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Determinants influencing ecological footprints of China; An empirical evidence from factor analysis

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ABSTRACT

China has advanced significantly in the last decades, but ecological concerns raise questions about the nation's long-term affluence. The hunt for possible determinants in explaining the quality of the environment (ecological footprint) is still in progress. Therefore, the current study attempts to investigate the influencing factors from various explanatory variables (eco-innovation, economic complexity, renewable energy consumption, economic growth, natural resource rent, foreign direct investment, the energy intensity level of primary energy, economic development, Public-private partnerships investment in energy, electric power consumption, and population growth) through factor analysis augmented with Back Propagation Neural Network (BPNN) approach. The annual data from 1995 to 2021 for China is retrieved for empirical analysis. The data set comprises the factors classified into training, validation, and testing divisions with a ratio of 2:1:1. The outcomes revealed that extracted factors are robust in explaining China's ecological footprint variation. Outcomes of the BPNN algorithm suggest that renewable energy consumption, eco-innovation, economic complexity, natural resource rent, and electric power consumption are the most useful determinants in explaining the ecological footprints of China. The study furnishes the possible policy implications of the research.

1. Introduction

The progress of human society is associated with the environmental issues prevailing around the world (Umar et al., 2021). The protection of the environment is now allied with the major societal concerns in various developed and developing nations. The human environment declaration presented by United Nations in 1972 would become a seminal effort in the conservation of ecology all over the globe (Su et al., 2021). In this vein, the recent agreement of COP21 endorsed by 196 countries, including China, is a significant step towards a sustainable environment. The fruitful results can be attained by minimizing harmful discharge by implementing effective environmental saving policies in the respective countries (Zhang et al., 2022). For this, the ecological footprint is extensively used to measure the human doings on the earth as it is assumed to be an inclusive metric utilized to evaluate the environmental quality (Ulucak and Khan., 2020: Umar et al.,2020; Zhang et al.,2022). The recent statistics released by Global Footprint Network states that the earth requires more than two planets to engross harmful wastes and enough natural resources for the survival of future peers. As Matustík and Kocí (2021) highlighted, economic expansion policies exploit natural resources and increase the burden of wastage in the environment. Various countries are now implementing resource-saving policies during their economic progression (Zhang et al., 2022). Throughout the world, China is the prime emitter of carbon emissions producing ecological disparity (see Fig. 1).

Green development seems to have evolved in chasing the solution of ecological destruction accompanied by economic and industrial prosperity. In 2008, the United Nations was keen to ensure that the governments implement green economic policies at the country level. Later, in 2015, the sustainable development goals of 2030 were presented based on several achievable goals like defending, reestablishing, and promoting a maintainable environment around the world. In response to these goals' implications, the concept of green development is growing expectedly (Zhang et al.,2022). Besides, China is suffering from ecological apprehensions that might hinder its economic progression (Song et al.,2020). The ecological functioning of China and its corresponding sensitive regions are mainly convoyed with the rural zone and thus supposed to be an obstacle to environmental safety (Yanli et al.,2010). Additionally, these zones confine the natural resources creating a conflict between development and preservation. Khan et al. (2022) state that the Chinese government is vigorously implying environmentally friendly policies to attain sustainability as suggested by United Nations. Keeping these natural resources, eco-innovation, economic complexity, economic growth, and energy resources are in danger, while China continuously stresses the significance of green innovation policies in the country (C-W. Su et al.,2021). For this, implementing green innovation policies in the manufacturing sectors to achieve economic growth is challenging for Chinese society (Z-W.Su et al.,2021). The manufacturing industry is indissolubly associated with economic growth. Hence, China's government must innovate its traditional modes of business and launch green policies to establish a carbon-free atmosphere in the country (Wang et al.,2021). The Chinese governme nt should investigate the intrinsic link between technological resources and industrial progress. The Suzhou Consensus stated that the conventional energy-producing method should be replaced by technological development (green energy) to bring energy revolution in China. The main driver for achieving green energy development and expanding the energy revolution as a crucial component of the modern energy system is to augment electrical energy with green development. Green development emphasizes protecting the environment's resources while creating an economy (Zhu et al.,2020).

It is a well-known fact that nature and society are indistinguishable, causing a deep linkage between social and ecological health. Thus, it is vital to preserve nature mutually with economic prosperity (Katircioglu and Katircioglu., 2018). Misusing natural resources is one of the primary reasons for causing environmental destruction. There are many factors contributing to this depletion of natural resources, but human activity is the main factor and a serious threat to the sustainability of the natural ecosystem (Ahmed and Wang.,2019). Umar et al. (2021) emphasized that production methods of resource extraction threaten biodiversity. This crucial imbalance between supply and demand reduces the planet's bio capacity, exhausts resources, and increases greenhouse gas emissions. The abundance of natural resources and their environmental impact has long been a divisive concern (Johnson et al.,2019). This correlation asserts that economic development causes industrialization, resulting in a rapid increase in resource exploitation that eventually accelerates the ecological footprint. In this vein, green investment/technology and natural resource rent ate important determinants in explaining environmental deprivation. Therefore numerous variables are responsible for enhancing the ecological hazards, and their consequences must be addressed with empirical evidence.

