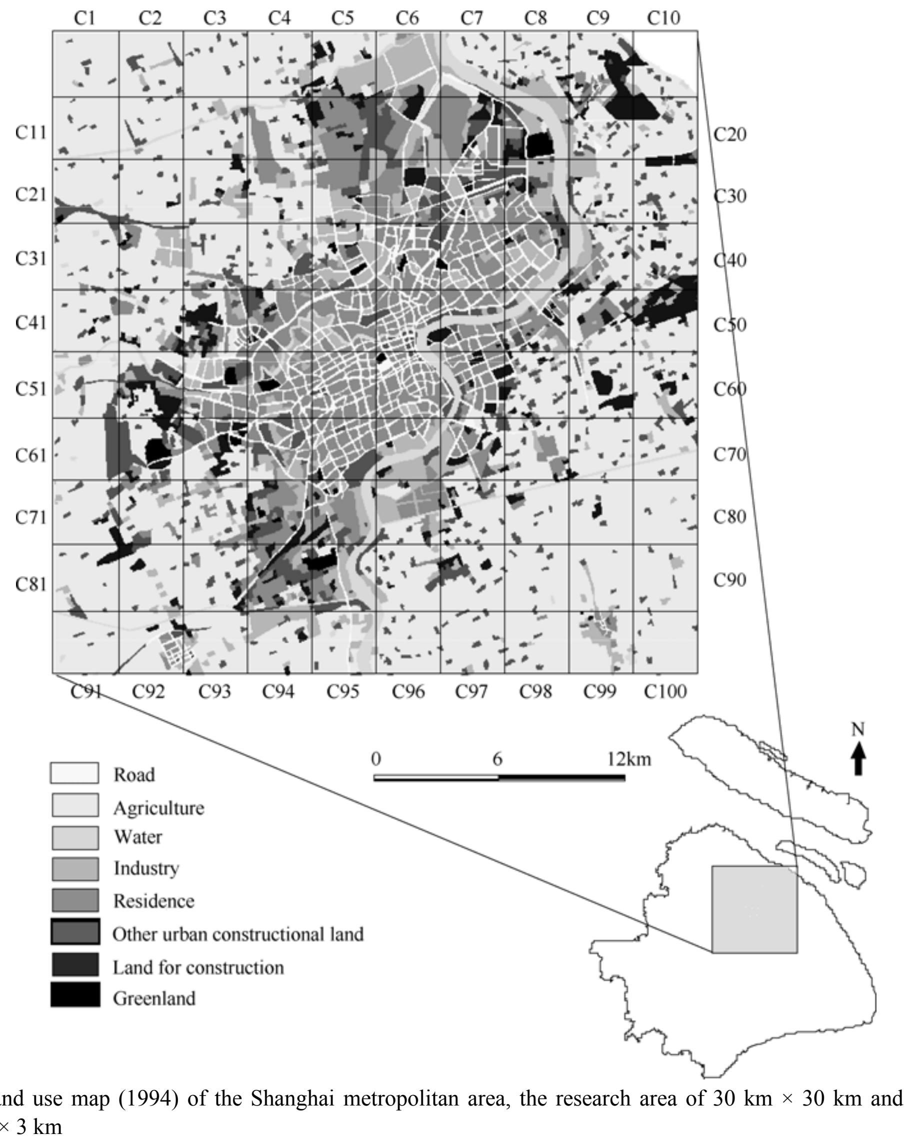

Fig. 1 GIS-based land use map (1994) of the Shanghai metropolitan area, the research area of 30 km × 30 km and 100 sampling plots (C1－C100) of 3 km × 3 km

2.2 Landscape pattern analysis

A sample area of the Shanghai metropolitan region was divided into 100 squares of 3 km × 3 km for landscape pattern analysis and ANN model building. These samples were labeled C1 to C100 from west to east and from north to south (Fig. 1). The original data set of 16 kinds of land use was reclassified into 8: residential, industrial, urban and others, agricultural, land for construction, road, water and green land. Then, reclassified data set was turned into grids of 10 m × 10 m using ESRI ArcView Spatial Analyst and analyzed by FRAGSTATS 3.3 for landscape metrics calculation (McGarigal and Marks, 1995; Zhang et al., 2004).

