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Research Article

New Insights into Development of an Environmental – Economic Model Based on a Composite Environmental Quality Index: A Comparative Analysis of Economic Growth and Environmental Quality Trend

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Abstract
In order to fill the research gap regarding the use of a comprehensive index that includes all dimensions of environmental pollution, this study sought to develop a composite environmental quality index to tackle with the possible bias and remove the possible linearity in the experimental research model. Principal Component Analysis (PCA) and Artificial Neural Network (ANN) methods were used to obtain this composite index. This study used six environmental indicators from two groups of Organization of Petroleum Exporting Countries (OPEC) and Organization for Economic Co-operation and Development (OECD) during 2008-2019. According to the obtained error criteria related to the two methods, ANN method was used to calculate the weight of environmental indicators due to having the lowest error criteria and therefore reliable results. Finally, using this composite index, the trend of economic growth and environmental quality were analyzed graphically. The results showed that along with the upward trend of economic growth, the quality of environment follows a downward trend in OPEC countries and an upward trend in OECD countries. At the end of this paper, some limitations of study are presented, and some suggestions for future studies are provided as well.
Keywords: Composite environmental quality index, Environmental indicators, Economic growth.

Introduction

One of the main issues for economic-environmental policymakers is to explain and regulate the relationship between development with capital and natural resources since nature, on the one hand, provides the energy and resources required for production, consumption, and thus utility achievement, and, on the other hand, makes men free from the undesirable consequences of increased pollution by absorbing, refining, or storing pollution and wastes. In contrast, these economic developments have been accompanied with some environmental consequences as such protecting the environment against continuous damages resulting from environmental

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problems has imposed high costs on states (Fakher, 2019; Kassi et al. 2020). Accordingly, this issue has attracted the attention of many environmental economists, leading to the expansion of environmental economics literature and abundant research investigating the relationship among the principal economic variables and environmental quality (Fakher, 2021; Arminen and Menegaki, 2019; Dogan and Inglesi-Lotz, 2020). Consequently, in recent years, there has been established a favorable relationship between economics and environment by different studies, including studies on the environmental Kuznets curve (EKC). Although the theoretical foundations of these empirical studies have confirmed the relationship between economic variables and environmental quality, there is still no sufficient and comprehensive information on the type and nature of these relationships. For example, studies investigating the relationship between economic growth and environmental quality are not revealing the same results with regard to EKC. This might be caused by the lack of a robust theoretical basis and the limitations of most EKC studies on pollution and environmental indicators at national and international levels. This is illustrated in figure 1 properly.

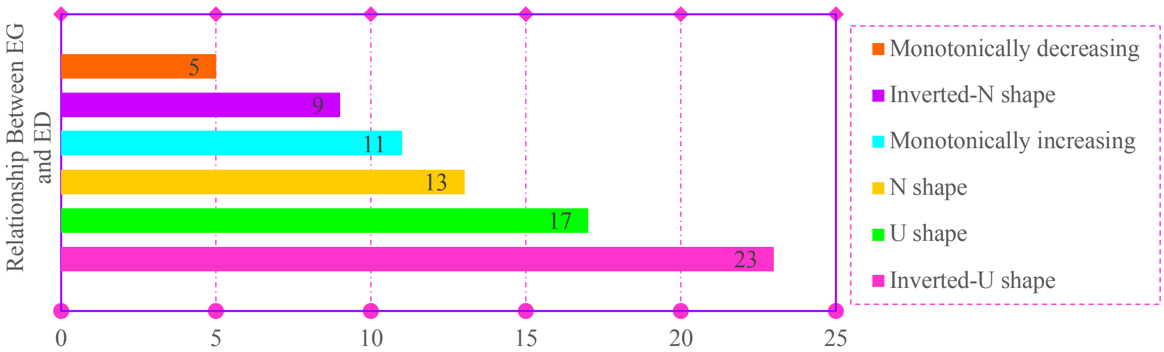


Figure 1. Relative frequency on different types of economic growth- environmental degradation nexus

Considering the different and contradictory results of many studies in this field and given that the type of environmental indicators adopted in all these studies is not a representative and comprehensive index for environmental quality and that the results cannot thus be a right criterion for adopting and implementing appropriate economic-environmental policies, the use of indicators addressing all aspects of environmental pollution seems to be of paramount importance. The simultaneous use of these environmental indicators (namely ecological footprint, environmental performance, environmental sustainability, environmental vulnerability, adjusted net saving and pressure on nature indices) as well as the use of a composite environmental quality index can address all pollutants affecting environmental quality and thus provide us with more accurate results in future research. Accordingly, a composite environmental quality index (consisting of six environmental indicators) is also of paramount significance.

Since the individual use of all environmental indicators may lead to multicollinearity problems and unreliable results (Salahuddin et al. 2019; Sarkodie and Strezov, 2019; Khan and Qayyum, 2007), this study sought to develop a composite environmental quality index to tackle with this bias and remove the possible linearity in the experimental research model. To this end, the Principal Component Analysis (PCA) and Artificial neural networks (ANN) methods were used for the first time to develop a composite environmental quality index for two groups of selected OPEC and OECD countries as such the effect of each economic variable on this composite index would be examined. This provides us with more accurate results on the relationship between economic and environmental variables and an appropriate solution for future planning to reduce environmental pressures and meet consumer needs. As a matter of fact, this can be a vital renovation because of the contradictory and paradoxical relationship between economic growth and environmental degradation in different studies. On the other hand, the sample of the study includes the selected OPEC countries with the highest oil revenues. These features can provide a particular framework to compare results of this study with that of earlier studies applying different environmental quality indicators in this context. Generally, the results of this study are supposed to provide appropriate strategy suggestions for economic-environmental policymakers to achieve sustainable and green economic growth.

Regarding the gap of practical and appropriate research on the possibility of using the PCA and ANN results in calculating the composite environmental quality index, this study aimed to examine the application of these techniques for environmental indicators representing environmental quality and present the findings to be used by future researchers in environmental quality studies. More specifically, the study sought to find out which of them can be used to develop a composite environmental quality index in two groups of the selected OPEC and OECD countries with regard to appropriate statistical criteria and how their estimation equation is.

Looking at the previous empirical studies and considering their shortcomings in the use of proper methods to construct a composite environmental quality index, this study is innovative for several thematic and methodological reasons, and this differentiates it from other studies. Firstly, in this study, for the first time, six environmental indicators have been used to construct a composite environmental quality index. Secondly, in this research, the applicability of two methods including PCA and ANN approaches are investigated for creating a composite environmental quality index. Finally, since these environmental indicators are different between the two groups of selected OPEC and OECD countries, these countries are studied as countries that are in the early stages of economic growth and countries that have gone through these early stages and are developed, respectively.