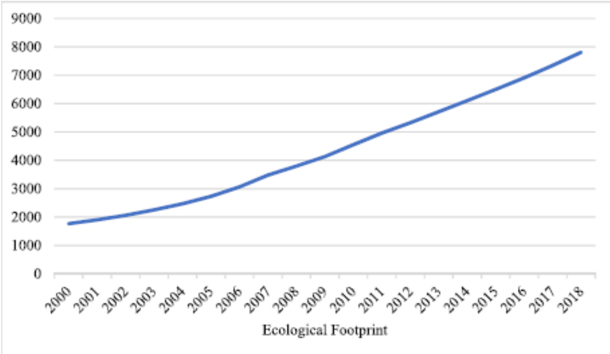

Fig. 1. Trend of Ecological Footprint in China

Based on the above background, the quest for the appropriate independent variables to explain the footprint of China is of immense importance in the environmental economics literature. In this regard, the current study benefited in several ways with novel research questions. Firstly, the current study proposed a novel hybrid framework of factor analysis and back propagation neural network (BPNN) method to investigate the ecological quality parameters. Various economic, social and financial indicators are utilized in the previous studies to explain the variation in the ecological footprint, yet the results are inconclusive. The sophisticated proposed methodology will tackle these variables through factor analysis, and an estimated model through BPNN will confirm the extracted factors' consistency. Secondly, China is supposed to be the largest emerging nation around the globe; thus, it is essential to elucidate the possible reasons behind the increasing environmental degradation, so the current study is a comprehensive attempt to explore the empirical evidence in the context of China. Thirdly, the study outcomes will benefit the policymakers, stakeholders, and government officials of all the developing countries to maintain their ecological strategies and take proper steps to preserve their environment without hurting economic development. For the accomplishment of these objectives the current study considers the annual data from 1995 to 2021.

The rest of the study is organized as follows; the second section discusses the previous literature, the third section explains the proposed methodology, and the results and discussion are presented in the fourth section. The study concludes in the last section of the study.

2. Previous Studies

This section briefly discusses the existing literature to investigate the potential gaps. The ecologist Wackernagel et al. (1999) first ever initiated and employed the ecological footprint hypothesis to the ecological footprints of 52 states. In addition, Ying et al. (2012) and Wu et al. (2013) considered the provinces of China Hunan and Hainan to mark out ecological footprints through dynamic development. Later, they noticed that these two provinces had gone through major ecological degradation. Similarly, Guo et al. (2018) used the input-output technique to estimate the carbon emission of international trade organizations; likewise, Hubacek et al. (2009) employed the same input-output approach as well as a combination model of ecological footprints to study the complexity of China's environment due to modernization and consider changing in lifestyles of China. On the contrary, the ecological model has been implemented to observe the ecological out-turns of the provinces of China, Henan, and Shanxi (Peng et al. 2019). As highlighted by (Ahmed and Du, 2017), the ecological footprints largely in demand for high-yielding areas like farmland, wooded, marine, and highland areas, as affirmed by William Rees, also commenced the idea of biological capacity. Moreover, he supposed that footprints and biological capacity go against, in essence, national, geographical, and large-scale levels individually. Steiner et al. (2017) show that biological capacity and footprint alteration depend on yearly headcount, per-capita consumption, and ecological inventions. (Jorgenson, 2016) hypothesized that environmentally friendly and appropriate environmental management are key factors in detecting carbon emissions annually. Though, (Peng et al., 2019) urged that modernization and the rise in population are the foremost reasons to affect China's environment. That is why the study of (Wang et al.2020) examined the control and substantial impact of green investment, natural resources, innovation in eco-friendly technologies and economic sustainability on the ecological footprints and found these elements are quite responsible for environmental footprints in China. Another study (Wang et al. 2020) stated that industrial developments are the root cause of polluting and harming the environment because of the usage of substantial energy resources. Correspondingly, Yang (2020) claimed that the rise and expansion of any industries, from farming to production, are the sources of damage to the natural environment. The basic connection between economic structure and ecological system is that industry and industrial developments significantly impact the environment. Utilizing research and development and encouraging environmental sustainability with ecological footprints have been widely appreciated (Naderi Mahdei et al., 2018). Researchers have done several studies on economic structure linked with ecological footprints and mainly focused on the factors that destroy the environment's balance by modifying some industrial growth styles. As per Song et al. (2017), green innovations have immediate consequences on the environment and endow various improvements in long-term ecological footprints. Petroleum generators and other conventional innovations tear down the environment severely, and green innovations are the only best option for organizations and other regions to save the atmosphere. Nguyen and Kostarakis. (2018) proposed that corporations and other sectors should start funding green innovations like renewable energy as their supplies never consume the environment and have a massive effect on sustainable environmental footprints. Besides, this green innovation assists industries in lessening carbon emission, wastage, consumption of resources, and preservation and usage of water are the factors that significantly influence the consistency of ecological footprints (Luke .,2019). Fu et al. (2011) utilized the cointegration technique on the ecological footprints of the Poyang Lake region, economic aggregate, and three industries. In this study, they planned to check the effect of industries on ecological footprints, i.e., tertiary, secondary, and primary, for the reason that industrial development is found quite beneficial for the environment as well as saves energy from consumption, also encourages the alliance of the financial industries with their specific bio-capacity as regard to ecology to ensure the economic development of the country. Nathaniel et al. (2021) ascertained that the economic rent of natural resources shows how to develop ecological footprints for nations with the same aims. On the contrary, the economic rent of natural resources lessens the effect of ecological footprints for the BRICS nation-states. The factors that lead to inconsistent estimates for the variable, like ecological footprints, are sometimes sample sizes, inappropriate approaches, time frame, and covariates variables for analysis. The industries based on green technology are growing fast; in that place, various ecological concepts have come to light on green technology and following (Cohen et al., 2016); Green technology creates the emergent thing and supplies that assimilate one or more keystone of eco-friendly resolutions. As per Song and Yu. (2018), for geographical determinism and care for the environment, the formation and practice of green innovation have been developed, and their goods boast the importance of green expenditures. Neoh et al. (2016) reported that the regions that appoint green technology objects have flourished in their financial and economic industries in contrast to those that do not yet adopt green technology. Currently, green technology's need and advancement facilitate the environment's survival in this difficult time (Sun et al., 2017). Consequently, (Baleˇzentis et al., 2019) the investment in green technology has become the most widely used tool to identify the performance of a stable ecological system (Hao et al., 2021). The economic sustainability and convenience of sources are associated. Since resources are the factor that sustains the economy to progress, capacity and growth, financial structures assess the level of resource development and competence. Even so, resources have a power that leads an economy to improve, as the demand for resources, insufficiency and ecological degradation necessitates the fastest-growing economy. Now a day, the quantitative research area based on ecological footprints is under study, which scrutinizes the utilization of natural resources for the sustainability of the regions, and also examines the solidity of the financial production of several types of land and human expenditures on its resources. The academic community exploits empirical evidence of a linkage between local resources and the atmosphere; for that reason, they used economic development as a resource and ecological predictor. To a different extent, numerous researchers and their societies have accessed the ecological footprints of various countries along with China. It also shows that ecological footprints and economic development are closely interrelated. According to Zhao et al. (2012), the economic process may highly relate to the variations in ecological footprints; also, financial development becomes a reason for changes in ecological footprint.

