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Original Research

Simulating the Total Ecological Footprint of Suzhou from 1990 to 2009 by BPANN

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Abstract

Suzhou, one of the most developed cities in Yangtze Delta, lies by Taihu lake in Jiangsu province, China. Because the city's economic development has been rocketing upward in the past 20 years, it is necessary to assess the influence on natural resources exerted by socio-economic growth. Ecological footprint (EF) is one of the sustainable development assessment indicators. How to simulate the EF's development trend of the past in a given region for a long time is a question to be solved. This paper calculates the total ecological footprint of Suzhou from 1990 to 2009, and attempts to simulate the total ecological footprint (TEF) of the city using the back propagation artificial neural network (BPANN) model, a widely used modeling approach fitting non-linear time series in artificial neural networks. Seven socioeconomic factors: gross domestic product, tertiary industrial products, secondary industrial products, urban population, rural population, annual income of rural residents per capita, and annual income of city dwellers per capita acted as drivers of the TEF in the quantitative analysis. The fitting performance of the model was accurate and TEF of the city from 1990 to 2009 could be simulated by a model. With the proposed approach in this study, the ecological sustainability of Suzhou could be analyzed.

Keywords: ecological footprint, simulation, BPANN, sustainable development indicators

Introduction

Ecological footprint (EF), one of the sustainable development indicators, was proposed by William, an ecological economist of Canada in the early 1990s and improved and developed by his doctoral student, Wackernagel, in 1996 [1, 2]. The model quantitatively reflects human activity influence on the natural resources that provide ecological services and natural products. EF integrates a variety of relevant resources used by one region into a common unit, "global hectares," namely bio-productive areas and then the consumption of natural resources can be tracked. Thus comparing it to the available ecological capacity, the region's sustainable status can be judged according to the ecological deficit being negative or positive.

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EF answers a specific research question: how much of the regenerative biological capacity of the region is demanded in a given period by a given human activity, which may be one of the processes of consuming resources, producing goods, or supplying a service [3]. It has emerged as a popular concept and approach for sustainability measurement. The method has been applied at various scales, including the whole globe, nations, provinces, cities, communities, and individuals [4-10]. The footprint approach has also been applied to related notions such as energy, carbon, and water footprints, and has been combined with such hotspots as climate change, environmental risk assessment, and policy analysis [11-17].

However, the EF method is based on the following assumptions:

(1) there exists a suppositional concept "hypothetical land area"

(2) we could reduce all ecological problems to these land areas
(3) total land demand could exceed total land supply in one region [2]

So inevitably EF itself has some flaws. It is a static indicator, which means it can't answer some other scientific questions, for example: how to accurately simulate EF development in the past for a long time series and forecast EF development trend in the future, according to the fitting model, and then provide reasonable and practical policy recommendations for regional sustainable development based on the estimated trend of TEF [18, 19]. Some critics argue that EF analysis could not provide a dynamic window for the future but rather a snapshot of real time [20, 21]. EF analysis produces static estimates, whereas both nature and economy are a dynamic system. So critics regard EF to be barely a surplus warning tool playing a weak decision support role.

To help decision-makers track ecological consumption over time, many researchers have been working on EF time series at different spatial scales to provide effective support for regional sustainable development [22-25]. Medved predicted the future EF of Slovenia for 2020 by analyzing the documents promoting energy conservation and renewable energy sources, without using any simulation model [25]. Wu used the autoregressive integrated moving average (ARIMA) model to predict temporal variation of water EF in Guangzhou, China [26]. Yue introduced two indices of "change rate" and "scissors difference" by a polynomial regression analysis to quantitatively describe the development trends of EF time series [18]. Jia simulated and predicted EF from 1949 to 2006 in Henan province of China using the ARIMA model [7]. In addition, Li simulated and forecast the urban total ecological footprint by using the radial basis function neural network (RBFNN) in Wuhan, China [8]. All the TEF simulation models can be classified into the following two types. Type A is the ARIMA model. The basic idea of this type is that the values of the variables are supposed to be a linear or non-linear combination of past values and past errors, and the future values of the time series can be simulated and predicted only from past values and present values, not considering any other factors. Type B: This type of method considered some impact factors on TEF, such as RBFNN and the polynomial regression method. The back propagation artificial neural network (BPANN), applied in this paper, belongs to this type.