The present paper is organized as follows: First the “Introduction” section is presented. In the “Literature review of empirical studies” section, the previous empirical studies are examined in the framework of various environmental indicators and methods of creating a composite index. The “Material and Methods” section covers a brief review of environmental indicators, PCA and ANN methods, and methods evaluation criteria. The “Empirical results and discussion” section provide a statistical description of the research variables and then, calculates and analyzes the composite environmental quality index. Later, the “Conclusions and policy implications” section presents conclusion and highlights of the policy implication based on the empirical results. Finally, the paper is completed with the main limitations of this study and some recommendations for future researchers in the “Limitations and future recommendations” section.

Literature review of empirical studies

Given that the main purpose of this paper is to create a composite index for environmental quality using the important environmental indicators, this section is divided into two parts. The first part is dedicated to studies related to various environmental indicators and the second part is devoted to the studies related to methods of creating a composite index. In this regard, the literature review search strategy is provided in figure 2. The main tool used for searching the relevant literature has been Web of Science (WOS) and Scopus search engine, which are the largest abstract and citation databases of peer-reviewed literature. The “various environmental indicators” and “methods of creating a composite index” are considered as the queries in these search engines. The filtering (Keywords) used in the search engine are as follows: The “six environmental indicators used in this study”, “PCA method”, “KPCA method” and “FRPCA method”.

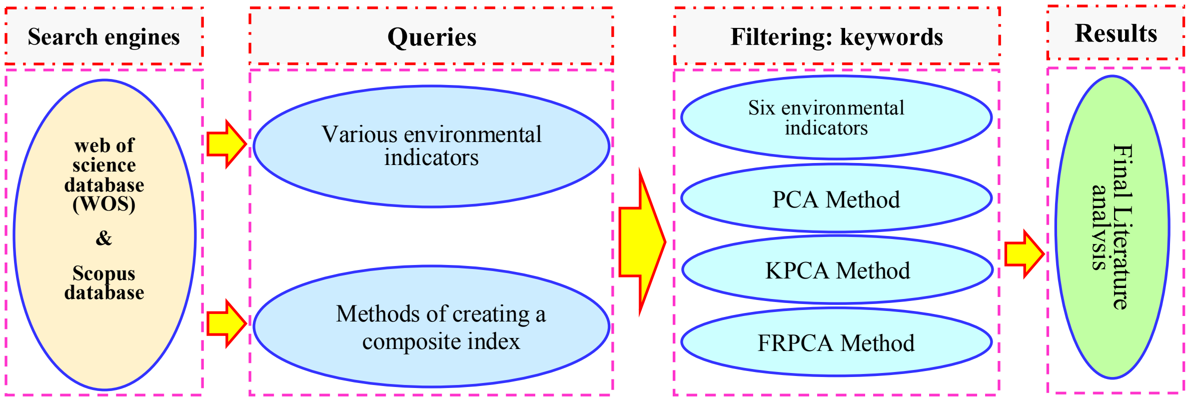


Figure 2. Literature review search strategy in this study

Studies related to various environmental indicators

Due to the great importance of the interaction between two important economic and environmental variables and also with the development of experimental literature on the impact of these variables on each other, several indicators were defined for environmental quality and applied in economic-environmental models. The reason for this multiplicity of environmental indicators was that the previous indicators could not be a comprehensive and complete representative of the environmental situation, and accordingly, several indicators were created. However, the important point that we found by using these indicators is that the results obtained are not the same and consistent with each other. Accordingly, constructing a composite index that can be a proper indicator for the environment status. Because the use of this combined index in economic-environmental models can result in interesting and new findings for researchers and environmental economic analysts. Table 1 presents summary literature review of environmental indicators.

The relative frequency of various environmental indicators (indicators used in this study) that have been applied in previous empirical studies as indicators for the environmental status in economic models is well illustrated in figure 3.

Figure 3 represents a summary illustration of table 1. As can be seen from this figure, the ecological footprint allocates the highest share (with 50%) to itself in the empirical studies as the representative of the environmental status among all other types of environmental indicators. The next index that has largest share and has been used in more empirical studies as a dependent variable in environmental economic models, is the environmental performance index (with 15%). The adjusted net savings index (12.5%) also is another highly applicable index in the empirical studies. Other indicators such as environmental sustainability index, environmental vulnerability index and pressure on nature index with 10%, 7.5% and 5% respectively, have the lowest share as a representative of environmental status (dependent variable) in environmental economic models.

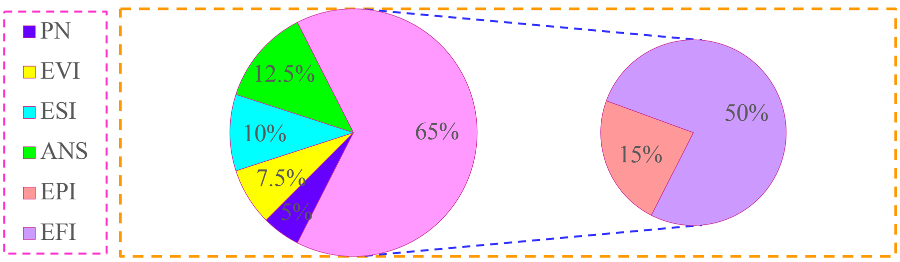


Figure 3. Relative frequency in the use of a variety of environmental indicators

Table 1. Summary literature review of environmental indicators

Author/s	Period	Author/s	Period
Ecological Footprint Index **(**EFI)			
Sarkodie (2018)	1971-2013	Dogan et al. (2020)	1980-2014
Destek et al. (2018)	1980-2013	Godil et al. (2020)	1986-2018
Bello et al. (2018)	1971-2016	Danish et al. (2020)	1992-2016
Fakher (2019)	1990-2016	Kongbuamai et al (2020)	1974-2016
Sabir and Gorus (2019)	1975-2017	Usman et al. (2020)	1985-2014
Hassan et al. (2019)	1970-2014	Yilanci and Gorus (2020)	1981-2016
Ahmed et al. (2019)	1971-2014	Nathaniel et al. (2020)	1990-2016
Aydin et al. (2019)	1990-2013	Nathaniel (2020)	1971-2014
Danish and Wang (2019)	1992-2013	Pata (2021)	1980-2016
Danish and Wang (2019)	1971-2014	Naqvi et al. (2021)	1990–2017
Environmental Performance Index (EPI)			
Ozcan et al. (2020)	2000-2014	Fakher et al. (2018)	1996-2016
Elsalih et al. (2020)	2002-2014	Fakher and Abedi (2017)	2002-2012
Ozcan et al. (2019)	2000-2013	Neagu et al. (2017)	2000-2016
Adjusted Net Saving (ANS)			
Asici (2013)	1970-2008	Ganda (2019)	2001-2012
Salahuddin and Gow (2019)	1980-2016	Peter (2010)	2001-2006
Gnègnè (2009)	1971-2000		
Environmental Sustainability Index (ESI)			
Shah et al. (2019)	2006-2017	Long and Ji (2019)	1997-2016
Charnkit and Kumar (2014)	1992–2005	Olafsson et al. (2014)	2005-2017
Environmental Vulnerability Index (EVI)			
Olafsson et al. (2014)	2005-2017	Lee and Lin (2020)	2000-2014
Ho et al. (2019)	2007-2014		
Pressure on Nature (PN)			
Chen et al. (2020)	2000-2015	Asici (2013)	1970-2008

Studies related to methods of creating a composite index

Many studies have investigated the important economic variables' effect on environmental quality using a variety of indicators as dependent variables indicating the environmental condition. The simultaneous use of all these indicators may lead to multi-linearity, spurious regression and inappropriate analysis of the obtained results; Accordingly, it is necessary to adopt an appropriate technique to create a composite index indicating an appropriate proxy for selected variable. Table 2 summarizes the types of principal component analysis methods (PCA, KPCA and FRPCA) used in experimental studies to create a composite index.

