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Assessment and prediction of environmental sustainability in China based on a modified ecological footprint model

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ABSTRACT

This study analyses the environmental sustainability status of China using a modified ecological footprint (EF) method which takes into account the freshwater ecological footprint, improves the energy ecological footprint, and amends the equivalence factor and yield factor. Then the linear autoregressive integrated moving average (ARIMA) and non-linear artificial neural network (ANN) models are applied to predict future ecological security. The results show that: (1) The *per capita* EF increased by three times from 1978 to 2013, whereas the *per capita* ecological carrying capacity experienced only a slight increase although the equivalence and yield factors were both enhanced. (2) The 'degree of ecological security' appeared to show a tendency to increase, indicating that China is in a 'pretty unsafe' ecological state. (3) EF intensity, which is used to represent the resource consumption level corresponding to unit economic output, indicated that the utilisation ratio of Chinese natural resources was greatly enhanced during the study period. (4) The ecological footprint diversity index, and ecological and economic coordination coefficient, peaked in the 1990s and then began to fall, indicating that China's ecological environment, as well as its coordination with the economy, was considered to be better in the 1990s but then gradually deteriorated. (5) The predictions of ARIMA–ANN model indicated that the degree of ecological security in China would reach an unsafe state in a few years if certain effective measures were not taken. These findings could be helpful for decision-makers as they strive to make a better package of plans to ensure an ecological balance and a more sustainable future.

1. Introduction

Sustainable development is a hot issue all around the world (Wackernagel et al., 2004a,b). To date, many methods have been proposed to quantify sustainable development, including Material/Substance Flow Analysis (Huang et al., 2006; Barles, 2009; Browne et al., 2011; Yuan et al., 2011; Wu et al., 2012; Huang et al., 2012; Calvo et al., 2016), Life Cycle Assessment (Guinee et al., 2010; Sara et al., 2017), Emergy Analysis (Vega-Azamar et al., 2013; Yu et al., 2016), and Ecological Footprint (EF) (Erb, 2004; Graymore et al., 2008; Zhou and Imura, 2011; Galli et al., 2012; Geng et al., 2014; Miao et al., 2016; Marrero et al., 2017). Among them, Material/Flow Analysis uses mass (*e.g.*, tonnes) as a metric to assess material inflows and outflows, but the same mass does not mean the same function with regard to economic development (Yu et al., 2016). It is crucial to enable quality distinctions between various resources (Matthews et al., 2000; Huang et al., 2006). Life cycle assessment aims at quantifying environmental impacts and resource consumption of a product or service and their relevant processes from "cradle to grave"; however, it is a typical bottom-up environmental tool, containing only up-stream and down-stream data about a product or service. Thus, it cannot embody indirect flows outside the system boundary (Reap et al., 2008; Dong et al., 2016). Emergy analysis is a bio-centric method used to assess intrinsic natural resources, nevertheless, but it has been criticised due to its methodological limitations. For instance, the lack of region-specific transformation (known as transformity) data leads to the uncertainty for accurate emergy accounting of various economic products and services. Moreover, transformity is a path-dependent coefficient, which means that the same product can be produced by different production routes and result in different transformities (Baral and Bakshi, 2010). With regard to EF, it uses a land-based indicator on assessing resource sustainability, namely, the amount of bioproductive land needed to

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ensure supply for a given population or system (Wackernagel and Rees, 1996). Although the EF has been widely used as an effective instrument to measure ecological pressure and ecological carrying capacity, it is also criticised for oversimplifying a static perspective of resource use and cannot reflect the variability of population, technological improvements, and material consumption (van den Bergh and Gruzi, 2010; De Alvarenga et al., 2012). Even so, EF is able to reflect, in part, the human appropriation of ecologically bioproductive areas following traditional geographical and ecological principles (Shao et al., 2013). As Senbel et al. (2003), Chen et al. (2010), and Gao and Tian (2016) noted, EF provides an indirect index for the long-term ecological status and an early warning for potential ecological risk. Moreover, EF has the advantages of a transparent accounting metric, readily available data, and a standardised method of measurement (Hopton and White, 2012; Lei et al., 2012; Galli et al., 2012; Miao et al., 2016). Additionally, it should be noted that some researchers have made the improvements necessary to address its shortcomings. Therefore, it should be acknowledged that EF is a simple, but comprehensive, measure of environmental sustainability.

EF, which was developed by Wackernagel and Rees in 1996, reflects how much of the regenerative biological capacity of one general area is needed by human activities (Kitzes and Wackernagel, 2009). It calculates the ecological footprint of human consumption and the ecological carrying capacity of land supply based on a set of relevant quantified indices. Both can be compared to evaluate the environmental sustainability of the research subjects (Hopton and White, 2012; Butnariu and Avasilcai, 2014; Galli, 2015). This method has received a considerable amount of attention and is widely used for sustainability assessment within a certain period of time in some regions (Holmberg et al., 1999; Harber et al., 2001; Chen and Chen, 2007; Huang et al., 2007; Begum et al., 2009; Galli et al., 2012; Hopton and White, 2012; Li et al., 2016); however, trends in EF development and ecological security in the future were not discussed in that research. Senbel et al. (2003) explored the factors affecting EF in North America and predicted an ecological deficit over the coming century. However, their method of scenario analysis was rather random and had a large uncertainty. Yue et al. (2006) applied the rate of change and scissors difference to quantify the trend in EF from 1991 to 2004, and to predict it thereafter. However, the relative errors involved in the rate of change and scissors difference increase as the data volumes grow, moreover, the method's applicability conditions are too strict in some extreme situations. Taking Henan Province in China as the study area, Jia et al. (2010) computed the EF and EC from 1949 to 2006 and used the ARIMA model to forecast the EF indicator. However, the real time-series data is rarely purely linear or non-linear (Zhang, 2003; Khashei and Bijari, 2011). In addition, some traditional regression methods (grey system theory, system dynamics, *etc.*) have been applied to forecast EF, but the accuracy decreases markedly with an increase in the amount of data (Zhang et al., 2008; Lu et al., 2010; Zhu et al., 2011).

As mentioned above, real-world time series often integrate both linear and non-linear patterns. EF, moreover, reflects complex environmental problems and so as that single model may not be adequately to capture its characteristics. ARIMA model has been widely employed for time series forecasting, even though their accuracy is variable owing to their linear representation of non-linear systems (Goyal et al., 2006; Wang et al., 2012). The ANN, which uses a multi-layer perceptron architecture, has been developed as a non-linear tool for time-series forecasting (Pérez and Reyes, 2006; Thomas and Jacko, 2007; Zhang, 2011; Xie et al., 2012). Using hybrid model combined several models with different characteristics has become a common practice to overcome the limitations of single model and enhance the forecasting accuracy (Tseng et al., 2002; Zhang, 2003). To date, the hybrid techniques have been widely used in some studies (Tseng et al., 2002; Aslanargun et al., 2007; Koutroumanidis et al., 2009; Khashei and Bijari, 2011; Liu et al., 2012; Babu and Reddy, 2014; Shukur and Lee, 2015). Thus, in this paper, a hybrid approach, combining the ARIMA and ANN models, is also developed to predict EF time-series data.

Overall, the aims of this study are to: (1) improve traditional EF accounting and make the assessment of China's environmental sustainability more reasonable; (2) develop a hybrid model to predict EF time series data so as to evaluate and predict China's ecological security (and thus provide a reference method for decision-making to derive further ecological protection measures).

The remainder of this paper is organised as follows: Section 2 presents the modified EF model and the forecasting model combining ARIMA and ANN methods, as well as data sources, Section 3 presents the empirical results, and the conclusions are summarised in Section 4.

2. Methods

2.1. Modified ecological footprint accounting

EF is a resource and pollution emissions accounting tool to measure human consumption on the planet's regenerative capacity. The land requirement that makes up the EF is divided into six main area types: (1) cropland to provide plant-based food for grains, fruits, vegetables and oil products; (2) grazing land to provide animal-based food; (3) forest areas to provide timber and other forest products; (4) fishing grounds to provide fish-based food; (5) fossil energy land for the absorption of CO_2 emissions from fossil-based energy consumption; and (6) built-up areas to provide infrastructure for industrial activity, transportation, and housing. EF is a flow indicator and each individual flow can be translated into the corresponding appropriation of bioproductive land area, as described by the following equation:

$$EF = \Sigma r_j(aa_i) = \Sigma r_j\left(\frac{C_i}{P_i}\right) \tag{1}$$

where *EF* is the per capita EF (ha); *i* is the consumption item ($i = 1, 2, \ldots, n$); r_j is the equivalence factor of land of type *j*, which can be obtained from the literature (Wackernagel and Rees, 1997; Wackemagel and Yount, 1998); aa_i is the productive land area converted from consumption item *i*; C_i is the amounts of *per capita* consumption for item *i* (kg/ha) which is affected by the productivity and trade balance amount; and P_i is the average productivity of item *i* (kg/ha)in a certain area in a certain year.