None of these studies has provided us a definite effective tool for predicting the development trend of EF in the future, and what we should choose as impact factors or drivers of EF development. Further work is needed to find appropriate approaches for simulating the development trend of EF and to give us valid, plausible results and sound advice for policy-making in a specific region.

Some researchers are already concerned about the ecological footprint of Suzhou. Yang modified the EF model and combined several social indicators with EF and assessed the sustainable development status of Suzhou from 1993 to 2002 [27]. Bai calculated the EF of the Suzhou-Wuxi-Changzhou (SWC) region of Jiangsu province and compared it with the global average level [28]. EF in Suzhou was also applied in some other fields, such as environmental assessment on urban planning and analysis about the development pattern in Suzhou [29, 30]. In this paper, we calculated the total ecological footprint (TEF) of Suzhou, China, from 1990 to 2009, a longer time series, and attempted to simulate the TEF of the city by BPANN model through this time series.

Materials and Methods

The Studied Area

Suzhou is one of the developed cities in Yangtze Delta alongside Taihu lake in Jiangsu province, China (Fig. 1). The city consists of 12 counties and covers an overall area of 8,488.42 km^2. In 2009 the total population of Suzhou was 6.33 million, and from 1990 to 2009 the average annu-

Fig. 1. Location of the studied area.

al population growth rate was 0.6408%. The gross domestic products (GDP) in 2009 of the region reached 774 million yuan and the percent of the secondary industrial products in GDP was 58.8%. The average annual GDP growth rate reached 21.73% from 1990 to 2009. With the persistent high growth speed of population and economy in the past 20 years, human influence on natural resources has been increasing, pollution brought by socio-economic growth was critically serious, and conspicuous conflicts appeared between huge numbers of the population. Also, rapid economic development and insufficient natural resources led to increasing ecological damage.

Calculation of Total Ecological Footprint

The ecological footprint consists of two sections: biological resource consumption and energy consumption. In this study, the basic calculation procedure follows the quantitative method for ecological footprint [31]. Equations (1) and (2) are used in the TEF calculation.

$$\mathrm{EF}=\sum_{j=1}^{6}(r_j\sum_{i=1}^{26}(\frac{UC_i}{UP\cdot GP_{ij}}+\frac{RC_i}{RP\cdot GP_{ij}})) \quad (1)$$

$$\mathrm{TEF}=\mathrm{EF}*(UP+RP) \quad (2)$$

...where EF is the average ecological footprint per capita (gha/cap); j is the type of land being considered, which includes arable land, pasture, forest, water, fossil energy land, and built-up land; r_j is the equivalence factor for the j^{th} land-type, and represents the ratio of the biological productivity of the j^{th} land-type to the global average biological productivity for all types of bio-productive land, which equals the average bio-productivity for the six types of global land included in the present study [31]; i is the number of products being analyzed; UC_i is the total consumption for the ith product by city dwellers (kg/year); RC_i is the total consumption for the ith product by rural residents (kg/year); UP is total urban population; RP is total rural population; GP_{ij} is global biological yield for the ith product provided by the jth land-type (kg/gha); and TEF is the total ecological footprint in the studied area.

Back Propagation Artificial Neural Network

BPANN, one kind of artificial neural network ANN, was used to simulate the trend of TEF in Suzhou. ANNs have been used to solve a wide variety of problems in science and engineering, particularly for some areas where the conventional modeling methods fail. A well-trained ANN can be used as a predictive model for a specific application, which is a data-processing system inspired by biological neural systems. The predictive ability of ANN results from training on experimental data and then validation by independent data. The net has the ability to relearn and adapt for improving its performance with the availability of updated data [32].

An ANN model can accommodate multiple input variables to predict multiple output variables. It differs from conventional modeling approaches in its ability to learn about the system that can be modeled without prior knowledge of the process relationships. The prediction by a well-trained ANN is normally much faster than the conventional simulation programs or mathematical models. However, the selection of an appropriate neural network topology is important in terms of model accuracy and model simplicity.

Among learning algorithms, back propagation algorithm, proposed by Rumelhart and McCelland in 1986, is a widely used learning algorithm in artificial neural networks. Error propagation consists of two passes through the different layers of the network: a forward pass and a backward pass. In the pass process, the input vector is applied to the sensory nodes of the network and its effect propagates through the network layer by layer. Finally, a set of outputs is produced as the actual response of the network. During the forward pass, the synaptic weights of the networks are all fixed. But during the back pass, the synaptic weights are all adjusted in accordance with the error correction rule. The actual response of the network is subtracted from the desired response to produce an error signal. This error signal is then propagated backward through the network against the direction of synaptic conditions. The synaptic weights are adjusted to make the actual response of the network move closer to the desired response [32, 33].