According to the above-mentioned empirical studies, the relative frequency on different types of composite indicators in the economic, social and political field which is created using the factor analysis methods is well illustrated in figure 4.

As can be seen from figure 4, various composite indicators in the economic, social and political fields have been constructed using factor analysis methods and have been used as an important variable in research models. Moreover, according to the above-mentioned empirical studies, the relative frequency on applying a variety of factor analysis methods (PCA, KPCA, FRPCA) in order to create composite indicators is well illustrated in figure 5.

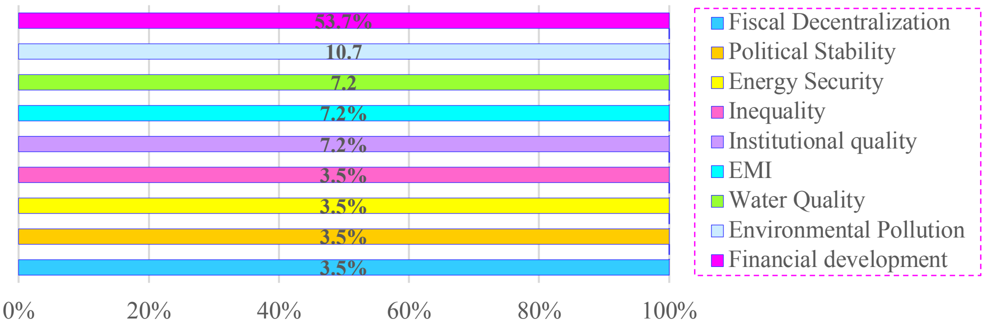


Figure 4. Relative frequency on different types of composite index

Table 2. Summary literature review of creating a composite index

Author/s	Composite index	Author/s	Composite index
Principal Component Analysis (PCA)			
Fathi Assi et al. (2021)	Financial Development	Ouyang and Li (2018)	Financial Development
Kassi et al. (2020)	Financial Development, Institutional Quality	Chu et al. (2018)	Environmental Pollution
Alemzero et al. (2020)	Energy Security	Zhong and Enke (2017)	Financial Development
Mohammadi et al. (2020)	Fiscal Decentralization	Zeinalzadeh & Rezaei (2017)	Water quality
Kazerooni et al. (2020)	Political Stability	Cano-Orellana and Delgado-Cabeza (2015)	Environmental Pollution
Ahmadi et al. (2020)	Inequality	Hargreaves andMani (2015)	Financial Development
Liu et al. (2019)	Environmental Pollution	Zhang et al. (2014)	EMI
Tripathi and Singal (2019)	Water quality	Coban and Topcu (2013)	Financial Development
Singh and Aneja (2019)	Financial Development	Adu et al. (2013)	Financial Development
Rizk and Slimane (2018)	Institutional Quality	Van Maaten et al. (2009)	Financial Development
Faisal et al. (2018)	Financial Development	Saci and Holden (2008)	Financial Development
Kernel Principal Component Analysis (KPCA)			
Zhong and Enke (2017)	Financial Development	Van Maaten et al. (2009)	Financial Development
Saci and Holden (2008)	Financial Development	-	-
Fuzzy Robust Principal Component Analysis (FRPCA)			
Zhong and Enke (2017)	Financial Development	Zhang et al. (2015)	EMI

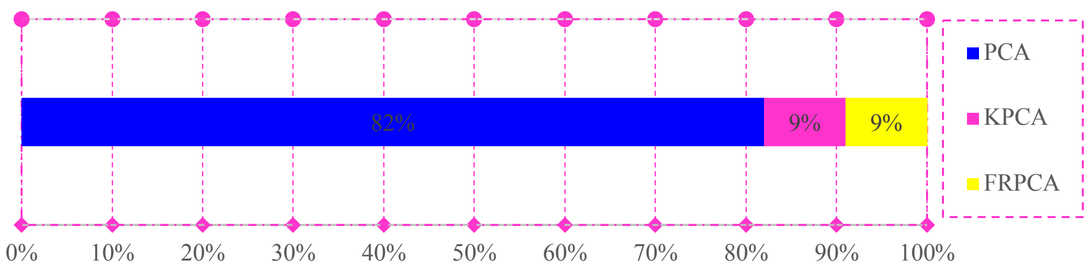


Figure 5. Relative frequency on applying a variety of methods to create composite indicators

As can be seen from Figure 5, the principal component analysis (PCA) method is one of the highly applicable methods of factor analysis in creating composite indicators. This indicates the appropriateness of this method in constructing a composite index. This is while in a study conducted by Mazziotta and Pareto (2018) on the efficiency of the principal component analysis method in creating a composite index, this method cannot work properly in weighting the desired variables and creating a composite index due to misleading information. Accordingly, the results of this method cannot be reliable. According to their study, the PCA method is exclusively based on the covariance structure between the individual indicators. Therefore, using this method for creating composite indices can give misleading information about the latent variable of interest (Mazziotta and Pareto, 2019; Fayers and Hand, 2002). Accordingly, in this study, in order to achieve reliable results and prevent spurious results, the artificial neural network (ANN) approach is used as well, and the performance of these two methods in creating a composite index is compared.

Material and Methods

In this section, a concise review of environmental indicators that are considered and used as the main research data is first reviewed. Then, the PCA method and ANN method are discussed. In the following, the evaluating indices of the method performance are explained. Finally, a schematic diagram of the methodology for this study is presented.

Description and measurement of environmental indicators

In this study, we used the data from selected OPEC countries (including Iran, Iraq, United Arab Emirates, Qatar, Venezuela, Saudi Arabia, Angola, Algeria, Ecuador, Nigeria, Libya, Indonesia, and Kuwait) and selected OECD countries (the United States, Australia, Canada, France, Germany, Switzerland, Portugal, Spain, Austria, Norway, New Zealand, Iceland, Slovakia, Finland, Czechoslovakia, South Korea, Japan, Hungary, Luxembourg, Sweden, Ireland, Italy, Mexico, Netherlands, Denmark, England, Poland, Greece, Belgium and Turkey). Regarding the unavailability of statistics and data for all countries during 2008-2019, the aforementioned countries, which had more complete data and statistics, were included in this study. In this regard, six environmental indicators, including ecological footprint (See www.footprintnetwork.org), environmental performance, environmental sustainability, environmental vulnerability, adjusted net saving and pressure on nature indices, were considered. To accumulate the data of these indicators, different sources from the World Bank publications and annual reports issued by Yale Center for Environmental Law and Policy (See https://epi.envirocenter.yale.edu/) to the Global Footprint Network, and the National Ecological Footprint Account (NFA 2019) were used. Each of these indicators are briefly described in table 3. Additionally, per capita real GDP is used as proxy for economic growth.