The quantity ecological carrying capacity reflects the ability of available land resources to sustain anthropogenic activity and is calculated using:

$$EC = a_j \times r_j \times y_j \tag{2}$$

where *EC* is the *per capita* ecological biocapacity (ha); a_j is the *per capita* biologically productive area of land type *j* in a region; and y_j is the yield factor of that type of land, again obtainable from the literature (Wackernagel et al., 2004a,b).

As for the majority of the existing methods that evaluate sustainability, traditional EF accounting has been improved, as shown below:

(1) Fresh water is not included in the traditional footprint accounting though water resource sustainability is highly concerned by the international scientific community (Chambers et al., 2000; Wang et al., 2013), however, the EF method fails to provide the average yield factor and equivalence factor for freshwater (Hang et al., 2008; Wang et al., 2013). Moreover, with rapid socio-economic development, the problem of water pollution has been paid more attention in China (and is increasingly becoming the main environmental problem). The research of Hang et al. (2008) incorporated reproduction and consumption of water resources into traditional EF, and there are many studies focused on the reproduction of the consumption water resource ecological footprint in different areas

(Wang et al., 2013). According to Wu et al. (2013), the EF of fresh water can be calculated as follows:

$$WEF = N \times \gamma \times \frac{W_C}{p}$$
$$WEC = N \times \gamma \times \eta \times \frac{W_T}{p}$$
$$p = \frac{V}{S} \tag{3}$$

where *WEF* denotes the water footprint (ha); *WEC* is the water biocapacity (ha); *N* is the population; γ is the equivalence factor; η is the yield factor; W_C is the *per capita* water consumption (m^3); *p* is the water-yielding capacity (m^3/ha); W_T is the fresh water used *per capita* (m^3); *V* is the amount of water (m^3); and *S* is the total area (ha).

- According to the traditional EF model, the energy ecological footprint (EEF) refers to the area of forest necessary to absorb the carbon emissions caused by the combustion of fossil energy. The forest ecological system plays an important role in the global carbon cycle and balance, but the other components of the terrestrial ecosystem are also significant in the carbon cycling progress. Hence, the potential flaw in the traditional EEF is that the land structure and carbon absorption capacity do not get full consideration. Venetoulis and Talberth (2008), Siche et al. (2010), and Wang and Yang (2014) used the net primary productivity (NPP) to represent the carbon absorption capacity of different components of terrestrial ecosystem. This index reallocates the carbon budget and reports carbon sequestration biocapacity of the entire earth's land surface. The global average NPP of different ecosystems is shown in Table 1.

To sum up, NPP–EEF improves the traditional approaches from the following aspects: (a) containing the carbon absorption capacity of the entire terrestrial ecosystem in a certain region; (b) considering the impact of land use structural change; and (c) changing original assumptions about carbon sequestration rates (Venetoulis and Talberth, 2008). Therefore, the results obtained from NPP–EEF model are more appropriate when evaluating the real state of a region's nature and society. According to the study of Fang et al. (2012), the method used for assessing EEF can be present as follows:

$$EEF = \frac{CO_2}{\overline{NPP}} = \frac{CO_2}{\sum_{j=1}^{m} A_j \times NPP_j \Big/ \sum_{j=1}^{m} A_j} \tag{4}$$

where *EEF* denotes the EF of energy consumption, CO_2 the carbon emissions due to direct energy consumption (tC), $\overline{NPP}$ the average net primary productivity, NPP_j the terrestrial ecosystem's net primary productivity of type *j* (tC/ha/year), and A_j the land area of ecosystem *j* in the country (ha).

Based on the method given in the IPCC's (2006) *Guidelines for National Greenhouse Gas Inventories*, the energy-related carbon emission can be estimated using the following expression:

$$CO_2 = \sum_i F_i \times CC_i \times O_i \times COF \tag{5}$$

where C_i denotes the carbon emissions from fuel type *i*; F_i the energy consumption due to fuel type *i*; CC_i is the carbon emission factor for fuel type *i*; O_i is the fraction of the carbon oxidised with fuel type *i*; and *COF* is the molecular weight ratio of carbon dioxide to carbon (44/12).

- Most of the studies on China's EF employed variable equivalence factors and yield factors derived from Living Planet Report published by World Wide Fund for Nature (WWF) or Global Footprint Network which have great advantages in terms of global comparability. However, there is no systematic study (to date) of productivity factors of China, which makes it hard to determine so as to reflect real natural resource consumption in China (Liu et al., 2015). For example, suppose that the products consumed and waste generated in a certain country are fixed annually, then, any improvement in land productivity in other countries would lead to improvement in the average global productivity, which results in enlargement of the EF in some countries. Moreover, the average global productivity used in traditional EF models is defined as 1, which masks the effect of technological progress on biological capacity.

In this paper, we estimate the equivalence factor according to China's productivity and area of all types of land productivity every year. This better reflects the effect of external factors on the land and eliminates the interference of static factors on the EF time series. The balancing factor is the ratio between the same type of productive land in the area and all types of land productivity. According to the study conducted by Liu and Li (2010):

$$\eta_i = \frac{\overline{P_i}}{\overline{P}} = \frac{Q_i}{S_i} \Big/ \frac{\sum Q_i}{\sum S_i} = \frac{\sum_j P_j^i \times \gamma_j^i}{S_i} \Big/ \frac{\sum_j \sum_j P_j^i \times \gamma_j^i}{\sum S_i} \tag{6}$$

where η_i represents the balancing factor; $\overline{P_i}$ the *i*th land productivity (GJ/ha); $\overline{P}$ the average land productivity of the whole country (GJ/ha); Q_i the *i*th land output; S_i the area of the *i*th type of land (ha); P_j^i the output (kg); and γ_j^i the calorific value (kJ/kg).

Yield factors, expressed in the form of ratios, represent the differences in the productivity levels of specific types of land (*e.g.* arable land) and the global average productivity level of this type of land. The calculation process for the yield factors is similar to that for equivalence factors.

Overall, the differences between the modified EF model used in this paper and the traditional EF model are presented in Table 2.

2.2. Evaluation of ecological security

2.2.1. Per capita ecological deficit/surplus

If the result of subtracting the ecological carrying capacity from the ecological footprint is positive, an ecological deficit arises, indicating that the region's *per capita* ecological footprint exceeds its carrying capacity. In contrast, an ecological surplus indicates that the *per capita* demand for natural resources remains within the scope of the ecological carrying capacity. This value, to a certain extent, can quantitatively reflect the sustainable development of a region. As Wackernagel et al. (2004a,b) emphasised, ecological overshoot is the core indicator reflecting environmental sustainability. That is, when the natural capital is consumed faster than it is regenerated, it can lead to a depletion of the resource stock. Although technical progress enables to reduce the ecological deficit through enhancing the carrying capacity, it seems to mask increasing resource scarcity more than solve it (Wackernagel and Silverstein, 2000).

2.2.2. Ecological pressure index

The concept of ecological footprint pressure index (EFPI) is the 'menace status' of ecological footprint to ecological capacity. This

Table 1
Global average NPP of different ecosystems.
Source: Developed from Venetoulis and Talberth (2008).

Ecosystem-type	Arable land	Forest land	Grassland	Water area	Sea	Construction land	Wet land
NPP (tC/hm^2/year)	4.243	6.583	4.835	5.344	0.959	0.997	11.800

Table 2
Comparison between the traditional EF model and modified EF model.

	Traditional model	Modified model
Balancing factor and yield factor	Static	Dynamic
Water footprints	Water products footprints	Water products and fresh water resource
Area of ecological footprints	Global standards	Standard of area of China
Measurement of sustainable development	Only one year	Time series analysis
Worldwide correlation	Any country worldwide	Only the case study

indicator can be calculated as follows:

$$EFPI = \frac{EF}{EC}. \tag{7}$$

If $EFPI$ is greater than 0 but less than 1, the supply of ecological resources exceeds the demand for it. If $EFPI$ is equal to 1, the balance of supply of the ecological resource and the demand for it are equal and the ecological security is in a critical condition. Finally, if $EFPI$ is bigger than 1, our demand for ecological resources is greater than its supply and the regional ecology is in an unsafe condition. Using data calculated for the EFs of 147 countries or regions, as provided in the *Living Planet Report* by the International Monetary Fund in 2004, Yuan (2010) developed the ecological security evaluation index and classification standard (Table 3).