The above existing literature reveals that numerous research tried to identify the suitable determinants of environmental deterioration; however, they failed to observe the potential factors behind the increasing amount of carbon dioxide and harmful gases in the air. The current study thus helps identify the latent factors from the various explanatory variables used in various research by using the advanced statistical method of Factor Analysis and then augmenting those factors in the framework of the Artificial Neural Network models to explore the effects of environmental quality parameters. The study only focuses on China for the empirical analysis as it is supposed to be the top emitter of carbon (Afshan and Yaqoob., 2022).

3. Methodology

To achieve the required objectives, the advanced statistical modelling approaches are proposed in the current study to develop an understanding of the factors influencing China's carbon emissions.

3.1 Factor Analysis (FA)

The factor analysis (FA) approach is the statistical technique that helps to explain the variability between the observed, interrelated (correlated variables) concerning the lower number of potential unobservable variables known as factors. The function of FA is that many variables reduce to fewer factors. The factor analysis depends upon the linearity, no perfect multicollinearity, and correlation between the variables and factors assumptions. An observed variables model comprises the linear combination of factors (f) and residual error terms (ε). The p-observed variables (x_1, x_2, …, xp) are assembled in a group concerning their higher order of interrelationships. The FA possesses some potential factors (f_1, f_2, ….,f_m) that assist in defining the covariance and interrelation between the p-observed variables.

The factor analysis model puts in plain words the set of p-observable variables in each of n observations with a set of significant factors (f i,j), where (f < p). The "f" latent factors are associated with each of the "n" observations, and also these factors are connected with the loading matrix (L ϵ Rp×k), for every single variable. Statistically, the model can be written as;

$$X_{i,m} - \mu_i = l_{i,1}\, f_{1,m} + l_{i,2}\, f_{2,m} + \ldots\ldots + l_{i,k}\, f_{k,m} + \varepsilon_{i,m} \quad (1)$$

Here, $X_{i,m}$ denotes the ith observation of the mth factor, μ_i is the mean of ith observation, li,j represents the loading of ith observation of the jth factor, fj,m possess the factor coefficient of jth factor of the mth observation and εi,m are the (i.m) th stochastic error term.

In the matrix form,

$$X - \mu = Lf + \varepsilon \quad (2)$$

The crucial point of factor analysis is the interrelationship between the X's. Therefore, we mainly focus on the variance/covariance matrix (Σ) instead of the mean. The factor analysis model assumed that variance had been segmented into parts such as commonality (common) variance and unique variance; other unique variance has two types; specific and error variance. So the total variance can be shown in the matrix notation as $\Sigma_p = \boldsymbol{\tau\tau}' + \theta$ and the linear combination as;

$$V(xi) = \boldsymbol{\tau}^2{}_{i1} + \boldsymbol{\tau}^2{}_{i2} + \boldsymbol{\tau}^2{}_{i3} + \ldots\ldots + \boldsymbol{\tau}^2{}_{im} + \theta_{i.} \qquad (3)$$

Where h_i^2 = communality and comprises as following $h_i^2 = \boldsymbol{\tau}^2{}_{i1} + \boldsymbol{\tau}^2{}_{i2} + \ldots + \boldsymbol{\tau}^2{}_{im}$ and θ_i = specific variance. This larger communal variance of each individual would be the ideal candidate for factor analysis.

Likewise, Factor analysis has been effectuated with several approaches, but this study redeems factor Rotation with the VARIMAX approach. The VARIMAX rotation is an orthogonal rotation and is an alternation of coordinates employed in principle component analysis, emphasizing the sum of the variance of the loading matrix.

Let the coefficient of rotation is $\vartheta_{ij} = \frac{l_{ij*}}{c_i}$, where L* = [Lij*] is the rotated loaded matrix and ci = the square root ith commonality. The m-dimensional orthogonal matrix denoted by [P], so that L*= LP and F*= P.F, then the variance of [P] is,

$$V = \frac{1}{k} \sum_{j=1}^{m} [\sum_{i=1}^{k} (\vartheta_{ij}^*)^4 - \frac{1}{k} [\sum_{i=1}^{k} (\vartheta_{ij}^*)^2]\,]^2 \qquad (4)$$

This V represents the square of variance of the loading matrix of each variable. Although, identifying the groups of bulky and undersized coefficients in any of the columns of the rotated loading matrix is smoothly interpretable.

3.2 Artificial Neural Network

The Artificial Neural Network (ANN) goes well with the most extensively employed machine learning algorithms. Frank Rosenblatt invented the Artificial Neural Network for the first time in 1958. As long as computational capability rises today, we need such powers that function efficiently and accurately to unravel the real world's problems. The ANN piqued the world's curiosity over a few years and highlighted the interest in face recognition, image and speech recognition, medical conclusion, machine translation, and many more. The deep learning neural network works in such a manner as the human brain works. The neural system encourages computers to make up their mind like the human brain. Once the process is mechanized through the neural network, accurate and precise results are obtained. The exclusive feature of ANN is one; there is no need for any particular knowledge about the declared practical obstacles but still, apprehend its predicted target. Neural networks are highly commendable for their predicting and cataloguing issues. Sarle (1994) stated that in the neural network, the datasets are disassembled into two categories, the first category uses data for input variables, and the other is related to building up the outputs. In a neural network, the data refining process may facilitate our estimates more efficiently. Besides these, both quantitative and qualitative data variables are contemplated. The basic structure of a neural network comprises the architecture, Weights, and Transfer function. Furthermore, the artificial neural network model generally splits the datasets into two parts, i.e., the train and test datasets. The training datasets possess most of the data to train several ANN models, and testing datasets contain a smaller part of the data created to determine the function of the ANN model. These two datasets might help lessen the influence of data inconsistency and provide a better understanding of the model.