2.3 Back-propagation model

Most ANN applications preferred the back propagation (BP) model suggested by Rumelhart (1986). BP is multiplayer feed-forward neural network (Fig. 2) including input, output and hidden layers. Nods in the same layer do not have any coupling. Input signals were transferred from input to hidden and then to output layers. Outputs of each layer only affected outputs of the succeeding layer (Xu, 2002). The BP model was consider a highly non-liner mapping from input to output, F: $\mathbb{R}^n \rightarrow \mathbb{R}^m$, $f(x) = Y$. To an aggregate $x_i \in \mathbb{R}^n$ and $y_i \in \mathbb{R}^m$, then there is a mapping g, $g(x) = y_i$ (i = 1, 2, ⋯ n). There must be a mapping f, which made itself the best approximation of mapping g. Given any $\varepsilon > 0$ and any L_2 function, f: $[0, 1]^n \rightarrow \mathbb{R}^m$, there was BP network of three layers that could approximate to f within the mean square error (MSE) of any ε (Kitahara et al., 1992).

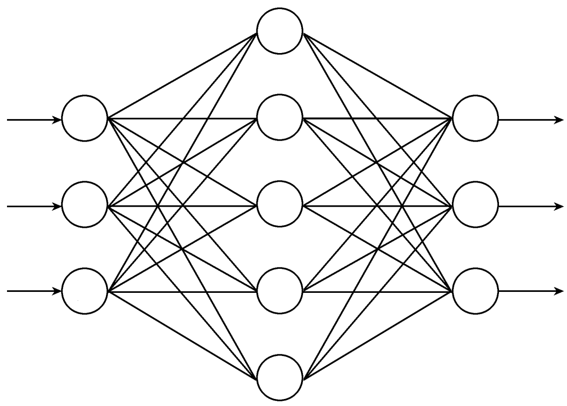

Fig. 2 The back-propagation network with three layers

The BP model's training includes:

1) Initializing weights and MSEs of each layer with small random number to avoid saturation of weighted inputs while initializing expected error minimum, circulation times the maximum, learning the rate of weight revision, circling the rate beginning from one;

2) Calculating the vector output and errors of each layers;

3) Calculating the MSE, revising weights and new weights;

4) Calculating the new MSE after revision of weight;

5) Checking the MSE with expected error minimum; the training will finish if the MSE is less than the latter, otherwise, training will continue.

2.4 Model building

Studies on the mechanism of landscape shaping need investigation of factors with regards to geography, ecology, society, economy and politics. Thus, we took the percentage of roads, the percentage of residence area, the distance from the city center, the distance from Huangpu River and the population density as input variables. Because the lack of population statistics for 1994, we took the population density from the population investigation of Shanghai in 1998 (Shanghai Statistics Bureau, 1999). Other inputs came from measurements on the data set using ArcView 3.2a. Outputs consisted of patch density, perimeter–area ratio, Shannon's Diversity Index and aggregation index. (Table 1)

Considering the difference in the origin data, the origin data set was adjusted with standardization for training (An and Lin, 1992). Standardization was utilized using the formula:

$$x_{ij}^{'} = \frac{x_{ij} - \overline{x_j}}{S_j} = \frac{x_{ij} - \frac{1}{m}\sum_{i=1}^{m} x_{ij}}{\sqrt{\frac{1}{m}\sum_{i=1}^{m}\left(x_{ij} - \frac{1}{m}\sum_{i=1}^{m} x_{ij}\right)^2}}$$

In the equation, x_{ij} was origin data, x_{ij}' the standardized data and i, j, m the sample ID, variables ID and sample amount, respectively.

A BP model was built with the help of NNTOOL BOX contained in MATLAB 6.5 (Wen et al., 2001). This model had five nods for input layer, 10 for hidden layer and 4 for output layer. With weight vector iw (1, 1) and threshold b1, this model conducted a liner switch from input layer to hidden layer. With weight vector iw (2, 1) and threshold b2, this model conducted an S-curve switch from hidden layer to output layer. (Fig. 3) After training intervals, training max epochs and targets were set, program-adjusted weights and thresholds reduced training MSE and tested MSE. The calculation would be finished as soon as MSE met the requirements, according to the experiment results on weights and thresholds.