2.2.3. Index of ecological footprint diversity

The ecological footprint diversity index (EFDI) contains two parts: (1) abundance (using a number of different land types); and (2) degree of fairness (distribution of ecological footprint measurement). In this paper, we adopt the Shannon–Weaver formula to calculate the EFDI (Shannon and Weaver, 1929):

$$EFDI = -\sum (p_i \ln p_i), \tag{8}$$

where p_i is the proportion of land type i in the total ecological footprint. The Shannon–Weaver formula is not a monotonic function. The more equal the ecological footprint distribution, the greater the diversity is for the ecological system with its given components (Xu et al., 2003; Yuan and Zheng, 2010).

2.2.4. Ecological and economic coordination coefficient

Ecological deficit is an absolute value and cannot reflect its relationship with resource endowment conditions. Therefore, it is necessary to introduce the concept of an ecological coordination coefficient to compensate for this deficiency in the ecological deficit (Liu et al., 2000). The ecological and economic coordination coefficient (EECC) represents the degree of coordination between socio-economic development and ecological environment and is calculated thus:

$$EECC = \frac{EF + EC}{\sqrt{EF^2 + EC^2}} \tag{9}$$

Also, $EF > 0$, $EC > 0$, and $1 < DS \leq 1.414$. The closer DS is to 1, the worse the coordination. If $EECC$ is close to 1.414, then the coordination is better. When $EECC = 1.414$, the ecological demand and supply are in the best (balanced) condition.

Table 3
Eco-security evaluation based on ecological pressure index.

Level	Ecological footprint pressure index	Characterisation state
1	< 0.50	Pretty safe
2	0.50–0.80	Relatively safe
3	0.81–1.00	Relatively unsafe
4	1.01–1.50	Quite unsafe
5	1.51–2.00	Very unsafe
6	> 2.00	Completely unsafe

2.3. The EF and EC forecasting model

A suitable integration of linear and non-linear models enables to make a more accurate prediction of time-series data (Babu and Reddy, 2014). In this paper, the linear ARIMA and non-linear ANN models are employed to forecast the EF and EC in order to provide early warning of future ecological security.

2.3.1. The ARIMA modelling approach

ARIMA, which is a linear modelling technique, is based on three parametric components, namely, the autoregression (AR), integration (I), and moving average (MA) (Box and Jenkins, 1970; DeLurgio, 1998). Fitting an ARIMA model contains five iterative processes: (i) stabilising the original data, (ii) determining the structure, (iii) estimating the parameter values, (iv) performing tests on the residuals, and (v) predicting future data. First, the given time-series data must be checked for stationarity, if not, a differencing operation would be performed. The integration order of the ARIMA model is determined to be d if the differencing operation is performed d times. For the differencing time-series obtained, an autocorrelation function (ACF) and partial autocorrelation function (PACF) are applied to determine the p and q orders of the ARIMA model (Box and Jenkins, 1970). The ACF determines whether, or not, earlier data have some relationship with later data. The PACF indicates the amount of correlation between the variable and the time-lagged version of itself which is not explained by correlations at all low-order lags. After all the model coefficients have been estimated, the time series are predicted by using the historical data and model coefficients. At last, the diagnostic check of the model's adequacy is needed to examine whether, or not, the model's assumptions about the errors ε_t are satisfied through several diagnostic indicators and plots of the residuals.

2.3.2. Artificial neural network

An artificial neural network is a mathematical and computational model which imitates the structure and function of the human brain. It consists of several layers of neurons (Tian and Gao, 2006). The back propagation neural network (BPNN), first proposed by Rumelhart and McClelland in 1986, is one of the most widely used ANN models. The commonly used BPNN is a multi-layer feed-forward network using an error reverse propagation algorithm and is composed of three parts, i.e. input layer, hidden layer and output layer (Skapur, 1999). It has strong mapping ability due to the error-reverse propagation algorithm.

In a BPNN, different layer nodes are connected by weighted arrows. The learning process, including forward and backward propagation, modifies the weights of the connections between neurons based on the deviation between the actual and target outputs (until the overall error is within an acceptable range). Forward propagation involves the input signal spreading from the input layer, through the hidden layer, and then to the output layer. The learning algorithm is complete when the expected output is obtained, or it turns into backward propagation. Backward propagation involves calculating the error along the forward route through the ANN and then adjusting the weights and thresholds between each layer node according to the gradient descent method to reduce the error (Zhang, 2011). The error signal is reduced by modifying the weights in each layer and the correct response rate increases in the output layer as the back-propagation of error is repeated (Skapur, 1999). In the BPNN model, the relationship between the output y_t and input y_{t-i} can be found in Appendix A.

To obtain the model coefficients, a known data sequence is first given considered as the input and then the network trained with this training sequence. This phenomenon can be regarded as minimising the multivariate global error function formed by the weight values (Zhang,

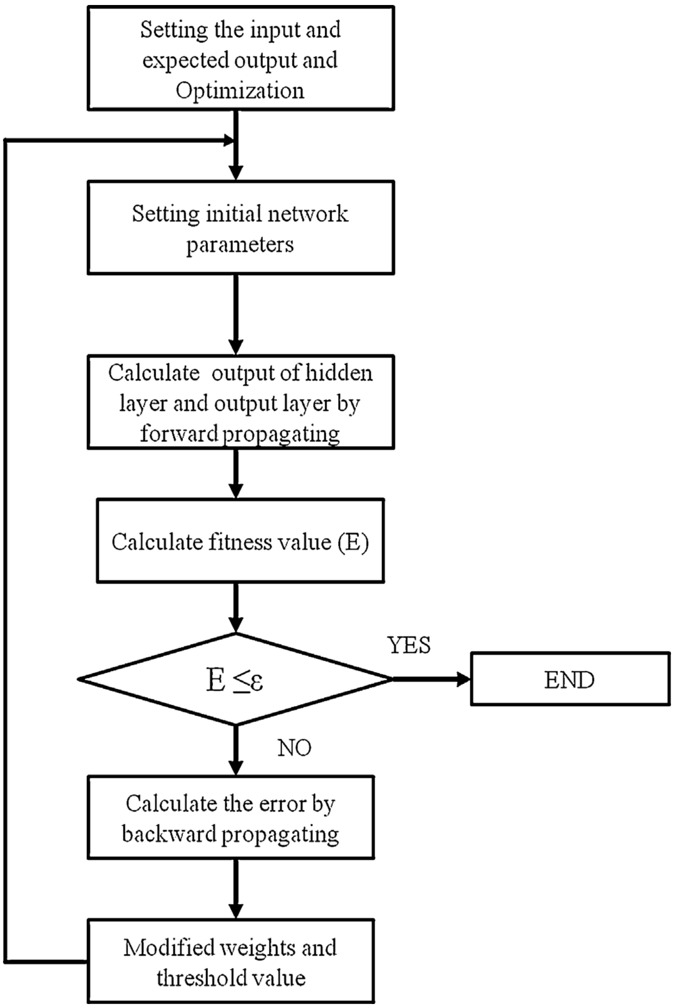


Fig. 1. The computing process BPNN model.

2003; Haykin, 2008; Khashei and Bijari, 2011). Many training algorithms have been used to train BPNN models, and we use a fast training function based on the Levenberg–Marquardt algorithm. This algorithm has the fastest convergence speed for moderate-scale BPNN models and takes advantage of the matrix calculations available within MATLAB™ (Wen et al., 2003). The computational process is shown in Fig. 1.

2.3.3. The hybrid model

Just as Zhang (2003) noted that either the ARIMA or ANN may not be adequate to model the times-series problem (Zhang, 2003). Hence, the hybrid model incorporating both linear and non-linear modelling abilities might be a good alternative when predicting time series data, *i.e.*,

$$X_t = L_t + N_t \tag{10}$$

where L_t represents the linear component and N_t the non-linear component. First, the ARIMA model is used to predict the original data, and then the residuals are found using:

$$y_t = X_t - \hat{L}_t \tag{11}$$

where $\hat{L}_t$ is the value predicted by the ARIMA model. Next, the residuals are modelled using the ANN to discover the non-linear relationships. Finally, the hybrid prediction is found in the form:

$$\hat{X}_t = \hat{L}_t + \hat{N}_t \tag{12}$$

where $\hat{N}_t$ represents the predicted non-linear component.