Sometimes, the ANN model's datasets are split into training, validating, and testing data. To avoid over fitting, the validating datasets are used to assign the train data that helps to judge which ANN–model is best fitted for given datasets (Maier and Dandy, 2000). Master (1993) employed a holdout approach and better-understood data. The testing datasets with the same features as training datasets have been checked out by (Lacthermacher and Fuller, 1994). Moreover, Maier and Dandy (2000), and Khotanzad et al. (1997) also manipulate a testing part to avail several spans from this testing data set, furthermore verified once a training process is stopped. After this, the testing datasets will be included in the training datasets to train the neural networks. The structure of the artificial neuron is presented in Fig. 2.

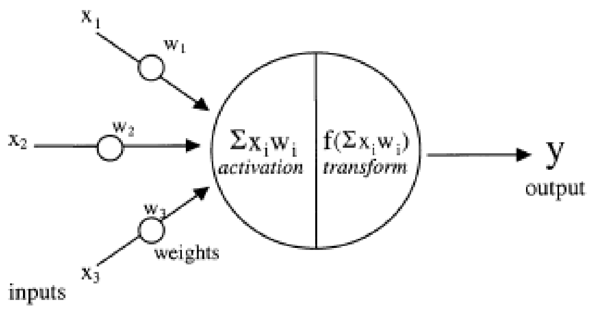

Fig. 2. Artificial Neuron

According to Zealand et al. (1999), ANN has the competency to solve the concerns related to the datasets, like missing values and non-stationary datasets the real tendency. The competent implication of the ANN model is that cleaning, normalization, and standardization is the primary practice in data processing and the variable reduction (selection of independent variables) method and division of datasets into train and test datasets. In an Artificial neural network system, training data plays an imperative role; the weights and biases are attached through learning progression (Haykin., 1994). The numbers of hidden layers, hidden neurons, transfer function, and learning algorithm may detect in the ANN model. Supervised and unsupervised are two styles of learning. The supervised learning put forwards that the collection of output training and input training datasets together may be renowned by the neural network. Supervised learning has a hold over input data to turn out a preferred output; besides, the preferred outcome is nearly close to training output data. Additionally, the Error criterion coordinates change the weight of ANN for training input. In unsupervised learning, the clustering method has been functioning; in this process, the output cannot be controlled; input training is utilized in the network and gather those clusters that exist close to each other. For this, the self-organized or vector-organized approach falls under unsupervised learning progression. The set means the square value is not accomplished after the network system stops working. Sometimes, a network anticipates a low output once the new input is set up in the neural system; these two foremost issues are going through in the training process.

The different types of neural networks have been acquired by modifying the transfer function and the learning progression; the neural architecture recommended numerous activation functions and various learning algorithms. The feed-forward and radial basis neural networks are the two leading types of neural networks. The feed-forward neural network is examined in the present study with the following mechanism.

First, the datasets have been categorized into training, validating, and testing data. (Maier and Dandy., 2000) The training data belongs to train the data, validating data proceeds to assess while testing data forms an opinion about the ANN model working. Lachtermacher and Fuller (1994) highlighted the overfitting and underfitting issues due to split up the datasets. The k-fold Cross-validation technique works out on these issues and draws on to stop the ANN criteria; during the training process, the minimum mean cross-validation (MSE) is chosen for the ultimate ANN model Keskin and Terzi (2006). Back propagation neural network (BPNN) is also used for feed-forward artificial neural network (FFANN) and minimizing the BPNN. Actual output differences are the main target of BPNN. This variability in the weights supervises by learning rates, i.e., initiation of step size in the ANN system. The BPNN error can be identified as the difference between the BPNN outputs (Di) or desired output and the actual values Ai. Each inputs Ii is chosen from the training data {(I1,A1),(I2,A2)…….,(In,An)}. The BPNN error can be formulated as,

$$E=1\ 2 \sum \| Ai - Di \|\ 2\ n\ i=1 \quad (5)$$

The iterative methods are employed to minimize the error term, and the partial derivative Ai and Di with the error may become the ΔAij and ΔDi, respectively, as,

$$\Delta Ai = -\ \partial E\ \partial Ai \quad (6)$$

$$\Delta Di = -\ \partial E\ \partial Di \quad (7)$$

The condition implies for these derivatives of Ai and Di is that $\Delta E < 0$, so that error will reduce up to a local minimum.

3.3 Hybrid Modelling Framework of FA-ANN

Understanding the importance of FA and ANN in the existing literature, the current study proposed a hybrid framework consisting of the extracted factors and mechanisms of the ANN. The output variable (y) served as the environmental quality indicator, i.e., the ecological footprints of China. In contrast, the input variables are the extracted factors retrieved through the numerous supposed determinants of ecological degradation. The diagrammatic flow of the feed-forward network is presented in Fig.3.

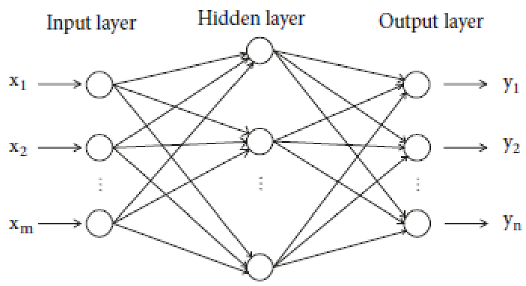

Fig. 3. Feed Forward Network Model

Estimating the influential factors has been done through the feed-forward neural network method. The data set comprises the factors classified into training, validation, and testing divisions with a ratio of 2:1:1. The training data is utilized for weight adjustment in the network, and the validation data is constructed for tuning the parameters. To monitor the hidden data characteristics, testing data will be used. Testing data also confirms the performance of the neural networks model. The parameters are further standardized through standardization (Keskin and Terzi, 2006). Levenberg-Marquardt is used to assign the weights for the neural network model. The hidden neurons and learning rate is attained by trial and error, whereas the hidden layer transfer function and the output layers are obtained through the sigmoid and linear functions. The ten-fold cross-validation mechanism is employed by combining the over and under-fitting of the neural network model. Mean square error (MSE), and coefficient of multiple determination (R^2) is used to check the adequacy of the training and testing data division.