The basic idea of using BPANN to simulate the TEF of the city is the mapping principle of the model. For a set of independent variables (the input of the net, denoted as vector X_i, i=1,2,…n) and a dependent variable (the output of the net (denoted as vector Y), mapping relation can be assumed to exist as equation (3), but the relation F is indistinct.

$$Y=\mathrm{F}(X_1,X_2,...,X_n) \quad (3)$$

To find optimal mapping value, the BPANN model converts the input sets and the output sets into a nonlinear optimization process. According to the combination of several simple nonlinear functions, the model may establish a hightally nonlinear mapping relationship between Y sequence and X sequence to realize the optimal approximation of function F.

Data Sources and Their Reliability

The calculation of total ecological footprint demands large amounts of data on human consumption and product consumption. The primary consumption and population data were obtained from Suzhou Statistical Yearbooks, as well as from the results of annual surveys of nearly 200 households within the region, provided by Suzhou statistical bureau [34]. Other related coefficients used in the TEF calculation were taken from the FAO Yearbook (1991-2010) published by the United Nations Food and Agriculture Organization [35]. Data sources concerning impact factors from 1991 to 2010 were all taken from Suzhou Statistical Yearbooks (1991-2010).

There were inadequate data sources for emissions of waste so the calculation of ecological footprints in this study did not include the assimilation of wastes and the consumption categories were not fully included. This limitation of data availability led to underestimating the TEF.

Results

TEF of Suzhou from 1990 to 2009

Suzhou's TEF from 1990 to 2009 was assessed by equations (1) and (2). The development trends of EF and TEF were shown in Fig. 2. The left scale on the vertical axis referred to the value of EF. EF in Suzhou increased rapidly from 1.299 gha per cap in 1990 to 5.995 gha per cap in 2009. Seeing the annual total ecological footprint continuously increasing, it was of great importance to caution people to pay close attention to regional sustainable development while the economy was developing at high speed.

EF was classified according to the customary EF category approach into six types of land areas: arable land, pasture, forest, water, fossil energy land, and built-up land. Fig. 3 shows the development trends of EF of the six types of bio-productive areas and the corresponding contributions to EF in Suzhou from 1990 to 2009. The consumption of fossil energy land (EFfos) and built-up areas (EFb) increased markedly and stood in absolute predominance in TEF (not especially in 2000, but in 2008 and 2009). This might be due to the speed of urban expansion and industrial development after 2000.

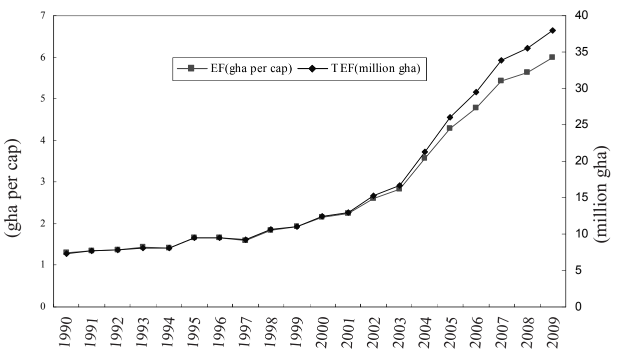

Fig. 2. Development trends of EF and TEF.

TEF's Impact Factors

EF represents the critical natural capital requirements of a region in terms of the corresponding bio-productive areas. Evidently, the total ecological footprint depends on the population size, residents' living conditions, and some other factors. Mohamed analyzed the EF of 140 nations and by linear regression analysis they concluded that the nation's world system position and its urbanization level positively influenced the indicator and that the distribution of incomes, as measured by the Gini coefficient, was negatively related to EF [36]. At the city level, Li selected six indices: gross domestic product, total population, urbanization level, total retail sales of consumer goods, total amount of energy consumption, and expenditures by city residents as TEF impact factors in Wuhan city, China [8]. Researchers suggested that EF analysis should be connected with economic and social indicators. But at various scales and in diverse regions impact factors of TEF may be different. Which factors should be taken into account in our TEF simulation using the BPANN model was still a question to us.