Twenty quadrates were randomly selected as test data sets, and other quadrates were used to train the BP model. Selected method of TRAINLM took advantage of the Leverberg-Marquardt learning rules, and rapidly reduced the training MSE of the model. MSE was used to calculate the error of the model. Other parameters were set as follows. Maximum training times was set to 1 000 and the result was showed per 25 times. MSE ranged from 0.001 to 10^{10}. MSE's raising rate was 10 and descending rate was 0.1. Maximum circling times was set to 5 and the gradient minimum was set to 10^{-10}.

Table 1 The inputs and outputs for an ANN model of the Shanghai landscape pattern

	Symbol	Index	Meaning
Input variables	I1	Percentage of roads/%	Transportation and economical activities
	I2	Percentage of residence area/%	Socio-economic factors
	I3	Distance from the city center/km	Urban development history
	I4	Distance from Huangpu River/km	Transportation and natural factor
	I5	Population density /(persons · km^{-2})	Social factor
Output variables	O1	Patch density/(m · hm^{-2})	Fragmentation of the landscape
	O2	Perimeter-area ratio	Complexity of the landscape
	O3	Shannon's Diversity Index	Landscape diversity
	O4	Aggregation index/%	Fragmentation of the landscape and complexity degree of the mosaic

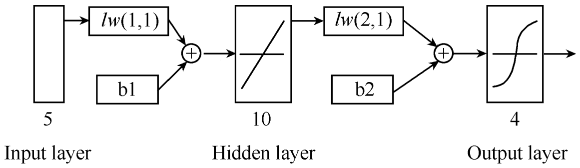

Fig. 3 The BP network for the Shanghai landscape pattern

3 Results and analysis

3.1 Metrics of landscape pattern for the Shanghai metropolitan area

At the landscape scale, the Shanghai landscape pattern presented a constant fluctuation along the suburb-urban-suburb area for the breaks of every 10 quadrates. From suburb to the urban center, patch density increased rapidly. This index climbed to the maximum at the urban center (sample ID: C46) and decreased rapidly as the distance from urban center increases (Fig. 4a). Perimeter–area ratio, which could reflect the complexity of patches, climbed up as urbanization was highly developed. This metrics showed that the shape of patches grew more complex in the more urbanized area. Shannon's diversity index also showed a similar rise (Fig. 4c). It inferred that landscape became diverse as agricultural land decrease and urban land increase. Different from other three indices, the aggregation index presented a sharp decline along the rural-urban transect (Fig. 4d)