PCA method

One of the oft-used statistical methods is Principal Component Analysis (PCA), which has been adopted in many studies as a data reduction method. This method makes it possible to reduce a set of data with a large number of variables to a data with a reasonable number of variables. In mathematics, PCA is defined as an orthogonal linear transformation, which imports data to a new coordinate system so that the first largest variance of the data is on the first coordinate axis, the second largest variance is on the second coordinate axis, and the same procedure is pursued for the other variances. The first principal component is a linear combination of the main predictions containing the highest level of variance in a data set, which determines the direction of maximum variation in the data (Liu et al. 2019).

Table 3. Description of environmental indicators

Indicators	Description
Ecological Footprint Index	This index is calculated as per unit of global hectares (gha). To calculate the ecological footprint, the land is divided into five different land uses. In this context, all human consumables and services are formed within these five land uses, i.e., cropland, grazing land, forest areas, fishing grounds, and built-up areas. Naqvi et al. (2021), Pata (2021) and Nathaniel (2020) have used this index in their studies as a proxy for environmental degradation.
Adjusted Net Saving	This index is a combination of three types of investment, including physical, human and natural capitals, and consists of four main components including net national savings, current education costs, renting of resources (minerals, forests and energy depletion), and damages arising from carbon dioxide (CO2). This indicator is applied in the studies of Salahuddin and Gow (2019), Ganda (2019), Asici (2013) and Gnègnè (2009).
Pressure on Nature	This index consists of carbon dioxide damage per capita, mineral depletion per capita, energy depletion per capita, and net forest depletion per capita or deforestation per capita. It is measured by the non-investment component extracted from the World Bank's data on adjusted net saving. Chen et al. (2020) and Asici (2013) used this index as a proxy of environmental degradation.
Environmental Performance Index	This index focuses on two main components, i.e., environmental protection and appropriate management of natural resources. These two components are measured by 16 indicators in six areas, such as environmental health, water resource quality, air quality, biodiversity and habitation, productive natural resources' quality and sustainable energy (Esty et al. 2006; Kashyna, 2011). Elsalih et al. (2020) and Chen et al. (2020) have considered it as a proxy of environmental quality.
Environmental Sustainability Index	This index was extracted from 76 statistical data groups, which were integrated in the form of 21 environmental sustainability indices. The higher a country's score on the environmental sustainability index is, the better its environmental status will be in the future. This index is applied in the studies of Long and Ji (2019), Shah et al. (2019) and Charnkit and Kumar (2014).
Environmental Vulnerability Index	A combination of 52 secondary indices was used to produce this index, of which 32 indices were classified as risk indices, 8 indices and 12 indices were indices of environmental sustainability and vulnerability, respectively (Skondras et al. 2011). Lee and Lin (2020) and Ho et al. (2019) have applied this index as a proxy of environmental degradation.

The higher the range of variations in the first component is, the more information the component contains. No other component can have variation range larger than the first principal component. The calculation result the first principal component is a line closest to the data, which minimizes the square of the distances between a given point and the line. Accordingly, this method preserves those components of a dataset, which have the greatest effect on variance. To determine the required component or components in this method, different criteria have been adopted, three of which are as follows. The first is to plot the eigenvalues versus the number of basic components, known as the scree plot. In this plot, the variations in the significance of eigenvalues are specified for each basic component. The second benchmark is the value of eigenvalue. The eigenvalues are considered to be the component values > 1, and the other components with eigenvalues < 1 are ignored. The third benchmark is the variance of the components. Components with a higher percentage of variance (i.e., variance explains distribution better) are considered to construct the composite index. A schematic diagram of a PCA method related to this study is illustrated in figure 6.

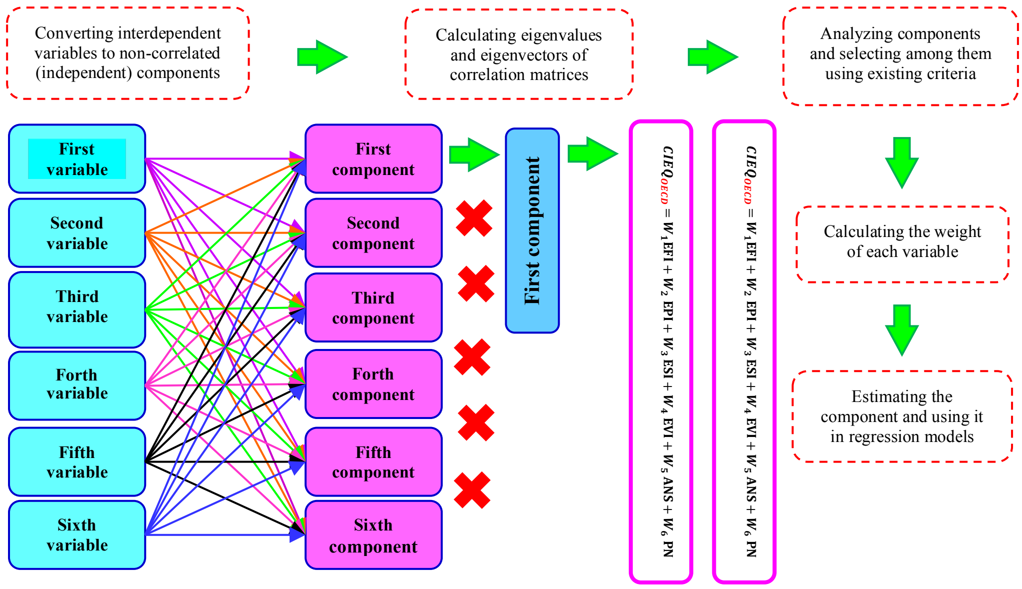


Figure 6. Schematic diagram of the PCA for this study

ANN method

The artificial neural network approach was first proposed by McCulloch and Walter Pitts (1943) and then used for the first time in the 1990s to predict and model econometrics. Since then, several studies have been conducted on the use of this approach in predicting various economic variables. Artificial neural networks are among the methods that are able to estimate multiple nonlinear cases in data and are a flexible computational framework for a wide range of nonlinear problems (Antonopoulos et al. 2020). One of the obvious advantages of such models over other nonlinear models is that artificial neural networks are a universal approximator that can approximate any type of function with desired accuracy. These types of networks do not require any assumptions about the shape of the model in the modeling process and are generally a data-based model. In fact, this type of model, with a hidden layer, is one of the most widely used estimation models to predict the relationships between target variables (Mazen et al. 2018). In their articles, Khanna (1990) and Dayhoff (1990) state that high processing speed and flexibility against unwanted errors are important features of artificial neural networks. A neural network consists of several neurons that make up the smallest unit of information processing. Upon receiving and processing the inputs on each of these neurons, an output signal is generated that either enters as input to the other neuron or is considered as network output. Each neuron plays the role of information processing and distribution center in the neural network and has its own input and output. The basic model of a neural network neuron is shown in figure 7. A schematic diagram of an artificial neural network related to this study is illustrated in figure 8.