4. Results and Discussion

The current study aims to identify the potential factors from several variables influencing the ecological footprint of China. For this purpose, the study considers eco-innovation, economic complexity, renewable energy consumption, natural resource rent, foreign direct investment, energy intensity, economic growth, Public-private partnerships investment in energy, population growth, and electric power consumption after the careful survey of the literature. The yearly data from 1995 to 2021 were retrieved from various sources for empirical analysis. A detailed description of the variable is depicted in Table 1.

Table 1

Data depiction

Variables	Symbol	Measurement	Data Sources
Ecological Footprint	EF	Global Hectares per capita	Global Footprint Network
Renewable Energy Consumption	RE	Percentage of total final energy consumption	WDI
Financial Direct Investment	FDI	Net Inflows (% of GDP)	IMF
Energy Intensity	EI	Consumption of energy measured as GDP per capita	WDI
Economic Growth	EG	Constant (2021) USD Per Capita	WDI
Public-Private partnerships investment in energy	PPI	Current (US$)	WDI
Eco-Innovation	ECI	Index of Economic Complexity	Atlas Media Database
Economic Complexity	EC	Economic Complexity Index	HAEC
Natural Resource Rent	NRR	NR depletion (percentage of GNI)	World Bank
Population Growth	PG	Annual Percentage	WDI
Electric Power Consumption	EPC	KWH per capita	WDI

Note: *HAEC (Harvard's Atlas of Economic Complexity, WDI (World Development Indicator), IMF(International Monetary Fund)

The first step in analyzing the data for extracting the required factors from various variables is to find the correlation among them. Fig. 3 portrays the strong correlation among the explanatory variables supporting the utilization of factor analysis. Economic and financial variables usually have multicollinearity concerns which can easily be tackled through a factor analysis approach. Thus, the extracted factors can easily be now interpreted.

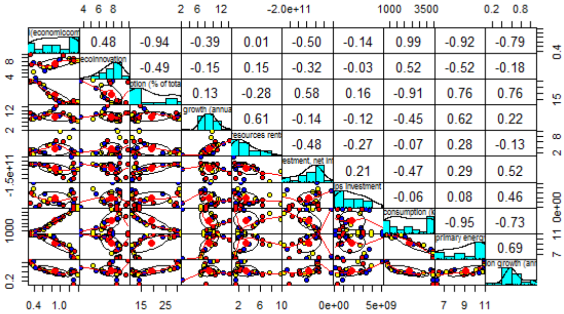

Fig. 4. Correlation of Ecological Quality Parameters and Principal Component Diagram

Factor Analysis has been utilized to explore the expected factors from the independent variables. Fig. 5 presents the scree plot presenting the three factors to be taken.

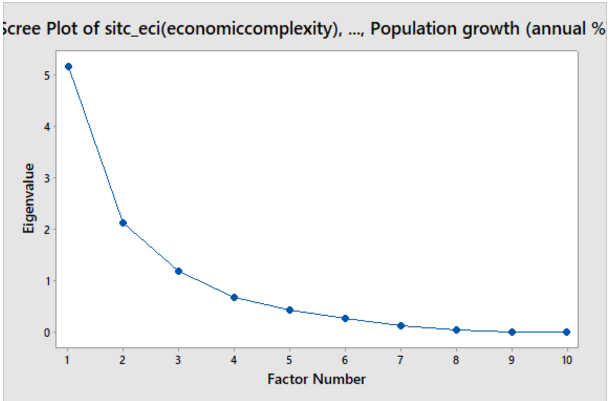

Fig. 5. Scree Plot of Independent Variables

The outcomes of Table 2 consist of three factors as maximum variance explained by them. The rule of thumb of 0.4 loadings is displayed and ignores the loadings less than the threshold. The significant Bartlett's test of sphericity and 0.81 value of Kaiser Mayer Olkins statistics support the applicability of factor analysis. Rotated Varimax loading factors show that the first factor explains 75.6% of the variation, the second factor causes 24%, and the third factor is responsible for 0.4% of the environmental quality parameters. The first factor comprises RE, FDI, EI, ECI, NRR, and EPC. It also reveals that renewable energy consumption and eco-innovation possess the highest loadings among other variables. Similarly, the second factor consists of RE, FDI, ECI, NRR, and PG, with ECI and FDI maximum loading values. The third factor is the combination of RE, FDI, EI, ECI, and EC. There are several implications of these retrieved factors. The first factor enables us to understand the importance of RE, FDI, EI, ECI, NRR, and EPC in explaining the variation of ecological footprints in China. The second factor emphasizes the RE, FDI, ECI, NRR, and PG, whereas the third-factor highlight RE, FDI, EI, ECI, and EC. It can be noticed that renewable energy consumption (Su et al.,2021), Foreign Direct Investment(Afshan and Yaqoob.,2022), and eco-innovation(Afshan et al.,2022) are common among all factors. These outcomes are similar to the study of Baloch et al. (2019), who did a study for the BRICS bloc. Renewable energy consumption holds positive loading for all factors, indicating that it influences the predictability of China's ecological footprint. Eco-innovation, i.e., encouraging green resources in the industrialization process, stimulates environmental degradation. Furthermore, increasing foreign direct investment to achieve high economic progress also seems crucial for sustainability.

Table 2

Varimax rotated factor loadings

Variables	FI	FII	FIII
RE	0.876	0.568	0.569
FDI	0.789	0.743	0.479
EI	0.853	-	0.743
EG	-	-	-
PPI	-	-	-
ECI	0.821	-0.789	0.764
EC	-		0.674
NRR	0.798	-0.586	-
PG	-	0.567	-
EPC	0.698	-	-
Proportion	0.756	0.24	0.045

The factors are then utilized as an input variable to predict the model for ecological footprint through the neural network method. Mean Square Errors are accessed for three factors for hidden layer combinations of the BPNN architecture. The results are presented in Table 3. The selection of the number of layers is based on the minimum MSE. The neural network model will validate the factors bu introducing several backweights and layers for determining the behavior of ecological footprint. The model has been selected with the minimum MSE, and training and testing data have been employed according to the proposed methodology in the previous section and will implicate the outcomes. The network structure has also depicted in Fig. 6.