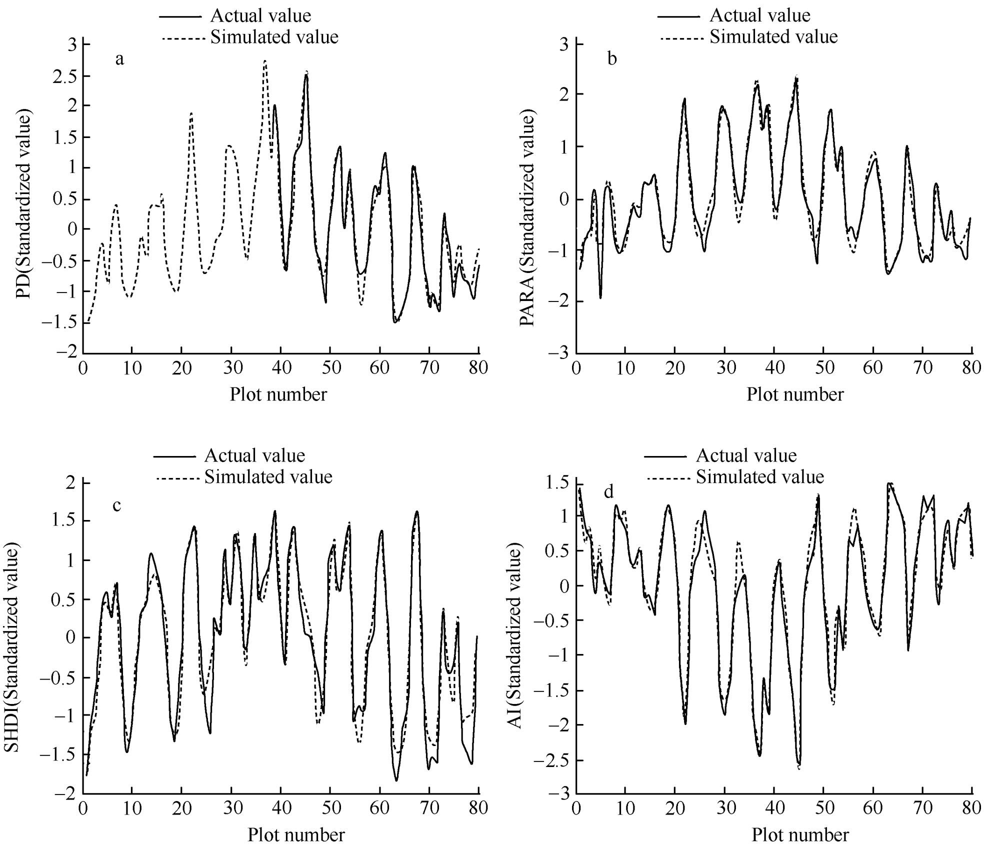

Fig. 4 The results of ANN training: a PD, b PARA, c SHDI, d AI, the plot numbers here represent the sampling plot numbers in Fig. 1 C1-C2, C4, C6-C17, C19-C23, C26-C33, C35-C36, C38-C40, C42-C43, C45-C49, C51-C54, C56, C58-C62, C64-C67, C69-C75, C77, C79-C82, C83-C86, C88-C90 and C92-C99, respectively

(Zhang et al., 2004). Generally speaking, the four indices presented drastic changes as the degree of urbanization increase: the landscape became more fragmentized, more diverse and more complex.

3.2 Training

From Fig. 5, we could see the whole process of training. Training MSE and testing MSE fluctuated drastically during the first 200 epochs, and stabilized from 200 to 1,000 epochs. When the model stopped training at the 1,000th epoch, training MSE was at 0.053 and testing MSE was at 0.25. Weight vectors and thresholds between layers were shown in Table 2 and Table 3.

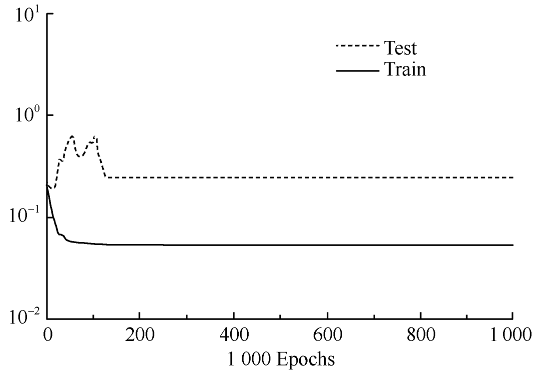

Fig. 5 The performance change during the ANN training

Figure 4 showed that testing and training data accorded well with each other. The ANN model gave a good simulation of landscape index changes forced by input factors. This model successfully simulated the change of gradient along the transect from suburb to urban center.

3.3 Validation of ANN model

The built BP model had to be validated to test its reliability. Twenty unused samples were input this model for validation. This validation brought a satisfactory result. Except that some testing MSEs were a little big, most test results went well with the actual data set. Mean relative error, which was constrained to 20%, inferred the reliability of this ANN model (Fig. 6).

4 Discussion

4.1 Significance of urban landscape pattern quantity analysis

Predicting of urbanization and according impacts on ecology, society and economy are most important issues concerning urban planning, natural resource management and biodiversity conservation (Zipperer et al., 2000; Pickett et al., 2001; Whitford et al., 2001). The mechanism of landscape forming is woven by geography, ecology, society,

Table 2 The weights *iw* (1, 1) and thresholds b1 between input layer and hidden layer

Hidden layer \ Input layer	I1	I2	I3	I4	I5	Threshold b1
Node 1	–0.36 956	1.6 982	–0.17 373	–2.3 749	–6.2 017	3.6 417
Node 2	2.2 418	0.013 196	1.5 017	–1.045	–2.2 455	–2.508
Node 3	23.193	3.2 898	21.152	–14.942	26.016	0.22 672
Node 4	4.458	19.499	24.906	–63.978	–110.4	–27.714
Node 5	25.048	–8.8 204	–41.631	45.611	14.268	–32.888
Node 6	1.0 326	4.1 185	5.6 818	–1.4 958	27.703	–23.964
Node 7	4.7 917	–1.0 782	0.89 889	4.14	12.259	6.0 831
Node 8	–1.3 393	–0.86 175	–0.10 452	0.004 156	–0.48 226	–3.9 442
Node 9	–0.45 725	–0.09 442	–0.21 507	0.7 581	–0.02 035	1.5 848
Node 10	0.43 486	2.8 424	4.7 612	–15.909	–0.87 166	–18.299