In this method, by entering the data related to environmental indicators and performing processes related to artificial neural network, a weight indicating the role and importance of each environmental indicator in creating a composite index, is obtained for each of the environmental indicators.

Evaluating performance indices of the method

The proposed method must have a minimum error to have a proper and acceptable performance. Accordingly, the performance evaluation criteria of these methods are used to compare the performance of the methods used in this research. There are various evaluation criteria to evaluate the performance of different methods, three most important of which are Mean Squared Error (MSE), Root Mean Squared Error (RMSE), and Mean Absolute Error (MAE).

Each of these criteria can be used in evaluating performance of methods used in this study. A schematic diagram of the methodology for this study is presented in figure 10.

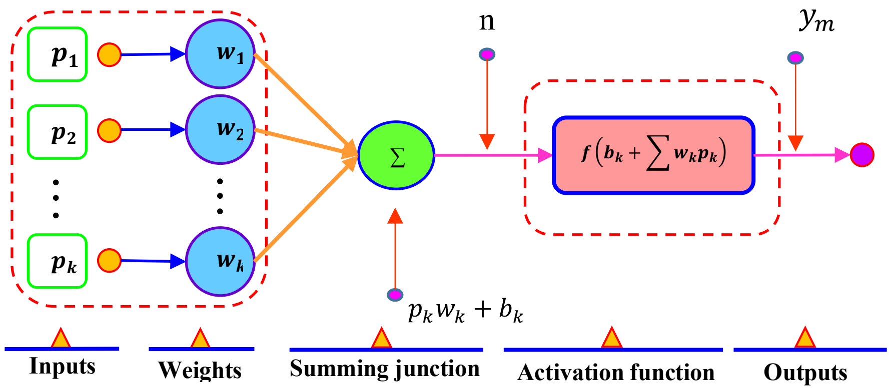


Figure 7. Basic model of a neural network neuron

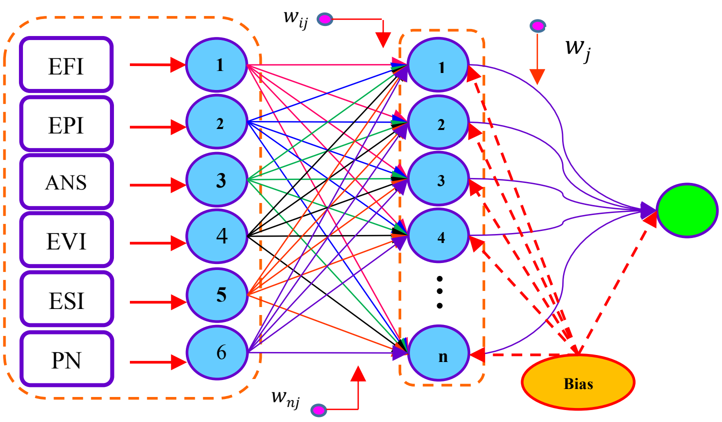


Figure 8. Schematic diagram of the ANN for this study

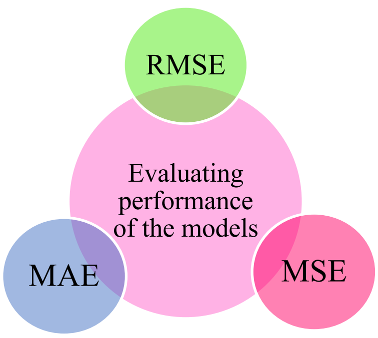


Figure 9. Performance evaluation criteria

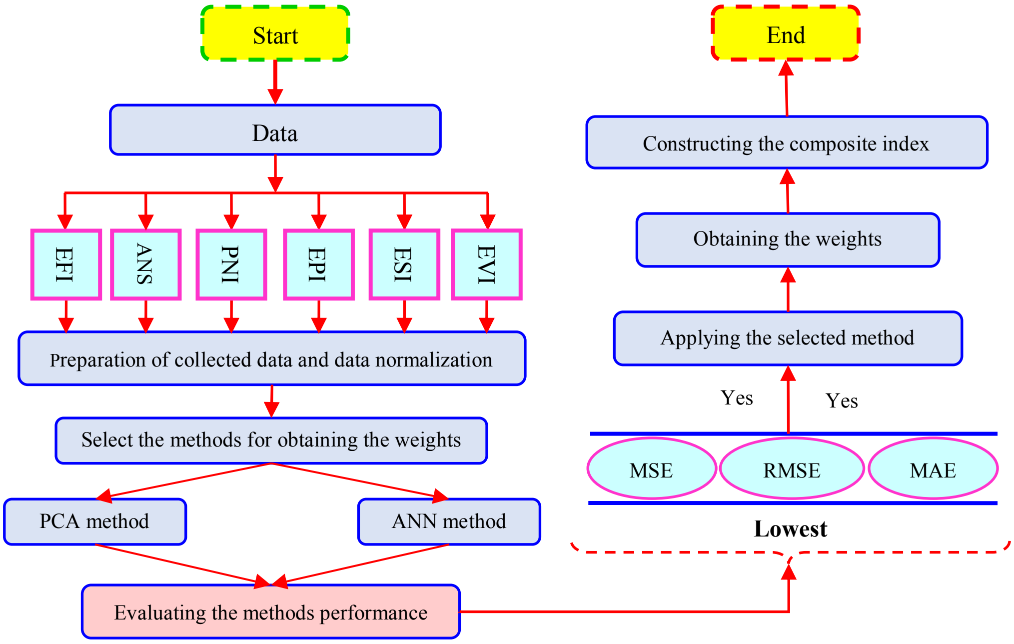


Figure 10. A schematic diagram of methodology for this study

Empirical results and discussion

In this section, there is a statistical description of the research variables for the selected OPEC and OECD countries, as shown in table 2. In the following, the results of PCA and ANN methods related to the calculation of the composite environmental quality index are presented and then using the methods evaluation criteria, the performance of these two methods to calculate the weight of indicators is evaluated. Finally, using the method with the least error criteria, a composite environmental quality index is created for two groups of selected countries.

Preliminary analyses

In this section, the preliminary analyses of the statistical characteristics of data used in this study are presented for two groups of OPEC and OECD countries. Table 4 contains the descriptive statistics (namely mean, maximum, minimum, standard deviation and the variation coefficient) of the concerned environmental indicators. The coefficient of variation was calculated based on the ratio of standard deviation to mean. These descriptive statistics greatly help us to analyze the research results appropriately since they provide us with important information about the data. Accordingly, it is necessary to address the descriptive statistics of estimation variables before conducting the estimations.