We chose eighteen potential impact factors and made the linear regression between TEF and all the subsets of these potential factors by SAS software. Then, according to statistical parameter analysis, the best subset was identified, including seven independent variables as follows: gross domestic product (GDP), tertiary industrial product (TIP), secondary industrial product (SIP), urban population (UP), rural population (RP), annual income of rural residents per capita (IncR), and annual income of urban dwellers per capita (IncU). In other words, these seven factors would act as the drivers of the TEF in BPANN analysis. The development trends of the seven factors in Suzhou were plotted in Fig. 4.

Simulation by BPANN

To develop the BPANN model for TEF simulation, inputs to the model contained the values of the seven impact factors from 1990 to 2009. These inputs were denoted as P matrix with twenty columns and seven rows. The output of the model was the TEF of Suzhou achieved by EF methodology, denoted as T matrix with 20 columns and one row.

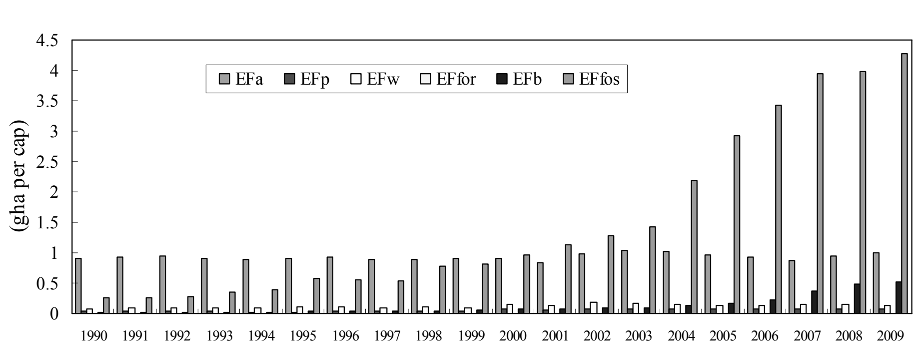

Fig. 3. Development trends of six categories of bio-productive areas

Notes: EFa denotes arable areas; EFp denotes pasture areas; EFw denotes water areas; EFfor denotes forest areas; EFb denotes built-up land areas; EFfos denotes energy land areas. Forest areas per capita are too few to be discerned.

Data Preprocessing

Data Preprocessing Includes Two Steps.

Step 1:
Data Refining

Generally, the larger the number of training samples, the better the regression performance. There were only 20 sets of raw samples, whereas the BPANN model needs multi input data to train, test, and validate the network. So the raw data, including the TEF (the T matrix) and the seven factors (the P matrix) were converted into 190 samples by equation (4). These 190 samples were characterized by INPUT matrix (7×190) and OUTPUT matrix (1×190), which indicated the differences between the values of any two years. Then the input neurons are the INPUT matrix, the differences of the same impact factor between any two years and the OUTPUT matrix is the output neurons, the differences of the TEF between the corresponding two years.

$$\begin{cases} \mathrm{INPUT}(m,k) = \mathrm{P}(m,i+j) - \mathrm{P}(m,i) \\ \mathrm{OUTPUT}(k) = \mathrm{T}(i+j) - \mathrm{T}(i) \end{cases} \tag{4}$$

m=1,2,…,7; i=1,2,…,20; j=1,2,…,20-i, k=1,...,190

Step 2:
Data Normalization

To avoid the over fitting, especially when the data span is big, it is necessary to standardize the input data set of the model. The normalization method was used to preprocess INPUT and OUTPUT. After the preprocess all the data values were between 0 and 1.

Samples Packeting

The model simulation process includes network training, test, and validation. Accordingly, the samples should be divided into three packets: training samples, test samples, and validation samples.

Shares of each sample set could all be adjusted as desired. In the study, the validation samples and test samples were both assigned to 20 percent of the total input data, and the percent of the training samples was 60. The samples packeting process could be realized by calling the function ‘dividevec’ in MATLAB software (Appendix 1), which could extract three classification data randomly in pairs from the INPUT matrix and the OUTPUT matrix.