2.3.4. Measures of accuracy applied to gauge model performance

Before any discussion of the results, the measures used to compare model performance and prediction accuracy should be examined. Two different forecast-consistency measures are employed to compare the performances of the models used in this research: (i) the root mean square error (RMSE), and (ii) the mean absolute error (MAPE),

$$RMSE = \sqrt{\sum_{i=1}^{n} \frac{(y_t - \hat{y}_t)^2}{n}} \tag{13}$$

$$MAPE = \frac{1}{n} \sum_{i=1}^{n} \left| \frac{y_t - \hat{y}_t}{y_t} \right| \tag{14}$$

where y_t and $\hat{y}_t$ are the predicted and observed EF or EC data, respectively, and n is the number of data points.

RMSE represents the average of the squared errors over the same prediction horizon. The MAPE represents the average of the absolute errors over a given prediction horizon. All in all, the smaller the measures, the better the model.

2.4. Data sources

A huge mass of data about human consumption and land use is need for the calculation of EF, and we therefore reviewed a great number of secondary information sources from published statistical yearbook, governmental reports, databases, web pages, and statistical reports. In this study, the primary consumption data of agriculture products, forestry products, aquatic products, energy consumption was directly collected from standard yearbooks, *e.g.*, CAY, 1980–2014, CCIY, 1982–2014, CISY, CESY, 1986–2014, CEY, 1990–2014, CFY, 1986–2014, CIESY, 1988–2014, and SYC, 1982–2014. Land data are taken from the Food and Agriculture Organisation (FAO) database provided by the Food and Agriculture Organisation of the United Nations, *China Land and Resources Statistical Yearbook* and *China Land and Resources Communiqué*. Trade balance data were sourced from SYC, *New China's 60-Year Statistical Data* and the FAO database. Provincial Gross Domestic Product (GDP) data were converted to constant 1978 prices. In this paper, some methods (*e.g.*, the registration processing of the spatial data, spatialisation processing of non-spatial data, rasterisation processing of the vector data, interpolation processing of the meteorological data, *etc.*) are used to standardise the collected data. This is consistent with the study conducted by Miao et al. (2016). Additionally, it should be noted that missing data for some certain years were estimated by applying linear interpolation.

3. Results and discussion

3.1. The state of sustainable development in China from 1978 to 2013

When analysing the EF for a certain period, a comparison between the equivalence and yield factors of various land types in the analytical period and those in earlier periods is a very important aspect; as shown in Fig. 2, the equivalence and yield factors of the various land types all increased during the study period. This is mainly because China has been continually upgrading her technological level since the time of reform and opening up, which resulted in a significant improvement in the productivity of different land types. It also means that the overall ecological carrying capacity in China has been strengthened.

The *per capita* EF in China increased by three times during the period from 1978 to 2013, peaking at 3.132 ha in 2013 (Fig. 3a). It can be seen that all types of EF increased during the whole of the period studied. According to the changes in each type of EF, it can be seen that the main growth in China's *per capita* consumption was due to fossil fuels (coal, oil, *etc.*), aquatic products, and animal products (meat, eggs, milk, *etc.*). The EEF increased from 0.113 ha in 1978, reaching a maximum of 1.716 ha in 2013. Moreover, the fastest growth was seen

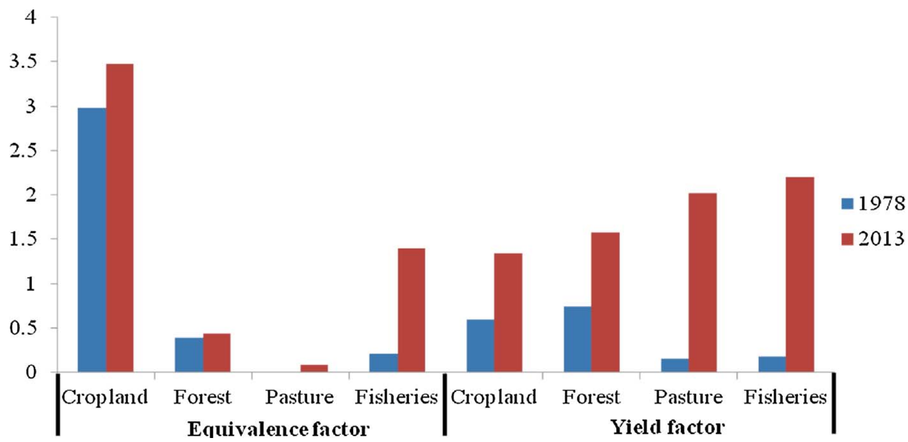


Fig. 2. Changes of China's balancing factor and yield factor from 1978 to 2013.

during the 20th century. The long-term fluctuation in the *per capita* EF of cropland stagnated throughout the study period (within the range from 0.439 ha to 0.674 ha). In addition, the EF for built-up land rose significantly corresponding to its beginning level (Fig. 3b). This could be explained by the fact that the area used for construction (e.g. housing, roads and telecommunication facility) increased rapidly during the whole study period. As shown in Fig. 3c and b, EFs for pasture and fisheries also experienced increases (rising from 0.011 ha and 0.014 ha in 1978 to 0.037 ha and 0.226 ha in 2013, respectively). This suggests that the rapid development of China's economy, and obvious improvement in the lifestyle of her people, has resulted in great demand for, and consumption of, dairy product, meat, eggs, and aquatic product. The EFs for forest and fresh water rose from 0.107 ha and 0.102 ha in 1978 to 0.223 ha and 0.266 ha in 2013, respectively, but their growth rates were relatively slower than the other types of EF accounts.

Compared with the *per capita* EF in the corresponding period (1978 to 2013), there is no significant change in *per capita* EC in China which does however have an overall ascending trend (Fig. 4). It is counteraction caused by population growth that makes the biocapacity *per capita* remain stagnant, even though the yield factors increased, compared to the trend in the *per capita* EF. The total *per capita* EC increased from 1.414 ha in 1978 to 1.704 ha in 1999, followed by fluctuation around 1.683 ha between 2000 and 2007: it peaked at 1.734 ha in 2008, falling to 1.666 ha in 2013. The range of variation of the *per capita* EC amounted to 0.320 ha.

With regard to the ecological overshoot for all types of land (Fig. 5), the EFs for water resources, built-up land, and pasture had surplus