According to table 4, the largest mean of the environmental indicators belonged to the selected OECD countries, while the selected OPEC countries had the smallest mean score of the environmental indicators. In this regard, the ecological footprint index (with the mean score of 5.840355), the environmental performance index (with the mean score of 12.38), the environmental sustainability index (with the mean score of 54.09) and the environmental vulnerability index (with the mean score of 344.09) had the largest mean values for the selected OPEC countries, compared to their corresponding indices. In contrast, the adjusted net saving index (with the mean score of 2.16) and the nature pressure index (with the mean score of 12.78) had the largest mean values for the selected OECD countries, compared to their corresponding indices. As it is presented, the largest mean score of the environmental indicators belongs to the environmental vulnerability index with the mean score of 294.60 and 344.09 in the selected OPEC and OECD countries, respectively. Moreover, the variation coefficient, (the standard deviation ratio to mean), is defined and analyzed in table 4. Accordingly, the ecological footprint index (with the variation coefficient of 0.936), environmental performance index (with the variation coefficient of 0.789), environmental sustainability index (with the variation coefficient of 0.339), and environmental vulnerability index (with the variation coefficient of 0.143) have the most variations among the selected OPEC countries, compared to the selected OECD countries. However, the adjusted net saving index (with the variation coefficient of 0.505) and pressure on nature index (with the variation coefficient of 0.858) have the least variations among the selected OPEC countries, compared to the selected OECD countries. It should be mentioned that the largest coefficient of variation belongs to the pressure on nature index (1.100) in the selected OECD group, and the smallest coefficient of variation belongs to the environmental vulnerability index (0.143) in the selected OPEC countries.

Table 4. Descriptive statistics analysis for environmental quality indicators by panel

Countries	Des. Stat.	ANS	EFI	EPI	ESI	EVI	PN
	Mean	2.165215	4.195194	6.819044	36.96436	294.6067	12.78455
OPEC	Max	5.648086	16.66270	17.71566	71.00000	382.0000	85.55836
Countries	Min	0.236617	0.654458	0.000283	14.00000	201.0000	0.913675
(Panel)	Std. Dev.	1.094643	3.930305	5.384240	12.54867	42.38793	10.97835
	CV	0.505559	0.936859	0.789589	0.33948	0.14388	0.85872
	Mean	0.753559	5.840355	12.38751	54.09784	334.0954	1.340026
OECD	Max	4.336888	16.85953	18.93560	89.00000	399.0000	10.43215
Countries	Min	0.128637	0.611687	0.102520	8.000000	215.0000	0.090752
(Panel)	Std. Dev.	0.589110	2.413017	5.044345	15.59099	42.48392	1.474293
	CV	0.78177	0.413163	0.407212	0.2882	0.127161	1.100197

Note: Std. dev. and CV represent the standard deviation and the countries variation coefficient, respectively.

Given that some of the variables (environmental indicators) have negative relationships with environmental quality (indicating environmental degradation) and that the other variables have positive relationships with environmental quality (indicating an improvement in environmental quality), Rumina's normalization method is used. In many multi-criteria decision-making methods, we tackle with positive (usefulness) and negative (loss) criteria. A normalization method proposed in this regard is called Rumina's method. For the positive criteria, the value of each criterion is divided by the largest value of that criterion. For the negative criteria, the smallest value of the concerned criterion is divided by each value of the criterion. Using this method, all variables (indicators) would have a same direction and a positive aspect. This means that the higher these criteria (indicators) are, the better the quality of the environment is. This method is presented in equation (1):

$$n_{ij}\begin{cases}\dfrac{x_{ij}}{max x_{ij}} & For\ positive\ proxies\\ \dfrac{min x_{ij}}{x_{ij}} & For\ negative\ proxies\end{cases} \tag{1}$$

PCA method related to the composite environmental quality index

As stated in the research literature, many studies have considered only one index to determine the status of environmental quality. However, the separate use of all environmental quality indicators may raise multiple collinearity problems (Khan and Qayyum, 2007), resulting in inaccurate and unreliable findings. Accordingly, this study developed a composite environmental quality index to prevent possible biases and linearity in the experimental model as well as the creation of a false regression.

Similar to a method used in studies by Kassi et al. (2020), Liu et al. (2019), Faisal et al. (2018) and, Rizk and Slimane (2018), PCA was also used in this study, which is one of the main and basic methods in factor analysis, to develop a composite environmental quality index for the selected OPEC and OECD countries. To measure the environmental quality, the six aforementioned environmental indicators were used. Integrating these indicators into each other and developing a composite index would provide more complete dimensions of the environmental quality, in comparison to the separate use of the indicators.

There are some methods, by which the researcher can determine the appropriateness of data for PCA. One of these methods is KMO coefficient, the value of which always ranges from zero to one.

To make sure of the suitability of data for factor analysis, besides using the KMO coefficient, Bartlett's sphericity test can also be used. Bartlett's sphericity test examines the hypothesis indicating the lack of relationship among the variables. For a practical model to be useful and meaningful, the variables need to be correlated; otherwise, there is no reason to explain the factor model (Cano-Orellana and Delgado-Cabeza, 2015). The results of these tests are shown in table 5.

Table 5. The results of K–M–O statistic and Bartlett test

		OPEC countries	OECD countries
Kaiser–Meyer–Olkin measure of sampling		0.809	0.781
Bartlett's test of sphericity	Approx. Chi-square	1768.336	1566.321
	Dg.	78	71
	Sig.	0.000	0.000

According to the table 5, the KMO value of 0.809 and 0.781 for the two groups of selected OPEC and OECD countries denotes the appropriateness of data for PCA. The Bartlett's test results are also significant, indicating that the null hypothesis is rejected and that there exists a significant correlation among the variables. Accordingly, we use all the six environmental indicators (namely EFI, EPI, ESI, EVI, ANS and PN) and perform PCA to develop a composite environmental quality index. Table 6 shows the PCA results for the environmental quality index in the two groups of the selected OPEC and OECD countries.

According to table 6, for the selected OPEC countries, these results indicate that the first factor with an eigenvalue of 4.52 plays the most significant role in the composite environmental quality index. Then the second and third factors with eigenvalues of 1.06 and 0.19 are less significant in the composite environmental quality index, respectively. The fourth factor with an eigenvalue of 0.11, the fifth factor with an eigenvalue of 0.07, and the sixth factor with an eigenvalue of 0.02 play the least remarkable roles among the six indicators. Moreover, PCA results show that about 75% of the variations are explained by the first factor, followed by the second (17.72%) and third (3.31%) principal components, respectively. The remained components less explain the variations. For the selected OECD countries, the results reveal that the first factor with an eigenvalue of 4.34 plays the most significant role in the composite environmental quality index. Then the second and third factors with eigenvalues of 0.83 and 0.46 as well as the fourth factor with an eigenvalue of 0.27 are less significant in the composite environmental quality index, respectively. The fifth factor with an eigenvalue of 0.06 and the sixth factor with an eigenvalue of 0.01 play the least remarkable roles among the six indicators. In addition, PCA results show that about 72% of the variations are explained by the first factor, followed by the second (13.87%) and third (7.71%) principal components, respectively. The remained components less explain the variations. Figure 11 presents the orthonormal loadings biplot related to the results of PCA.