Network Topology

After comparing the convergence of various network topologies, we established the network with two hidden layers. Thus the neural network included four layers: input

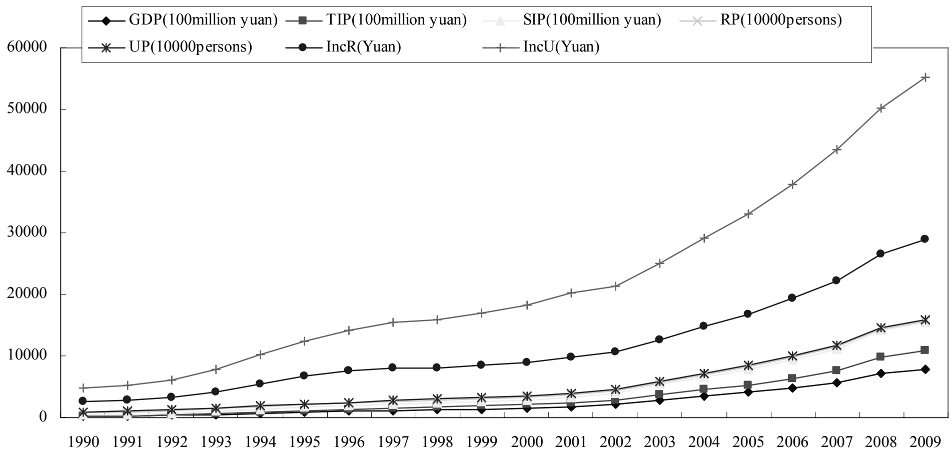

Fig. 4. Development trends of the seven impact factors.

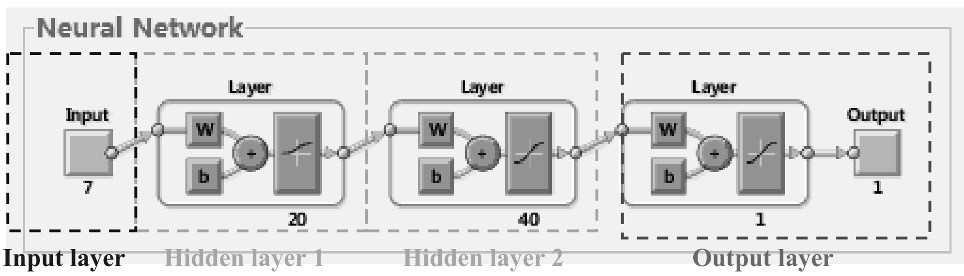

Fig. 5. Graph of network topology.

layer, hidden layer 1, hidden layer 2, output layer. The numbers of hidden nodes were 20 and 40, respectively (Fig. 5). Consequently, network topology in the simulation was 7-20-40-1.

Transfer Functions

The log-sigmoid transfer function ('logsig') and hyperbolic tangent sigmoid transfer function ('tansig') are two of the commonly used neural transfer functions, calculating a layer's output from its net input. The algorithms of the two functions are listed in equations (5) and (6), respectively.

$$a = \mathrm{logsig}(n) = 1/(1 + \exp(-n)) \quad (5)$$

$$a = \mathrm{tansig}(n) = 2/(1+\exp(-2*n))-1 \quad (6)$$

...where n is the input of the layer and a is the output of the layer.

When data are transformed from one layer to the next layer, transfer functions play the decisive role. In our study, the transfer functions were 'logsig,' 'tansig,' and 'vtansig,' respectively. From input layer to hidden layer 1 the transfer function was 'logsig,' the transfer function from hidden layer 1 to hidden layer 2 was 'tansig,' and the transfer function from hidden layer 2 to output layer was also 'tansig.'

Training Function

The training function in the paper is gradient descent with momentum back-propagation ('traingdm'), which is a network training function that updates weight and bias values according to gradient descent with momentum. The function 'traingdm' allows a network to respond not only to the local gradient, but also to recent trends in the error surface. Acting like a low-pass filter, momentum allows the network to ignore small features in the error surface. Without momentum a network could get stuck in a shallow local minimum, but with momentum a network might slide through such a minimum. It can train any network as long as its weight, net input, and transfer functions have derivative functions.

Gradient descent with momentum depends on two training parameters. The parameter '*lr*' indicates the learning rate, similar to the simple gradient descent. The parameter '*mc*' is the momentum constant that defines the amount of momentum. '*mc*' is set between 0 (no momentum) and values close to 1 (lots of momentum). A momentum constant of 1 results in a network that is completely insensitive to the local gradient and, therefore, does not learn properly.