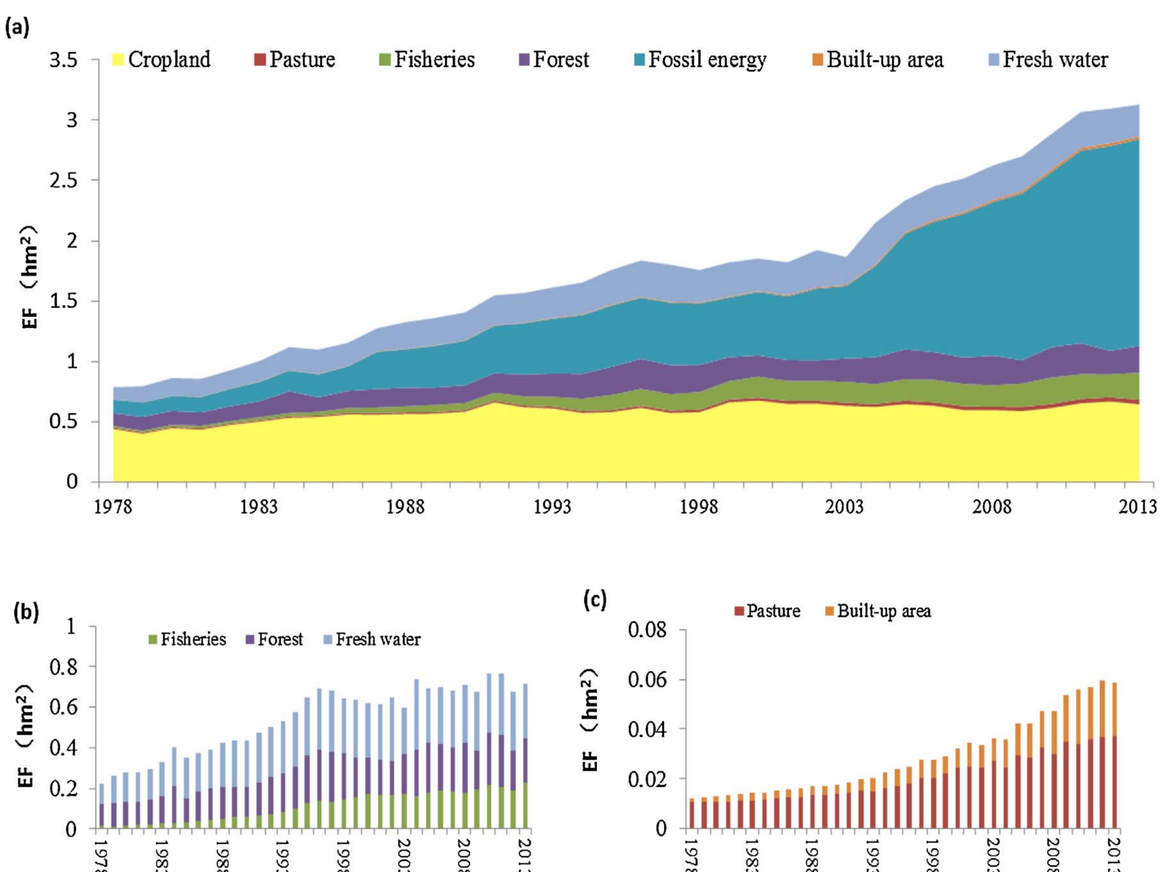


Fig. 3. China's per capita EF, by component, 1978–2013.

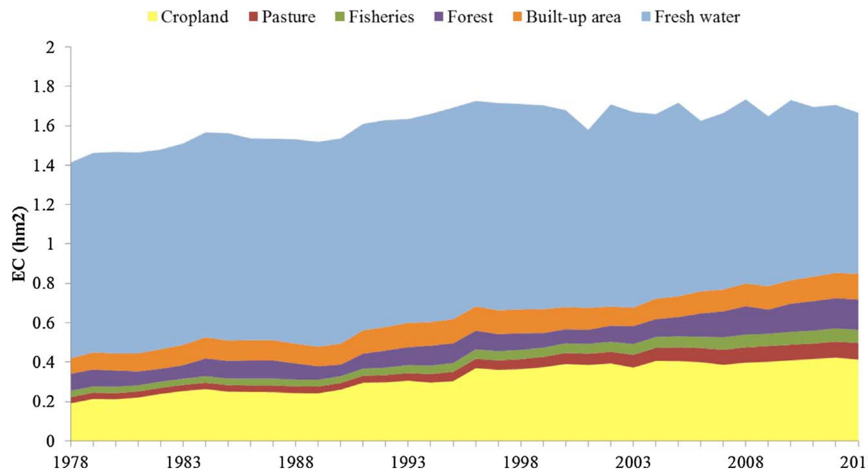


Fig. 4. China's per capita EC, by component, 1978–2013.

natural supply during the whole of the study period. In particular, the water carrying capacity accounted for the largest percentage of the total EC. In addition, as shown in Fig. 5, the *per capita* EF for fossil energy exceeded that for arable land in 2013. This means that the increase in EF mainly attributes to consumption of energy-related production and energy issue should be paid adequate attention in recent years. As regards the EFs for pasture and built-up, it can be observed that although both of them had increased, they only make small contributions to the total EF and can thus be ignored.

Above all, the EFs for built-up and pasture made negligible contributions to the total *per capita* EF (0.69% and 1.19%, respectively), and the EFs for fossil energy and cropland accounted for the largest proportion of the total *per capita* EF (54.79% and 20.51%, respectively). This means that grain, vegetables, meat, and fossil-energy are the main sources required to support life. Since China reformed and opened up, her economy has kept growing rapidly. However, the 'high input, high pollution' way of consuming energy is putting more pressure on its energy sector: coal accounts for approximately 70% of the total primary energy consumed in China, which is significantly higher than the average global level of 27.1%. In addition, as the economy, science, and

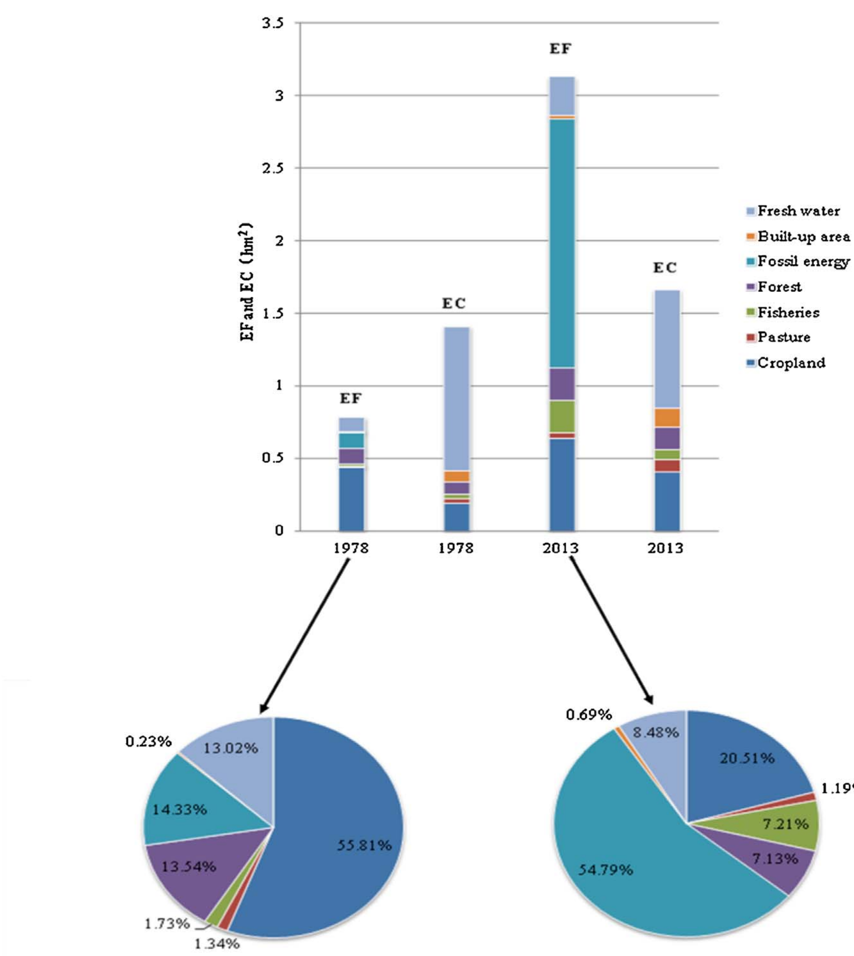


Fig. 5. Comparison of China's per capital EF and EC.

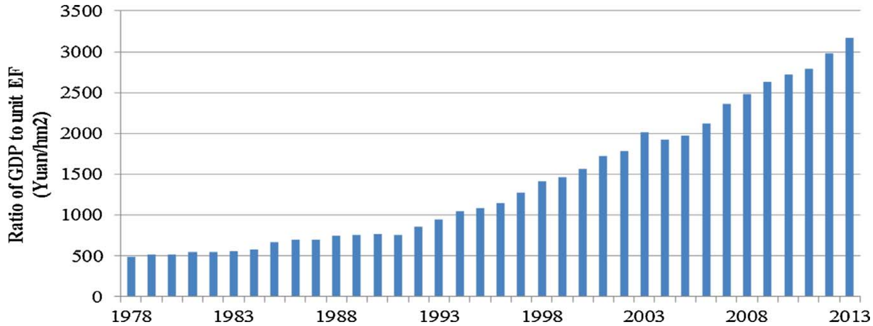


Fig. 6. Time series of ratio of per capita GDP to EF in China from 1978 to 2013 (1978 = 100).

technology have developed, there have been changes in people's diets and concepts of consumption, which rapidly increased demand for nutrient-dense foods. Under such circumstances, the structure of the agricultural industry requires constant adjustment in line with market orientation to develop.

EF intensity, defined as the ratio of the economic output (represented by GDP) and EF, is used to present the intensity of economic output to corresponding unit resource utilisation. It may be considered as an attempt to show the correlation between economic output and land demand. To improve the situation, we should do more with less, or produce economic outputs which use minimal natural resources and cause less environmental degradation (Kuosmanen, 2005). As discussed by Chen et al. (2004), this index can be regarded as a direct measure of resource utilisation efficiency.