Table 6. Total variance of principal components for six Environmental indicators

OPEC countries							
Eigenvalues: (Sum = 6, Average = 1)							
	Initial analysis				Final analysis		
Component	Value	Cumulative Value	Proportion	Cumulative proportion	Selected principal component		
PC1	4.520072	4.520072	0.7533	0.7533	4.520072	0.7533	0.7533
PC2	1.062930	5.583002	0.1772	0.9305	5.583002	0.1772	0.9305
PC3	0.198359	5.781361	0.0331	0.9636	-	-	-
PC4	0.111406	5.892767	0.0186	0.9821	-	-	-
PC5	0.077828	5.970595	0.0130	0.9951	-	-	-
PC6	0.029405	6.000000	0.0049	1.0000	-	-	-

Eigenvectors (loadings)						
Environmental quality indices	PC1	PC2	PC3	PC4	PC5	PC6
EFI	-0.439323	-0.266733	0.041713	0.403249	0.587534	0.475714
EPI	0.429047	-0.130745	0.854098	0.044263	0.243426	-0.090140
ESI	0.449655	0.068763	-0.401013	0.531835	0.390328	-0.443921
EVI	0.393832	0.489561	-0.165876	-0.408072	0.408144	0.494577
ANS	0.449256	-0.186876	-0.074202	0.429759	-0.499302	0.568986
PN	-0.252566	0.795260	0.273759	0.448740	-0.165252	0.012364

OECD countries							
Eigenvalues: (Sum = 6, Average = 1)							
Component	Value	Cumulative Value	Proportion	Cumulative proportion	Selected principal component		
PC1	4.347148	4.347148	0.7245	0.7245	4.347148	0.7245	0.7245
PC2	0.832488	5.179636	0.1387	0.8633	5.179636	0.1387	0.8633
PC3	0.462370	5.642007	0.0771	0.9403	-	-	-
PC4	0.274107	5.916113	0.0457	0.9860	-	-	-
PC5	0.065547	5.981661	0.0109	0.9969	-	-	-
PC6	0.018339	6.000000	0.0031	1.0000	-	-	-

Eigenvectors (loadings)						
Environmental quality indices	PC1	PC2	PC3	PC4	PC5	PC6
EFI	-0.352158	-0.564421	-0.487214	0.559008	0.052408	0.069278
EPI	0.453946	0.114169	-0.037755	0.447724	-0.757961	-0.067171
ESI	0.466023	0.000824	0.011352	0.332109	0.530266	-0.625471
EVI	0.469753	-0.029892	0.113670	0.237339	0.343217	0.769019
ANS	-0.288731	0.817002	-0.329807	0.330452	0.154135	0.086100
PN	-0.385626	0.002699	0.799609	0.459596	0.003399	-0.025889

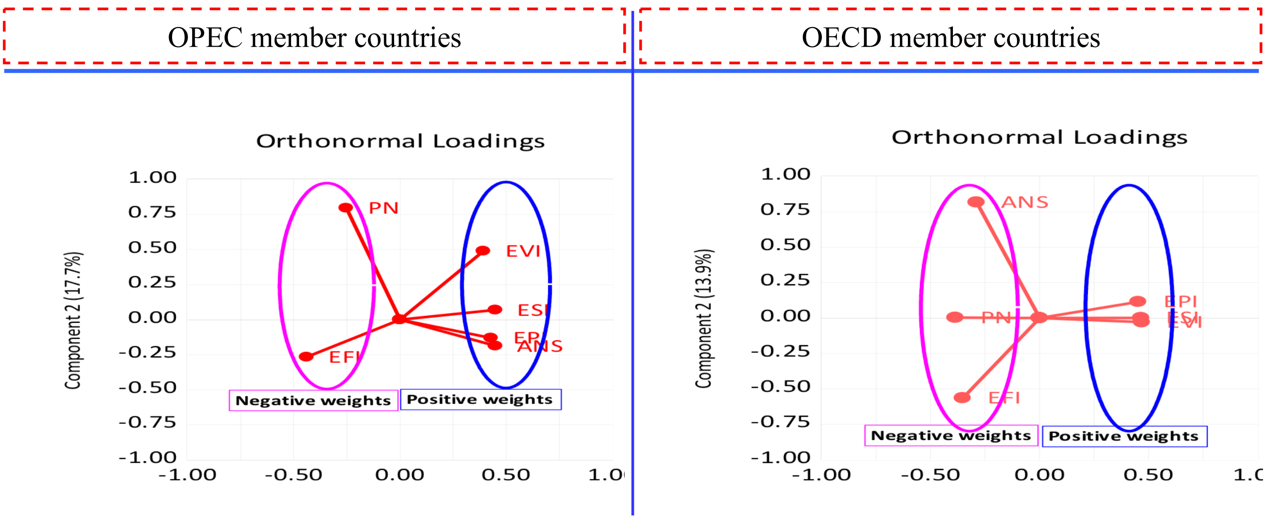


Figure 11. Orthonormal loading biplot related to results of PCA

ANN method related to the composite environmental quality index

The results of the correlation matrix between the research variables are presented in tables 7 and 8. Table 7 is for OPEC selected countries and table 8 is for OECD selected countries.

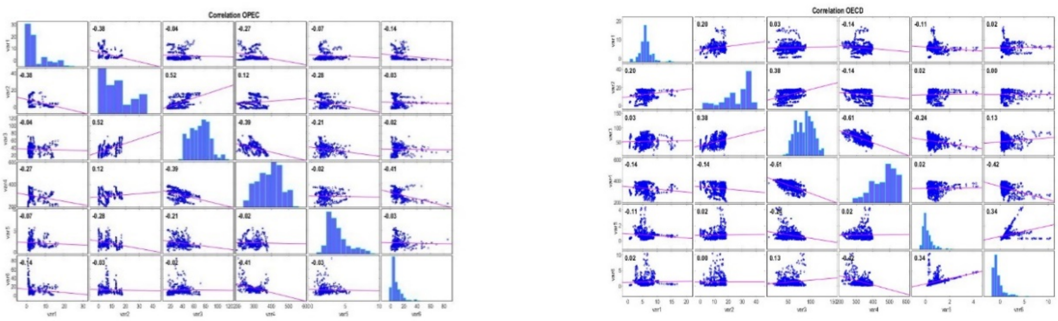
Table 7. The correlation matrix related to selected OPEC countries