Back-propagation is used to calculate derivatives of performance *perf* with respect to the weight and bias of variable X. Each variable is adjusted according to gradient descent with momentum using equation (7):

$$\mathrm{d}X = mc*dX\mathrm{prev} + lr*(1-mc)*\mathrm{d}perf/\mathrm{d}X \quad (7)$$

...where mc is the momentum constant and the default value of mc is 0.9, dXprev is the previous change to the weight or bias.

Training stops when any of these conditions occurs:

(1) The maximum number of epochs (repetitions) is reached
(2) The maximum amount of time is exceeded
(3) Performance is minimized to the goal
(4) The performance gradient falls below min_grad (the default value is 1e-10)
(5) Validation performance has increased more than max_fail times (the default value is 5).

Simulation Preferences

The simulation parameters mainly consist of the maximum number of epochs (repetitions), the precision target (goal), and the learning rate. In fitting preferences, the learning rate should be set as a value as small as possible, because if the value is too big the convergence process might speed up at the beginning and fluctuate, resulting in discrete in the end, when it is near the optimal point. In our study, the maximum number of repetitions was 100,000, the precision goal was 0.005, and the learning rate was 0.005.

Model Fitting Performance

The training packet, validation packet, and test packet included 114 samples, 38 samples, and 38 samples, respectively. Performance of training, test, and validation is shown in Fig. 6. The three packets had similar fitting characteristics and trends. They converged very quickly before epoch 2000 and then slowed down gradually to the set target steadily and smoothly. All the packets can reach the required precision goal of mean square error 0.005 and the best validation performance is 0.0041 at epoch 13326.

Fig. 7 showed the fitting performance of the model. The horizontal axis was the target of the simulation. The vertical axis referred to the model's outputs, simulating results. From Fig. 7 (a-d), the differences between the simulation targets and simulation outputs were described. All the outputs, including training packet, validation packet and test packet, were highly consistent with the targets and the dots in the figure distributed close to the line "Y=T." In the regression formulae "output=m*target+n" describing the relationship between the outputs and the targets, the values of coefficient "m" were all bigger than 0.9, which means the fitting is accurate.

The simulation progress went through 2 minutes and 47 seconds and the times of validation check was zero (the default max_fail times value is 5). Values of every output in the simulation were at an acceptable level with a fast convergence rate, short simulating time, few validation times, and high precision. Thus the connection weight coefficients and the offset had been determined. The complex corresponding relationship between the seven socioeconomic factors and the TEF of the city could be established by the BPANN model.

Discussion

BPANN Model in Simulating the TEF of Suzhou

BPANN model was established to fit and simulate the total ecological footprint for Suzhou. The model is different from the traditional statistical regression models. The differences lie mainly in the following points.

(1) BPANN can express the nonlinear indistinct relationship between the TEF and the related impact factors. The development trend of TEF in one region is always complicated. The impact factors are multivariate and the process of influence is complex. These uncertainties determine that the impact on the TEF by social and economic factors is multi-dimensional. The relationship can't be objectively described by a simple linear model. But nonlinear mathematical expression seems to be very difficult. The BPANN model can overcome these difficulties and express the nonlinear mapping relationship.

(2) The BPANN model showed high precision and validity in fitting the development trend of the TEF for Suzhou from 1990 to 2009. Because the model applies the neural network tool with strong nonlinear approximation function and uses the back-propagation algorithm with the correction effect, the model is able to achieve the accuracy and validity goals set in advance if the training sample data are enough and the quality of the data is ensured to be qualified.

(3) The BPANN model can adjust the weights automatically according to various factor performances in the TEF's evolution trend during the process of learning and training, which can't be achieved by statistical regression models. So the model can effectively avoid the lack of mistakes in index selection and some other problems in general regression analysis.

At the same time we realized that the model had some objective limitations and defects. The BPANN model is prone to appear as the phenomenon of over-learning and over-fitting and thus the generalization ability of the model will be reduced. But we can attempt to avoid over-fitting by setting the validation samples in the training process. We can also increase the training sample size and select data with a strong representation deliberately when necessary so that the network can learn the internal principles of the samples accurately and the generalization ability can be greatly improved.

It is noted that the total ecological footprint of one region is a complex indicator, so whether the model can be used in other cities or other spatial scales should be further studied, and whether the model can be applied in the long term prediction also needs to be verified.