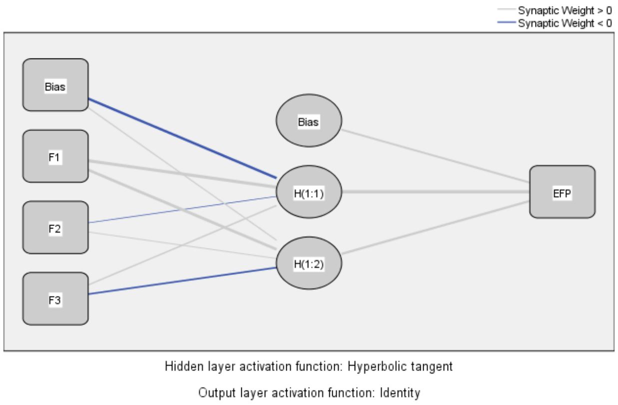

Fig. 6. The Network Structure

Table 3

Mean square error (MSE) of rotated factor neural network model

Output	Inputs	Hidden Layers Combination	Mean Square Error (MSE)
		6-6-6	0.059
	F-I	2-2-2	0.043
		2-6-11	0.015
		6-6-6	0.067
EF	F-II	2-2-2	0.156
		2-6-11	0.098
		6-6-6	0.065
	F-III	2-2-2	0.015
		2-6-11	0.021

Table 4 furnishes the outcomes of the training and test data. It has been observed that minimum MSE augmented with maximum R-square is for factor I with the hidden layer of 2-6-11. The first factor of RE, FDI, EI, ECI, NRR, and EPC is the consistent model according to the BPNN algorithm; thus, it can be concluded that Renewable energy consumption, eco-innovation, economic complexity, natural resource rent, and electric power consumption are the most useful determinants in explaining the ecological footprints of China.

Table 4

Comparison of training and testing data sets

Output	Inputs	Hidden Layers Combination	Training		Testing	
			MSE	R-Square	MSE	R-Square
	F-I	2-7-10	0.005	0.82	0.001	0.829
EF	F-II	2-7-10	0.0345	0.786	0.02	0.705
	F-III	2-2-2	0.0032	0.852	0.002	0.812

5. Conclusion

Environmental degradation has been one of the debatable issues for the last decade. In this regard, it is desirable to investigate the potential determinants in explaining the ecological indicators. Therefore, the present study aims to find the possible variables through factor analysis and validate these factors through neural network models. The study took yearly data from 1995 to 2021 and selected China as a case study. Three factors are extracted by varimax rotation and validated its robustness through various hidden layer combinations of Back Propagation Neural Network (BPNN). The outcomes were judged on the basis of statistical measures like MSE and R- square measures. Results revealed that renewable energy consumption, eco-innovation, economic complexity, natural resource rent, and electric power consumption are the most useful determinants in explaining the ecological footprints of China.

5.1 Policy Implications

Being an emerging nation China should enforce some important policies to improve their environmental quality. For instance, promotion of green technologies, stringent environmental regulations, investment in renewable eenergy, deforestation initiatives, waste reduction and recycling programs, and collaboration with international organizations.

5.2 Future Implications

The current study explores the possible factors important to explain their role in enhancing/decreasing the ecological footprints of China. Yet there are some limitations in the study. For future studies, other explanatory variables can be taken. More emerging/Asian countries can be taken to ensure the possible factors contributing in enhancing their sustainability. Lastly, other advanced machine learning techniques augmented with statistical models can be a good addition to the literature.

5.3 Availability of Data and Materials

The secondary data has been taken for the formal analysis whose sources are provided inside the text.

5.4 Competing Interests

This study is free of Conflicts of interests

5.5 Funding

KURP: 2021-2022

5.6 Authors Contributions

Tanzeela Yaqoob: Idea Formation, Final editing and reviewing, Formal analysis

Rahat Bibi: Data curation and Writing Draft.

Hooria Akbar: Methodology designed, Writing Literature Review and Formatting

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7. References

[1] A. K. Jorgenson, "Environment, development, and ecologically unequal exchange", Sustainability, vol. 8, no. 3, p. 227, 2016. https://doi.org/10.3390/su8030227

[2] A. Khotanzad, R. Afkhami-Rohani, T. L. Lu, A. Abaye, M. Davis, and D. J.Maratukulam, "ANNSTLF-a neural-network-based electric load forecasting system", IEEE Transactions on Neural Networks, vol. 8, no. 4, pp. 835-846, 1997. https://doi.org/10.1109/72.595881

[3] B. E. Steiner, A. O. Peschel, and C. Grebitus, "Multi-product category choices labelled for ecological footprints: exploring psychographics and evolved psychological biases for characterizing latent consumer classes", Ecological Economics, vol. 140, pp. 251-264, 2017. https://doi.org/10.1016/j.ecolecon.2017.05.009

[4] B. Peng, Y. Li, E. Elahi, and G. Wei, "Dynamic evolution of ecological carrying capacity based on the ecological footprint theory: A case study of Jiangsu province", Ecological Indicators, vol. 99, pp. 19-26, 2019. https://doi.org/10.1016/j.ecolind.2018.12.009

[5] C. Fu, W. Chen, and Y. Ouyang, "Footprint and economic and industrial development around the Poyang Lake", Resources and Environment in the Yangtze Basin, vol. 20, no. 12, pp. 1525-1531, 2011.