Table 3 The weights *iw* (2, 1) and thresholds b2 between hidden layer and output layer

Hidden layer \ Output layer	O1	O2	O3	O4
Node 1	0.74 285	0.75 385	1.1 497	–0.48 654
Node 2	–0.56 133	–0.56 869	–0.9 897	0.40 137
Node 3	0.40 654	0.42 714	0.61 245	–0.35 713
Node 4	–0.65 193	–0.39 793	–0.13 885	0.43 821
Node 5	0.33 212	0.45 753	0.50 973	–0.41 928
Node 6	–0.6 575	–0.39 822	–0.05 096	0.49 927
Node 7	–0.74 921	–0.44 917	–0.3 767	0.45 835
Node 8	–50.589	–45.822	–71.325	44.213
Node 9	–2.7 447	–2.173	–0.25 745	2.2 318
Node 10	–1.0376	–1.3 183	–0.05 794	0.76 643
Threshold b2	–50.087	–45.822	–71.647	43.458

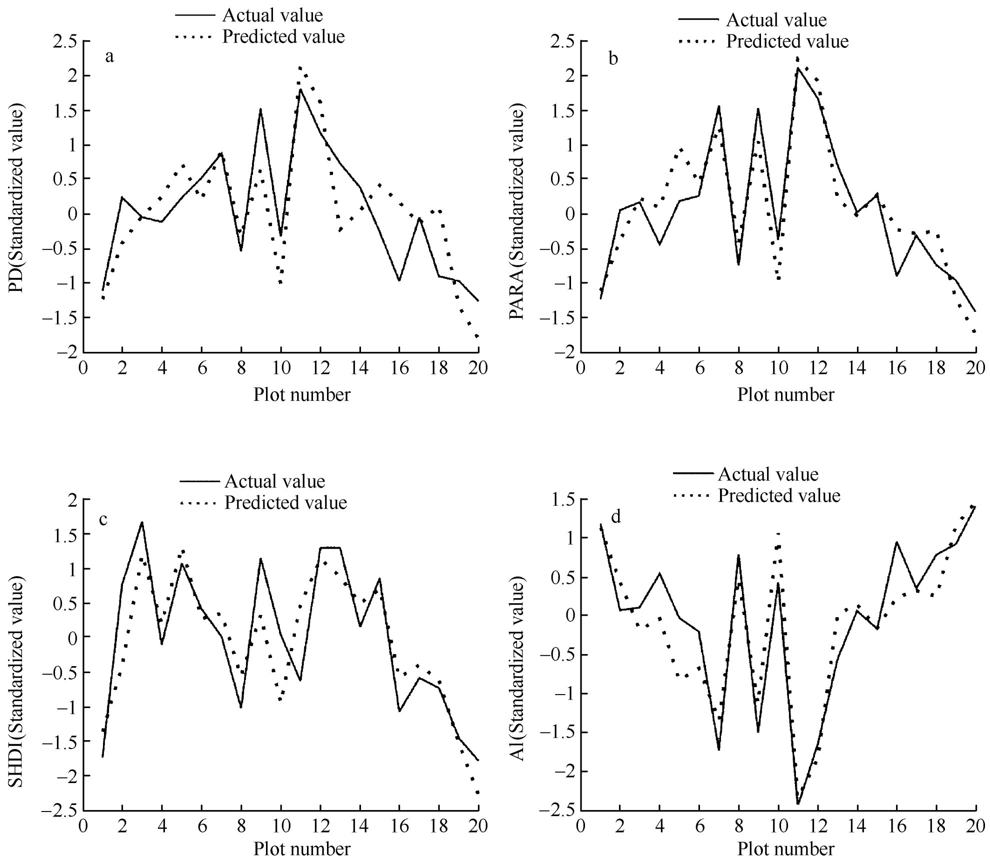

Fig. 6 Validation of the ANN model: a PD, b PARA, c SHDI, d AI, the plot numbers here represent the sampling plot numbers in Fig.1 C3, C5, C18, C24, C25, C34, C37, C41, C44, C50, C55, C57, C63, C68, C76, C78, C83, C87, C91 and C100, respectively

economy and politics, and quantity analysis is the first step to making a good sense on the relationship between landscape pattern and ecological process. It is also important to analyze the social and ecological sequences of urbanization. Physical, ecological and social processes can produce, maintain or destroy the present spatial pattern (Zhang et al., 2004). Meanwhile, spatial landscape pattern can assist, neutralize or counteract these processes. Our study shows quantity analysis and Geographic Information System are valid in measuring urban landscape pattern and in monitoring the changing metrics. The general character of the Shanghai landscape spatial pattern is increasing on diversity, complexity and fragmentation of landscape with reinforcement of urbanization.