As shown in Fig. 6, this indicator in China increased sharply over the study period (from 484 RMB/ha in 1978 to 3174 RMB/ha in 2013—an annual growth rate of around 15%). This shows that China improved her resource efficiency from 1978 to 2013. The improvement was due to the large growth rate of GDP which increased by a factor of 6.56, while the EF increased more relatively modestly (by a factor of 3.98) during the period 1978 to 2013 (Fig. 7). Structure and technology effects are the dominant factors improving the EF intensity indicator (Yu et al., 2013). With China's rapid economic development, the economic structure and economic growth have undergone fundamental changes, which have brought about a strategic adjustment. Therefore, the ratio of GDP to EF *per capita* has increased as the economic structure shifted from heavy to light industry. Technology affects EF intensity by advancements in technology in product manufacturing processes. In particular, there is an additional technological effect related to pollutant emission. After the production process, application of 'end-of-pipe' treatment facilities will reduce pollutant emissions. Since China started to implement a policy of opening up to the outside world, its total- or semi-closed state has changed and its economic and technological levels have been raised, which has contributed most to increasing the efficiency of resource use.

3.2. Evaluation of the ecological safety of China between 1978 and 2013

As shown in Fig. 8, China went from having reserve biocapacity to having a deficit from 1978 to 2013. The *per capita* ecological surplus of China decreased from 0.627 ha in 1978 and diminished in 1995, and then the *per capita* ecological deficit increased gradually, peaking at 1.466 ha in 2013. Overall, all EF types and the total EF had increasing trends from 1978 to 2013 (Fig. 3) while the total EC changed only slightly (Fig. 4).

The *per capita* EF remained less than the *per capita* EC from 1978 to 1993, implying a positive ecological deficit in China at that time. In other words, there was an ecological surplus. Then, the *per capita* EF exceeded the *per capita* ecological carrying capacity around 1994 and thereafter (Fig. 8). Thus, China's *per capita* consumption demand has gone far beyond the regeneration capabilities of e systems and the conflict between ecological system and economic development gradually increased. This warns us that current development in China comes at the cost of high consumption of the stock of natural resources and puts the ecosystem in an unsustainable state.

Fig. 9 shows the trend in ecological pressure from 1978 to 2013: the EFPI has been on the rise since the reforming and opening up of China. In fact, it increased 3.38 times, from 0.556 in 1978 to 1.879 in 2013. At the same time, the degree of security increased from level 2 (relatively safe) to level 5 (very unsafe). EF has already exceeded EC since 1950s in China. The increase in the ecological deficit and EF pressure index, indicate that the degree of use of natural resources, and the rate at which waste is being released, have already exceeded the system's recycling and self-purification capabilities.

As shown in Fig. 10, the index of ecological footprint diversity had an inverted 'U'-type variation over the study period. However, EECC experienced a slight increase from 1978 to 2002 after which it gradually dropped again. On the whole, both the IEFD and EECC peaked in the 1990s and then began to fall. This suggests that China's ecological environment, as well as its coordination with the economy, was in a better position in the 1990s but has deteriorated gradually since. When the ecological pressure rises to a certain point, the ecological environment becomes uncoordinated and unsafe. In this case, economic development is not sustainable and the ecosystem is insecure. In addition, correlation analysis shows that the development capability of the ecological system is positively correlated with ecological footprint diversity. Therefore, the development capability of the ecological system can be enhanced by increasing the diversity of

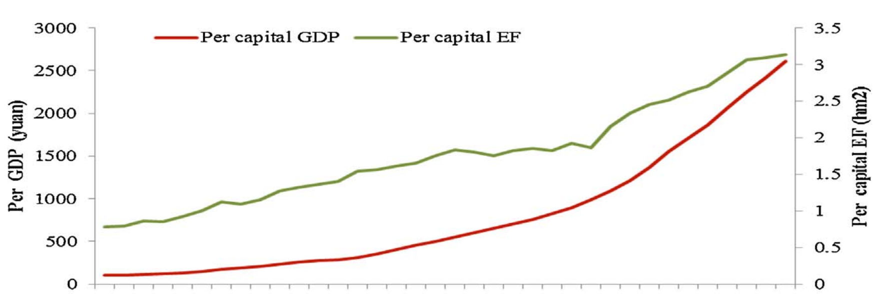


Fig. 7. The trends of EF and GDP of China in 1978–2013 (1978 = 100).

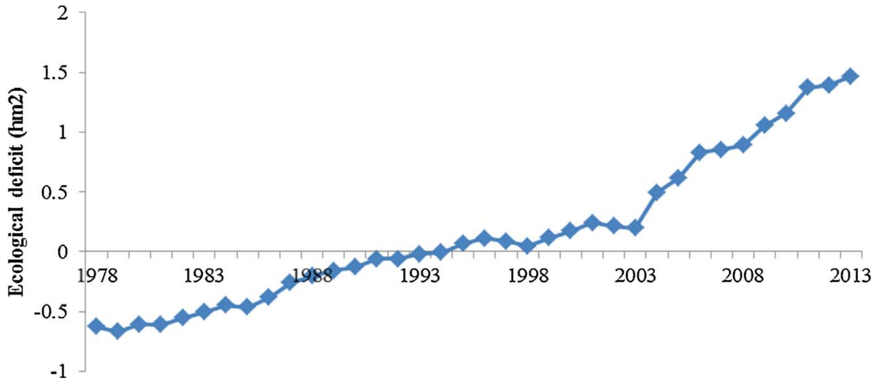


Fig. 8. The trend of ED of China in 1978–2013.

land use, using different types of land resources equally, and improving resource utilisation efficiency.

3.3. Forecast results for EF and EC

3.3.1. EF and EC predictions using the ARIMA model

A three-stage procedure was used to fit the ARIMA model to the available EF and EC time series data. First, however, we need to ensure that the simulated data are stationary. In this paper, the original EF and EC data both increased over time and were non-stationary. We computed their differential functions to obtain their derivative stationary time series. As shown in Fig. 11, the second-order difference series in EF and EC had no increasing/decreasing trends, and so could be stationary. Then, the autocorrelation and partial autocorrelation functions were used to determine any possibly persistent structures in the time-series data.

Using the Akaike information criteria (AIC), the best-fitting model was identified from among various competing models. As can be seen in Table 4, of all the ARIMA models examined to describe the time series and produce a prediction, the ARIMA (1,2,2) model was found to be most appropriate for *per capita* EF and the ARIMA (1,1,1) model for the *per capita* EF and EC. The correlation coefficients between the observed data and predicted values for EF and EC are 0.451 and 0.718, respectively. This is generally not satisfactory in common model applications and the diagnostic check of the estimated parameters was used to ensure that the best fitting model was selected.

As shown in Fig. 12, the residual sequence Q test was adopted to check if the model's error assumption was satisfied and their P-values were big enough. Hence, the ARIMA (1,2,2) and ARIMA (1,1,1) models were accepted as the ultimately fittest models. Then, the trained ARIMA model was then tested using the EF and EC data sets for the period from 1981 to 2013.

3.3.2. Residual modification of the ANN model

The residuals from the ARIMA model can be modelled using the ANN model. We adopted a BPNN in this paper. The first thing to do is to decide the basic structure of the BPNN model. After some experimentation, we used a three-layer BPNN model to establish the forecasting model for the non-linear patterns in the EF and EC data. We took the number of input layer nodes to be $n = 5$, representing the burial depth of the basement. We also took the number of output layers to be $l = 1$, representing the EF and EC content. The number of hidden layer levels and the number of hidden neurons also need to be defined. As the single hidden-layer BPNN is very good at non-linear mapping, this model is adopted here. Based on the Kolmogorov theorem and trial results, we chose 10 and 12 to be the best numbers of hidden neurons. Thus, 5-10-1 and 5-12-1 BPNN structures were adopted for the EF and EC data series.

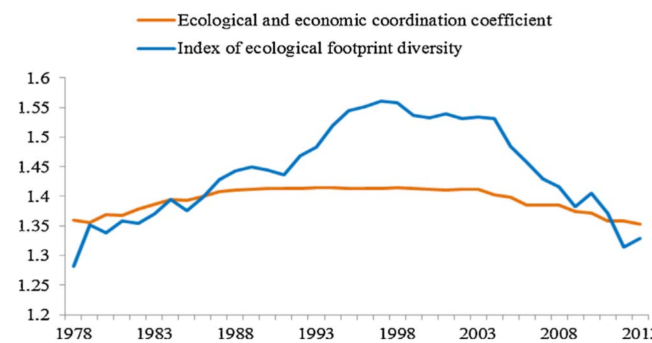


Fig. 10. The trend of IEFD and EECC of China in 1978–2013.