[6] C. H. Neoh, Z. Z. Noor, N. S. A. Mutamim, and C. K. Lim, "Green technology in wastewater treatment technologies: integration of membrane bioreactor with various wastewater treatment systems", Chemical Engineering Journal, vol. 283, pp. 582-594, 2016. https://doi.org/10.1016/j.cej.2015.07.060

[7] C. M. Zealand, D. H. Burn, and S. P. Simonovic, "Short-term streamflow forecasting using artificial neural networks", Journal of Hydrology, vol. 214, no. 1-4, pp. 32-48, 1999. https://doi.org/10.1016/S0022-1694(98)00242-X

[8] C. W. Su, Y. Xie, S. Shahab, C. M. N. Faisal, M. Hafeez, and G. M. Qamri, "Towards achieving sustainable development: role of technology innovation, technology adoption and CO2 emission for BRICS", International Journal of Environmental Research and Public Health, vol. 18, no. 1, p. 277, 2021. https://doi.org/10.3390/ijerph18010277

[9] F. Johnsson, J. Kjärstad, and J. Rootzén, "The threat to climate change mitigation posed by the abundance of fossil fuels", Climate Policy, vol. 19, no. 2, pp. 258-274, 2019. https://doi.org/10.1080/14693062.2018.1483885.

[10] H. R. Maier and G. C. Dandy, "Neural networks for the prediction and forecasting of water resources variables: a review of modeling issues and applications", Environmental Modelling and Software, vol. 15, no. 1, pp. 101-124, 2000. https://doi.org/10.1016/S1364-8152(99)00007-9

[11] H. Zhang, Y. Shao, X. Han, and H. L. Chang, "A road towards ecological development in China: The nexus between green investment, natural resources, green technology innovation, and economic growth", Resources Policy, vol. 77, p. 102746, 2022. https://doi.org/10.1016/j.resourpol.2022.102746

[12] H. Zhao, Y. Wang, X. Gu, Y. Wang, J. Zhou, and Y. Sun, "Establishment of environmental sustainability assessment indicators based on material flow and ecological footprint model in Tongling City of Anhui Province", Acta Ecologica Sinica (Shengtai Xuebao), vol. 32, no. 7, pp. 2025-2032, 2012.

[13] J. Matuštík and V. Kočí, "What is a footprint? A conceptual analysis of environmental footprint indicators", Journal of Cleaner Production, vol. 285, p. 124833, 2021. https://doi.org/10.1016/j.jclepro.2020.124833

[14] K. H. Wang, M. Umar, R. Akram, and E. Caglar, "Is technological innovation making world "Greener"? An evidence from changing growth story of China," Technological Forecasting and Social Change, vol. 165, p. 120516, 2021. https://doi.org/10.1016/j.techfore.2020.120516

[14] K. Hubacek, D. Guan, J. Barrett, and T. Wiedmann, "Environmental implications of urbanization and lifestyle change in China: ecological and water footprints", Journal of Cleaner Production, vol. 17, no. 14, pp. 1241-1248, 2009. https://doi.org/10.1016/j.jclepro.2009.03.011

[15] K. Khan, C. W. Su, and A. Khurshid, "Do booms and busts identify bubbles in energy prices?", Resources Policy, vol. 76, p. 102556, 2022. https://doi.org/10.1016/j.resourpol.2022.102556

[16] K. Naderi Mahdei, A. Bahrami, M. Aazami, and M. Sheklabadi, "Assessment of agricultural farming systems sustainability in Hamedan province using ecological footprint analysis (Case Study: Irrigated Wheat)", 2018. http://hdl.handle.net/123456789/3772

[17] L. N. Hao, M. Umar, Z. Khan, and W. Ali, "Green growth and low carbon emission in G7 countries: how critical the network of environmental taxes, renewable energy, and human capital is? ", Science of The Total Environment, vol. 752, p. 141853, 2021. https://doi.org/10.1016/j.scitotenv.2020.141853

[18] L. Wang, C. W. Su, S. Ali, and H. L. Chang, "How China is fostering sustainable growth: the interplay of green investment and production-based emission", Environmental Science and Pollution Research, vol. 27, no. 31, pp. 39607-39618, 2020. https://doi.org/10.1007/s11356-020-09933-4

[19] L. Y. Sun, C. L. Miao, and L. Yang, "Ecological-economic efficiency evaluation of green technology innovation in strategic emerging industries based on entropy weighted TOPSIS method", Ecological Indicators, vol. 73, pp. 554-558, 2017. https://doi.org/10.1016/j.ecolind.2016.10.018

[20] L. Yanli, D. Sibao, W. Rongcheng, and W. Yu, "Sustainable development of vulnerable ecological regions under the perspective of regional externalities", China Population Resources and Environment, vol. 20, pp. 68-73, 2010.

[21] L. Ying, T. T. Guo, and P. P. Li, "Study on the calculation of ecological footprint model parameters of Beijing urban water resources", in Advanced Materials Research, vol. 374, pp. 105-108, Trans Tech Publications Ltd, 2012. https://doi.org/10.4028/www.scientific.net/AMR.374-377.105

[22] M. C. Cohen, R. Lobel, and G. Perakis, "The impact of demand uncertainty on consumer subsidies for green technology adoption", Management Science, vol. 62, no. 5, pp. 1235-1258, 2016. https://doi.org/10.1287/mnsc.2015.2173

[27] M. E. Keskin and Ö. Terzi, "Artificial neural network models of daily pan evaporation", Journal of Hydrologic Engineering, vol. 11, no. 1, pp. 65-70, 2006. https://doi.org/10.1061/(ASCE)1084-0699(2006)11:1(65)

[28] M. Song, W. Zheng, and S. Wang, "Measuring green technology progress in large-scale thermoelectric enterprises based on Malmquist–Luenberger life cycle assessment", Resources, Conservation and Recycling, vol. 122, pp. 261-269, 2017. https://doi.org/10.1016/j.resconrec.2017.03.001

[29] M. Umar, X. Ji, D. Kirikkaleli, M. Shahbaz, and X. Zhou, "Environmental cost of natural resources utilization and economic growth: can China shift some burden through globalization for sustainable development?", Sustainable Development, vol. 28, no. 6, pp. 1678-1688, 2020. https://doi.org/10.1002/sd.2116

[30] M. Umar, X. Ji, N. Mirza, and B. Rahat, "The impact of resource curse on banking efficiency: Evidence from twelve oil-producing countries", Resources Policy, vol. 72, p. 102080, 2021. https://doi.org/10.1016/j.resourpol.2021.102080

[31] M. Wackernagel, L. Onisto, P. Bello, A. C. Linares, I. S. L. Falfán, J. M. García, and M. G. S. Guerrero, "National natural capital accounting with the ecological footprint concept", Ecological Economics, vol. 29, no. 3, pp. 375-390, 1999. https://doi.org/10.1016/S0921-8009(98)90063-5

[32] N. Ahmad and L. Du, "Effects of energy production and CO2 emissions on economic growth in Iran: ARDL approach", Energy, vol. 123, pp. 521-537, 2017.