The Overall Development Trend of Suzhou's Total Ecological Footprint

Suzhou bore an accumulative TEF of 37.97 million gha in 2009, which is 3.05 times that in 2000 and 5.22 times that in 1990. More and more of the natural resources required to support this rapid development will be obtained from outside the city.

It was found that the development trends of the six main categories of bio-productive areas demanded and the corresponding contributions to the TEF in Suzhou from 1990 to 2009 were not equilibrium (Fig. 3). Arable land areas and pasture areas in EF remained approximately constant; forest areas and water areas increased slightly and gradually for the whole period; and the consumption of fossil energy land and built-up areas increased markedly and stood an absolute predominance in TEF, especially in the 2000s. These trends suggested that consumption on people's living in Suzhou remained stable over the past 20 years, which was consistent with the perception of the residents in Suzhou. The driver of TEF's rocketing was mainly from energy consumption.

Most commonly a city's major energy consumption lies in secondary industrial production and urban construction. In Suzhou, the development trends of fossil energy land consumption and industrial products were nearly consistent before 2007 (Fig. 8). That is to say, industrial production might be the largest contribution to TEF rocketing upward in Suzhou. Thankfully in 2008 and 2009 the growth rate of fossil energy land consumption was more gentle than that of industrial products.

Not surprisingly, the sustainable development of Suzhou city will face great challenges in the future. In order to retain sustainable development of the city, the local government in Suzhou can make relevant regional strategic plans for the city's management and development. The analysis suggested two main strategies for the local governments:

(1) It must enhance energy efficiency and develop the high-tech industry.

(2) It must adjust the economic structure gradually, reducing the share of secondary industrial products and raising the portion of tertiary industries in GDP that consume fewer natural resources so as to restore Suzhou to the sustainable development track.

Conclusions

In this paper we calculated TEF of Suzhou from 1990 to 2009. In 2009 Suzhou's TEF was 37.97 million gha, 3.05 times that in 2000, and 5.22 times that in 1990. The development trends of the six main categories of bio-productive areas demanded and the corresponding contributions to the TEF in Suzhou from 1990 to 2009 were not equilibrium. The driver of TEF's rocketing lay mainly in increasing energy consumption.

The BPANN model attempted to fit the development trend of the TEF. The model can reflect the complex mapping relationship between the TEF and its associated impact factors to a certain extent. In this study, seven socioeconomic indicators were determined as the drivers of the TEF of the city by linear regression analysis between TEF and all the subsets of the potential factors. These seven independent variables were gross domestic products (GDP), tertiary industrial products (TIP), secondary industrial products (SIP), urban population (UP), rural population (RP), annual income of rural residents per capita (IncR), and annual income of city dwellers per capita (IncU). By model performance analysis, we concluded that the BPANN model can simulate the development trend of TEF for Suzhou precisely from 1990 to 2009. It is feasible to simulate the TEF in this time series.

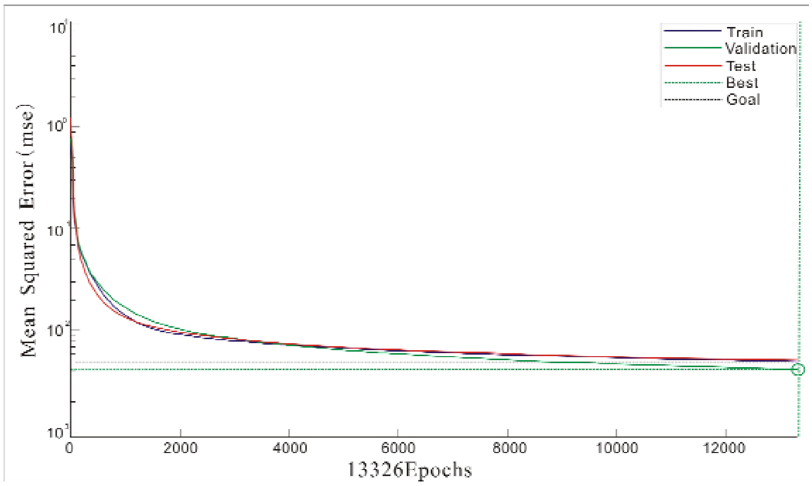

Fig. 6. Performance of train, test, and validation.