3.3.3. EF and EC predictions using the ARIMA–ANN model

Fig. 13 shows the forecasts obtained using the ARIMA and hybrid models for the EF and EC time series. It can be observed that both ARIMA and hybrid models follow the same trends as the real data, but the latter fits the real data better. In addition, two error measures were used to evaluate and compare models, *i.e.*, RMSE and MAPE. Table 5 compares the respective statistical errors for ARIMA and hybrid models. It can be seen that the RMSE and MAPE values obtained using the ARIMA–ANN model are much smaller than those obtained using the ARIMA model. Hence, it is clear that the ANN model has improved the performance of the pure ARIMA model and that the hybrid model proves to be a better alternative to the ARIMA model on its own.

Based on the resulting ARIMA–ANN model, EF in China can be forecast for several years in the future. The results suggest that total EF

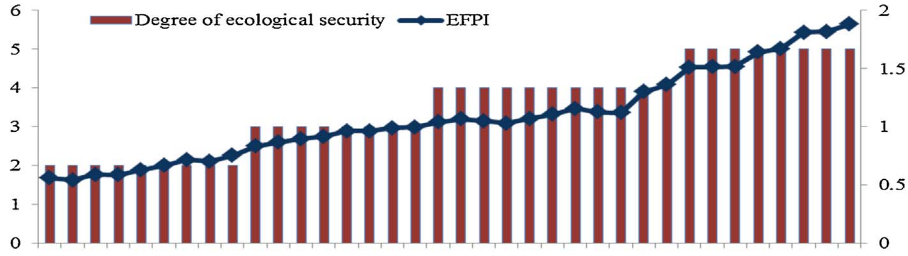


Fig. 9. The trend of EFPI of China in 1978–2013.

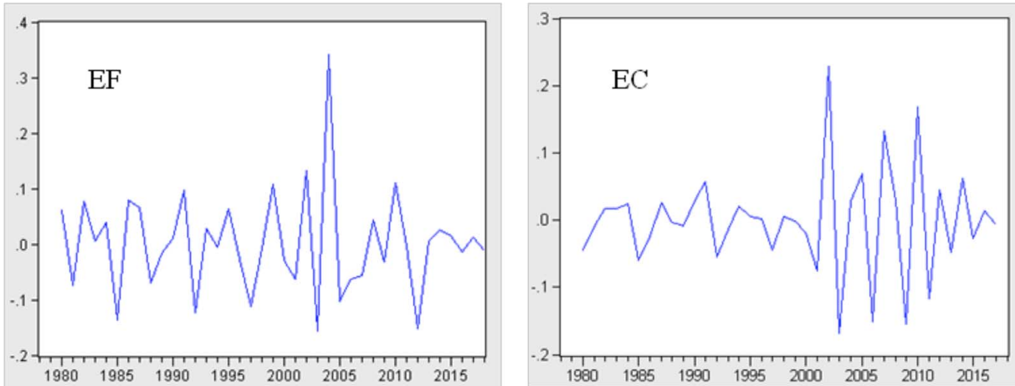


Fig. 11. The 2-order difference series of EF and EC.

Table 4
The forecasting results obtained from ARIMA model.

		Coefficient	*t*-Statistic	*P*-value	R^2	S.E.R	D.W
EC	AR (1)	−0.902	−10.208	0.000			
	MA (2)	−0.934	−10.418	0.000			
					0.451	0.075	1.866
EF	AR (1)	−0.448	−2.895	0.007			
	MA (1)	−0.998	−38.330	0.000			
					0.718	0.044	2.170

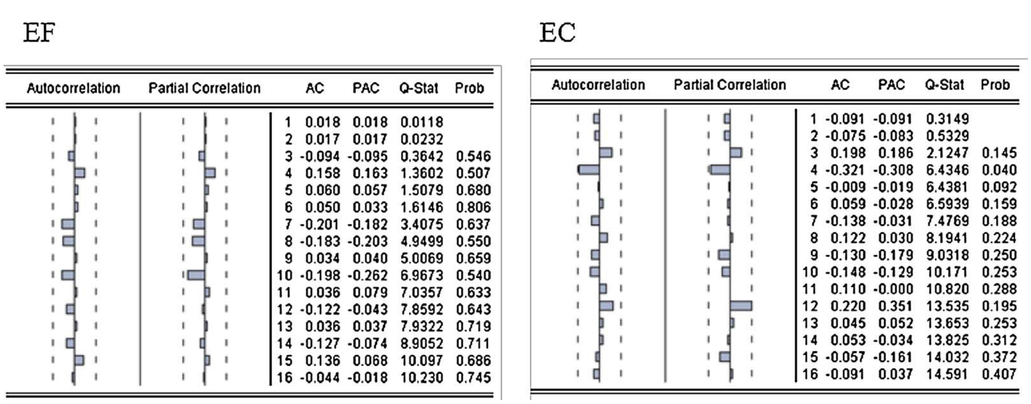
will continue to have an increasing trend and EC will fluctuate within a small range of values (see Table 6). Thus, ED will continue to increase and the situation of ecological imbalance in China will become worse. Meanwhile, the degree of ecological security will reach level 6 (completely unsafe) after 2018 (with a value of 2.211 at some time in 2019). According to these results, various levels of government need to make suitable strategic plans to address the ecological balance and sustainable development problems. People should be encouraged to have a healthier lifestyle (with more fruit and vegetables, and less meat), so as to slow the growing consumption of fishing and pasture resources. In addition, technological innovations should be taken full advantage of to increase land productivity.

It is evident that the hybrid ARIMA–ANN makes the prediction results more reliable. Hence, based on the prediction results above, decision-makers can make corresponding strategic plans for sustainable development. It can be seen that the only effective way to reduce this ecological pressure, and improve the level of ecological security, would be to decrease the production footprint or improve China's biocapacity. Nevertheless, the biocapacity changed only slightly during the study period and China may consume more energy and raw materials with the further development of her economy. Therefore, improving the level of ecological security will require a reduction of the production footprint by means of more appropriate allocation of resources, especially pasture and fishery resources, as well as the improvement of resource utilisation efficiency and some control over population increase. Additionally, land productivity should be enhanced through technological innovations.

4. Conclusions

EF has become an effective method of measuring environmental sustainability by comparing human consumption of natural resources and the availability of natural supplies. Based on the traditional EF model, this paper takes into account the fresh water footprint, improves the energy ecological footprint, and amends the equivalence and yield factors to simulate EF and EC in China. The improved treatment makes the analysis of China's sustainability more scientific and rational. Using an ARIMA–ANN model, we forecast the future potential status of EF and EC in China, which will be of great benefit to decision-makers to help them develop more appropriate strategic plans aimed at a better ecological balance and to improve ecological sustainability in the future. The main conclusions drawn from our research are as follows:

- The equivalence and yield factors of land significantly increased since China reformed and opened up due to significant improvements in the levels of scientific and technological knowledge therein. The *per capita* EF increased, in total, by a factor of 4.34 (from 0.763 ha in 1978 to 3.132 ha in 2013). Within this, arable land and fossil energy accounted for the largest share of the increase. In particular, EEF increased from 0.113 ha in 1978 to 1.716 ha in 2013 (a 15-fold increase). Meanwhile, there was no obvious increase in China's *per capita* EC. From the perspective of the supply–demand structure of *per capita* EF, the contradictions between supply and demand of EF for arable and fossil fuels are especially prominent. At the same time, the EF for water resources, built-up land, and pasture



EF

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	0.018	0.018	0.0118	
		2	0.017	0.017	0.0232	
		3	-0.094	-0.095	0.3642	0.546
		4	0.158	0.163	1.3602	0.507
		5	0.060	0.057	1.5079	0.680
		6	0.050	0.033	1.6146	0.806
		7	-0.201	-0.182	3.4075	0.637
		8	-0.183	-0.203	4.9499	0.550
		9	0.034	0.040	5.0069	0.659
		10	-0.198	-0.262	6.9673	0.540
		11	0.036	0.079	7.0357	0.633
		12	-0.122	-0.043	7.8592	0.643
		13	0.036	0.037	7.9322	0.719
		14	-0.127	-0.074	8.9052	0.711
		15	0.136	0.068	10.097	0.686
		16	-0.044	-0.018	10.230	0.745

EC

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	-0.091	-0.091	0.3149	
		2	-0.075	-0.083	0.5329	
		3	0.198	0.186	2.1247	0.145
		4	-0.321	-0.308	6.4346	0.040
		5	-0.009	-0.019	6.4381	0.092
		6	0.059	-0.028	6.5939	0.159
		7	-0.138	-0.031	7.4769	0.188
		8	0.122	0.030	8.1941	0.224
		9	-0.130	-0.179	9.0318	0.250
		10	-0.148	-0.129	10.171	0.253
		11	0.110	-0.000	10.820	0.288
		12	0.220	0.351	13.535	0.195
		13	0.045	0.052	13.653	0.253
		14	0.053	-0.034	13.825	0.312
		15	-0.057	-0.161	14.032	0.372
		16	-0.091	0.037	14.591	0.407

Fig. 12. Residual sequence *Q* test of EF and EC.