4.2 Mechanism of landscape forming

Convenient communication is most important to urban development. The rise of Shanghai's benefited from its water transportation. Shanghai lies in the middle of coastline of China and at the estuary of the Yangtze River. This city also connects to Tai Lake through the Huang Pu and Wu Song rivers. Highly developed water traffic provides the basis for Shanghai's preliminary urbanization. After that, Shanghai puts its boundary forward with the aid of land transportation, which rapidly and flexibly improves the communication between the rural and urban areas. This analysis on the Shanghai landscape pattern shows that landscape pattern forming of the city is highly related to the distances of the urban center to the Huang Pu River. Thus, fragmentation and complexity of landscape can be calculated as a function of distance. Before the 1990s, Shanghai urban development focused on the west of Huang Pu River, and the development of the east of the river is constrained to areas near the riverfront. There is an obvious asymmetry in the areas lying on both sides of the Huang Pu River. From 1990 on, Shanghai has constructed three bridges (Yang Pu Bridge, Nan Pu Bridge and Lu Pu Bridge) and two tunnels (East Yan An Road Tunnuel and Da Pu Road Tunnel) to accelerate Pu Dong's urbanization, and these connections are still changing the pattern of asymmetry (Zhu, 1996).

Social and economic factors also play an important role in Shanghai's urbanization. In 1292, Shanghai County is set up by the Yuan Dynasty. In the middle period of 19th century, Shanghai became a flourishing port. After the Opium War, Shanghai was set to become a port servicing international businesses, and the urban area was extended to the east and west during this period. After World War II, the urban area was extended to the north and south. The People's Republic of China was founded in 1949 and Shanghai turned its function from a consuming city to a productive city and built numerous factories around the city. The population grew from 5,200,000 in 1949 to 13,500,000 in 2001, and the downtown area grew from 91.5 km^2 in 1949 to 800 km^2 in 2000. From 1990 on, Shanghai has entered into an new area of development. Its industrial structure in the old downtown are has been adjusted and many plants moved into Pu Dong, Min Hang and Song Jiang (Zhu, 1996).

This study builds an exact model of ANN that successfully describes the mechanism of how urbanization forces (taking percentage of roads, percentage of residence area, distance from the city center, distance from the Huangpu River, population density) affected the landscape of the Shanghai metropolitan area in 1994. This model reliable and operable. Results show that ANN is a proper way to study the non-liner relationship between urbanization forces and landscape pattern. This research also provides a valid and effective approach to the mechanism of landscape formation, and to the interaction between landscape spatial pattern and ecological process.

4.3 About the ANN model

According to the law of Kolmogorov (Luo, 1998), given a continuous function $f\colon U^m \rightarrow R^m$, $f(x) = y$, U is a closed interval between [0, 1], f can be created precisely by a feed-foward network with three layers. In this model, the first layer (input layer) has n units of nodes, and the middle layer has $2n + 1$ units of nodes, and the third layer (output layer) has m units of nodes. As to the ANN model in this study, five input variables ($n = 5$) and four output variables ($m = 4$) were assigned to the model. According to the law of Kolmogorov, the proper number of nodes in the hidden layer was 11. Through times of comparisons, we found that 10 nodes was the best choice to ensure veracity of simulation and prediction. This result supported the law of Kolmogorov.

The ANN model was built to simulate the relationship of landscape pattern and forcing factors. Furthermore, it is used to predict the human effect on landscape and to provide countermeasures. Influential factors of Shanghai urban area differ a lot in various periods, so factors should be identified according to the situation at a certain time to set up a function of the relationship between the pattern and the process. This research focuses on the methods through building an ANN model with integrated data sets in 1994. Our future work will focus on building temporal ANN models to describe the urbanization effects on Shanghai's landscape pattern and to provide countermeasures for landscape optimization.

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