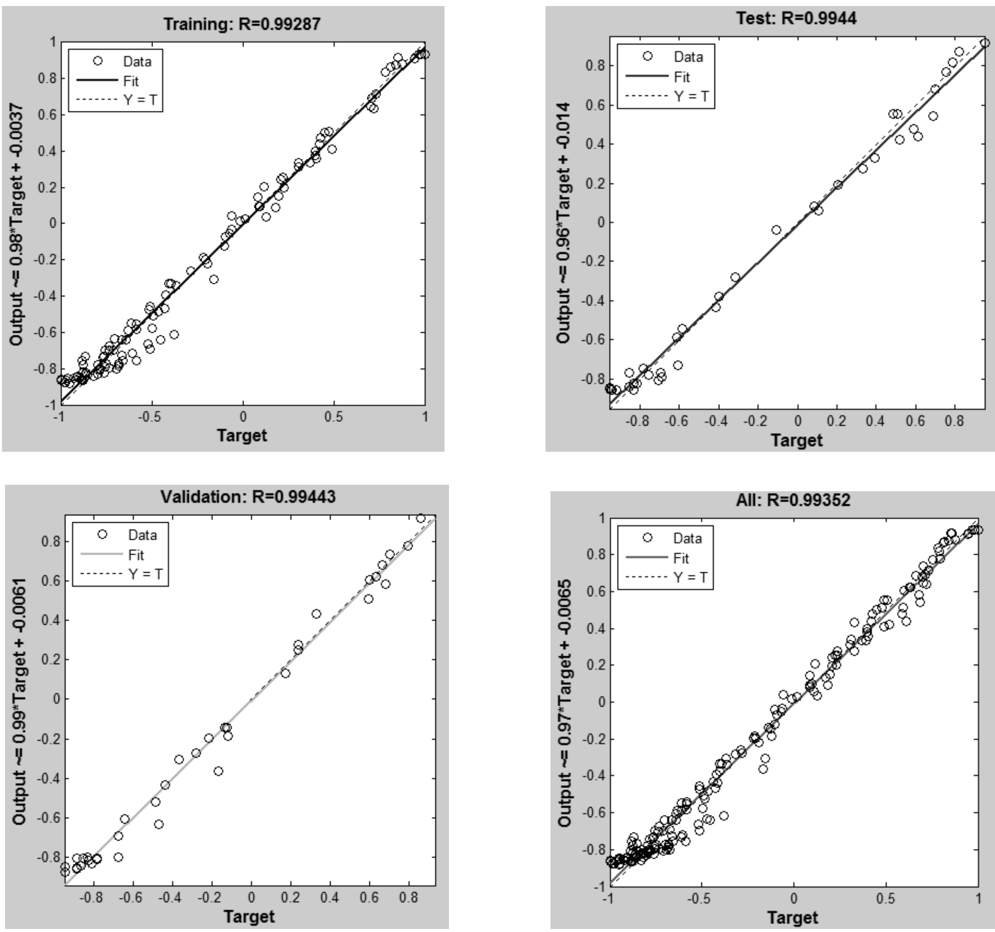

Fig. 7. Regression of the outputs and targets in the simulation.

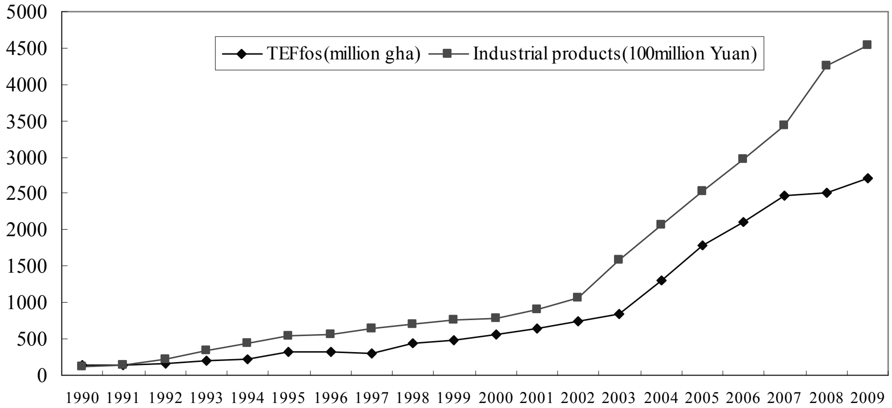

Fig. 8. Development trends of fossil energy land and industrial products.

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