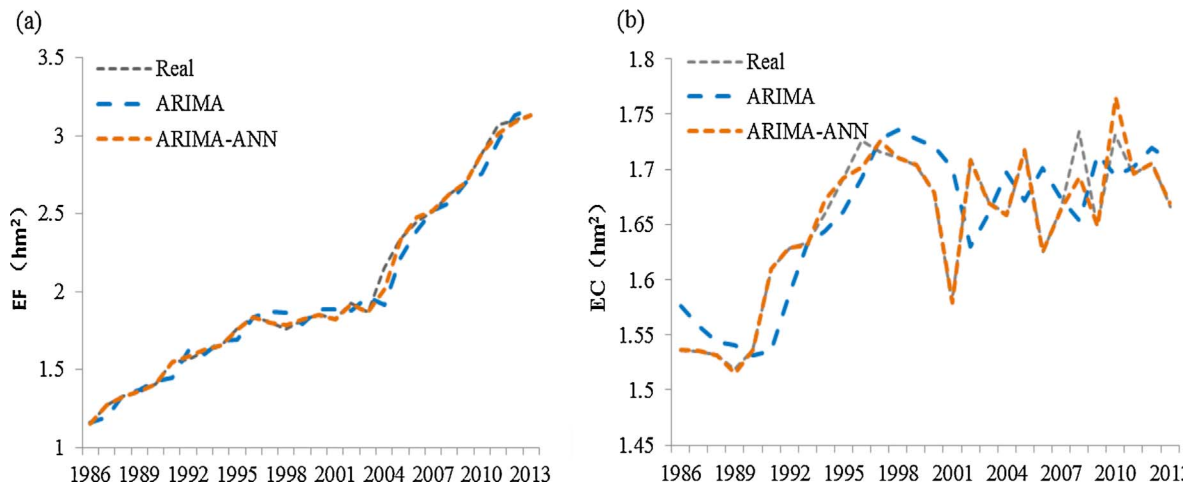


Fig. 13. Sample data forecasting utilising the hybrid and ARIMA models for the EF and EC.

Table 5
Statistical error measures for the ARIMA and hybrid models.

	Method	RMSE	MAPE
EF	ARIMA	0.073	3.025%
	ARIMA-BP	0.028	0.459%
EC	ARIMA	0.043	2.015%
	ARIMA-BP	0.011	0.274%

Table 6
The forecasting results of ARIMA–ANN model from 2014 to 2025.

	EF			EC			ED	EFPI
	ARIMI	BP	Hybrid	ARIMI	BP	Hybrid	Hybrid	Hybrid
2014	3.192	0.057	3.135	1.689	0.031	1.658	1.476	1.890
2015	3.266	−0.044	3.310	1.685	0.021	1.664	1.647	1.990
2016	3.327	0.031	3.296	1.693	−0.056	1.749	1.547	1.884
2017	3.401	0.035	3.366	1.695	−0.132	1.827	1.539	1.842
2018	3.463	0.174	3.289	1.700	0.010	1.690	1.599	1.946
2019	3.535	−0.130	3.665	1.704	0.047	1.657	2.007	**2.211**
2020	3.598	0.091	3.507	1.709	−0.017	1.725	1.782	**2.033**
2021	3.669	−0.061	3.731	1.713	−0.050	1.763	1.968	**2.117**
2022	3.733	0.152	3.581	1.717	−0.020	1.737	1.844	**2.062**
2023	3.733	−0.026	3.760	1.721	−0.046	1.768	1.992	**2.127**
2024	3.791	0.071	3.720	1.726	−0.044	1.770	1.950	**2.102**
2025	3.863	0.062	3.801	1.730	0.035	1.695	2.106	**2.243**

The bold values indicate that the degree of ecological security reaches level 6(completely unsafe).

were at a surplus with regards their naturally available supply during the whole study period.

- EF has already exceeded ecological carrying capacity since 1950s in China. The ecological deficit reached 1.466 ha in 2013, equivalent to 88% of the ecological carrying capacity in that year. Meanwhile, the degree of security increased from level 2 (relatively safe) to level 5 (pretty unsafe). The increases in ecological deficit and EFPI show that the degree of natural resource use and the rate of waste release have already exceeded the ecosystem's recycling and self-purification abilities.
- The ratio of the economic output and EF is applied to represent the economic output corresponding to unit resource utilisation intensity. This indicator in China increased sharply over the study period, from 484 RMB/ha in 1978 to 3174 RMB/ha in 2013 (an annual growth rate of 15%). This indicates that China has improved its resource utilisation efficiency over the period from 1978 to 2013.
- EFDI and EECC both peaked in the 1990s and have fallen since. Thus, China's ecological environment and coordination with her economy were in a better position in the 1990s but have gradually deteriorated since. Moreover, correlation analysis shows that the development capability of the ecological system is positively correlated with the diversity of the ecological footprint. Therefore, the development capability of the ecological system can be enhanced by increasing land diversity, using different types of land resources equally, and further improving resource utilisation efficiency.
- The combined use of ARIMA and ANN models can facilitate discussion of the predicted ecological situation over a long time-series data and make the results more reliable. The results suggest that EF in China will continue to rise with an annual growth of 0.055 ha while the EC will fluctuate within a certain small range of values from 2014 to 2025. As a result, EFPI will reach 2.211 (level 6) in 2019. Hence, the ecological security situation in China will continue to worsen in the coming years if some effective measures are not taken.

On the whole, the anthropogenic pressure imposed on the environment in China has exceeded its carrying capacity. With further development of the economy, the living standards and quality of life experienced by the people of China will improve continually, but this will certainly result in greater consumption of energy and raw materials. Our results have shown that the development capacity of the ecological economic system has a negative relation with ecological footprint, but has a positive relation with ecological footprint diversity. Hence, the only effective way to improve the level of ecological security is to reduce EF and enhance ecological footprint diversity. Several measures could be adopted to slower the growth in China's ecological footprint and improve ecological security level. These include, for example, efficiently utilising existing resource stocks, vigorously developing renewable energy sources, exploiting each city's own production potentials, changing the economic model of labour-intensive, cutting down resource consumption, improving people's cultural awareness, and controlling the increase in population and so on.

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support.

Appendix A

In the BPNN model, the relationship between the output y_t and input y_{t-i} can be expressed as:

$$y_t = w_0 + \sum_{j=1}^{n} w_j g\left(w_{0j} + \sum_{i=1}^{m} w_{ij} y_{t-i}\right) + \varepsilon_t \tag{15}$$

where w_{ij} ($i = 1, 2, 3, \ldots, m$; $j = 1, 2, \ldots, n$) and w_j ($j = 0, 1, 2, \ldots, n$) represent the model parameters, m is the number of neurons in the input layer and n the number of neurons in the output layer; and $g(x)$ is the transfer function. It has been proven theoretically that when the function of the hidden layer nodes is a sigmoid function, a multilayer feed-forward network can accurately fit any system (Wang et al., 2008; Zhang et al., 2010; Gao et al., 2011). Therefore, a sigmoid function is chosen as the transfer function here. The most common sigmoid function has the form as follows:

$$g(x) = \frac{1}{1 + e^{-x}}. \tag{16}$$

The BPNN model performs, in fact, a nonlinear functional mapping according to the past observations to the future value y_t, i.e.

$$y_t = f(y_{t-1}, y_{t-2}, \ldots, y_{t-p}, w) + \varepsilon_t \tag{17}$$

where w is a vector formed from all the parameters and $f(y_{t-1}, y_{t-2}, \ldots, y_{t-p}, w)$ is a function determined by the network structure and connection weights.

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