[33] N. Wang, T. Zhang, E. Wang, T. Song, X. Lu, and J. Su, "Dynamic correlation between industry greenization development and ecological balance in China", Sustainability, vol. 12, no. 20, p. 8329, 2020. https://doi.org/10.1016/j.energy.2017.01.144

[34] N. Zhu, Y. Bu, M. Jin, and N. Mbroh, "Green financial behavior and green development strategy of Chinese power companies in the context of carbon tax", Journal of Cleaner Production, vol. 245, p. 118908, 2020. https://doi.org/10.1016/j.jclepro.2019.118908

[35] P. A. Nguyen and P. Kostarakis, "Preliminary Design of a smart logic, electronic and green public health questionnaire (SLE-GPHQ) for investigating the proper compatibility between people and green facilities", Annals of General Psychiatry, vol. 17, no. 1, p. A11, 2018.

[36] R. Ulucak and S. U. D. Khan, "Determinants of the ecological footprint: role of renewable energy, natural resources, and urbanization", Sustainable Cities and Society, vol. 54, p. 101996, 2020. https://doi.org/10.1016/j.scs.2019.101996

[37] S. Afshan and T. Yaqoob, "The potency of eco-innovation, natural resource and financial development on ecological footprint: a quantile ARDL-based evidence from China," Environmental Science and Pollution Research, pp. 1-11, 2022. https://doi.org/10.1007/s11356-022-19471-w

[38] S. Afshan, I. Ozturk, and T. Yaqoob, "Facilitating renewable energy transition, ecological innovations and stringent environmental policies to improve ecological sustainability: evidence from MM-QR method", Renewable Energy, vol. 196, pp. 151-160, 2022. https://doi.org/10.1016/j.renene.2022.06.125

[39] S. Haykin, "Intelligent Signal Processing", Advances in signal processing for nondestructive evaluation of materials, Springer, Dordrecht, pp. 1-12, 1994. https://doi.org/10.1007/978-94-011-1056-3_1

[40] S. Katircioglu and S. Katircioglu, "Testing the role of fiscal policy in environmental degradation: the case of Turkey", Environmental Science and Pollution Research, vol. 25, no. 6, pp. 5616-5630, 2018. https://doi.org/10.1007/s11356-017-0906-1

[41] S. P. Nathaniel, K. Yalçiner, and F. V. Bekun, "Assessing the environmental sustainability corridor: Linking natural resources, renewable energy, human capital, and ecological footprint in BRICS", Resources Policy, vol. 70, p. 101924, 2021. https://doi.org/10.1016/j.resourpol.2020.101924

[42] T. Baležentis, D. Štreimikienė, R. Melnikienė, and S. Zeng, "Prospects of green growth in the electricity sector in baltic states: Pinch analysis based on ecological footprint", Resources, Conservation and Recycling, vol. 142, pp. 37-48, 2019. https://doi.org/10.1016/j.resconrec.2018.11.013

[43] T. W. Luke, "The cultural politics of ecological footprints in earth system governance", The Dialectic of Digital Culture, vol. 29, 2019.

[44] T. Yang, "Mindfulness complements sexual harassment and racial discrimination training by counteracting implicit gender and race biases", Industrial and Organizational Psychology, vol. 13, no. 2, pp. 142-146, 2020. https://doi.org/10.1017/iop.2020.27

[45] W. S. Sarle, "Neural networks and statistical models", 1994. https://cir.nii.ac.jp/crid/1570854174121927936

[46] W. Song and H. Yu, "Green innovation strategy and green innovation: The roles of green creativity and green organizational identity", Corporate Social Responsibility and Environmental Management, vol. 25, no. 2, pp. 135-150, 2018. https://doi.org/10.1002/csr.1445

[47] Y. Guo, G. Xu, X. Yang, K. Ruan, T. Ma, Q. Zhang, and Z. Guo, "Significantly enhanced and precisely modeled thermal conductivity in polyimide nanocomposites with chemically modified graphene via in situ polymerization and electrospinning-hot press technology", Journal of Materials Chemistry C, vol. 6, no. 12, pp. 3004-3015, 2018. https://doi.org/10.1039/C8TC00452H

[48] Y. Song, B. Chen, R. Tao, C. W. Su, and M. Umar, "Too much or less? Financial development in Chinese marine economic growth", Regional Studies in Marine Science, vol. 37, p. 101324, 2020. https://doi.org/10.1016/j.rsma.2020.101324

[49] Z. Ahmed and Z. Wang, "Investigating the impact of human capital on the ecological footprint in India: an empirical analysis", Environmental Science and Pollution Research, vol. 26, no. 26, pp. 26782-26796, 2019. https://doi.org/10.1007/s11356-019-05911-7

[50] Z. W. Su, M. Umar, D. Kirikkaleli, and T. S. Adebayo, "Role of political risk to achieve carbon neutrality: Evidence from Brazil", Journal of Environmental Management, vol. 298, p. 113463, 2021. https://doi.org/10.1016/j.jenvman.2021.113463

[51] Z. Wu, X. Shi, Q. Shi, and X. Pan, "The effect of nighttime temperature increase on the photosynthesis and activity of the protective enzyme of different early indica rice varieties at filling stage", Acta Agriculturae Universitatis Jiangxiensis, vol. 35, no. 6, pp. 1119-1125, 2013. http://xuebao.jxau.edu.cn/