Indexes	1	2	3	4	5	6
EFI	1.0000	-0.3801	-0.0430	-0.2732	-0.0670	-0.1411
EPI	-0.3801	1.0000	0.5150	0.1222	-0.2792	-0.0322
ESI	-0.0430	0.5150	1.0000	-0.3892	-0.2072	-0.0151
EVI	-0.2732	0.1222	-0.3892	1.0000	-0.0226	-0.4083
ANS	-0.0670	-0.2792	-0.2072	-0.0226	1.0000	-0.0287
PN	-0.1411	-0.0322	-0.0151	-0.4083	-0.0287	1.0000

Table 8. The correlation matrix related to selected OECD countries

Indexes	1	2	3	4	5	6
EFI	1.0000	0.1975	0.0339	-0.1380	-0.1134	0.0223
EPI	0.1975	1.0000	0.3846	-0.1359	0.0215	0.0010
ESI	0.0339	0.3846	1.0000	-0.6145	-0.2432	0.1312
EVI	-0.1380	-0.1359	-0.6145	1.0000	0.0172	-0.4221
ANS	-0.1134	0.0215	-0.2432	0.0172	1.0000	0.0000
PN	0.0223	0.0010	0.1312	-0.4221	0.0000	1.0000

Figure 12 represents the correlation matrices for selected OPEC and OECD countries. These histograms show the diagonal members of the matrix and the scatter plots of non-polar variables.



(a) OPEC (b) OECD

Figure 12. The correlation matrix: a) selected OPEC countries b) selected OECD countries

In the scatter plots, the slope of the red lines is equal to the correlation coefficients. Table 9 presents the mean, standard deviation, and weights calculated for the research variables by the two groups of OPEC and OECD countries.

In table 9, the weights indicate the degree of involvement for each index in the final results and the creation of a composite index. In the selected OPEC countries, the environmental performance index, the ecological footprint index, and the environmental vulnerability index mainly contribute to creating the composite environmental quality index. Other indices have a less significant share in the creation of the composite index. In the selected OECD countries, the environmental sustainability index, environmental vulnerability index, and ecological footprint index have the largest share in defining the composite environmental quality index. The other indices also have less contribution.

Table 9. The weights related to selected OPEC and OECD countries

OPEC countries			
Indexes	Mean	Std. Dev.	Weights
EFI	12.7846	10.9784	0.5891
EPI	2.1652	1.0946	0.6273
ESI	294.6067	42.3879	0.4410
EVI	36.9644	12.5487	0.5828
ANS	6.8190	5.3842	0.3852
PN	4.1952	3.9303	0.3255
OECD countries			
Indexes	Mean	Std.	Weights
EFI	5.8404	2.4130	0.5496
EPI	12.3875	5.0443	0.4021
ESI	54.0978	15.5910	0.7576
EVI	334.0954	42.4839	0.6219
ANS	0.7536	0.5891	0.4718
PN	1.3400	1.4743	0.4045

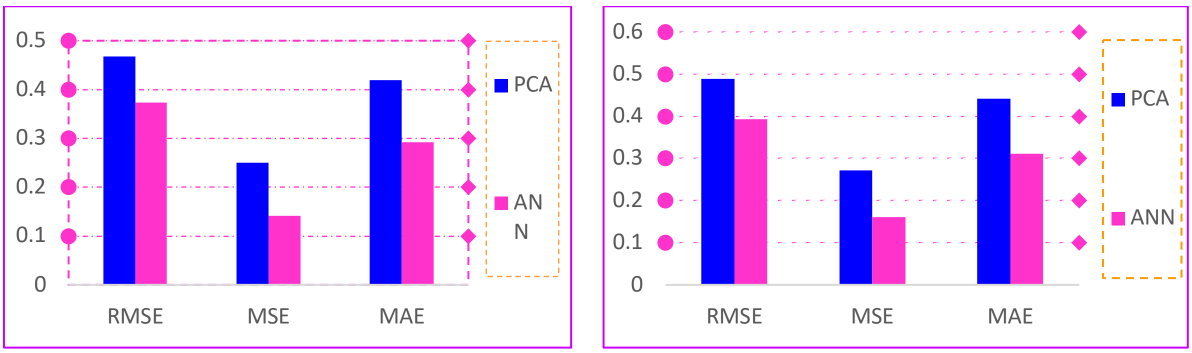
Analysis of performance evaluation criteria for PCA and ANN methods

In order for the proposed method to have a proper and acceptable performance, it should have a minimum error. Accordingly, the performance evaluation criteria are used to compare the performance of these two approaches (PCA and ANN) to calculate the weight of environmental indicators. Table 10 presents the results of these criteria for selected OPEC and OECD countries.

Table 10. Performance evaluation criteria related to the methods

Methods	Performance evaluation criteria					
	OECD			OPEC		
	RMSE	MSE	MAE	RMSE	MSE	MAE
PCA	0.4674	0.2503	0.4197	0.4884	0.2712	0.4417
ANN	0.3734	0.1415	0.2919	0.3934	0.1615	0.3119

According to the obtained error criteria for the two methods, ANN method is used to calculate the weight of environmental indices due to having the smallest error criteria. Furthermore, to run the comparison better, the results are also depicted in figure 13. As it can be observed, the ANN method has the smallest error; hence, the results of this method are more reliable.



(a) **(b)**

Figure 13. Performance evaluation criteria of PCA and ANN methods (a) Related to selected OECD countries **(b)** Related to selected OPEC countries

Selecting an appropriate method to calculate the weight of environmental indices

According to the analysis of the results for the smallest error, the ANN method is used to calculate the weight of environmental quality indices. According to the results of ANN method for the two groups of selected countries, table 11 shows the weight of each environmental index for the two groups of selected countries (namely OPEC and OECD).

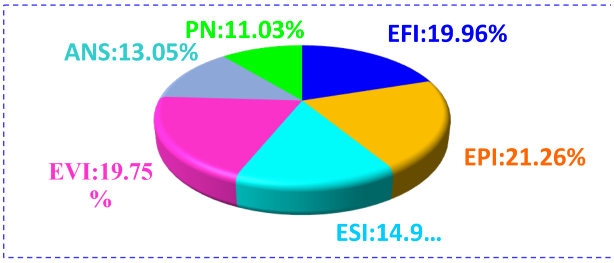
Table 11. Weights of environmental indicators

OPEC countries		OECD countries	
Indices	Weights	Indices	Weights
Ecological footprint index	0.5891	Ecological footprint index	0.5496
Environmental performance index	0.6273	Environmental performance index	0.4021
Environmental sustainability index	0.4410	Environmental sustainability index	0.7576
Environmental vulnerability index	0.5828	Environmental vulnerability index	0.6219
Adjusted net saving	0.3852	Adjusted net saving	0.4718
Pressure on nature	0.3255	Pressure on nature	0.4045

As can be seen from table 11 (for selected OPEC countries), the environmental performance and ecological footprint indices (with the weight values of 0.6273 and 0.5891) is of paramount importance in explaining the state of environmental quality and constructing the composite environmental quality index (CEQI). Then, the environmental vulnerability index (with a weight value of 0.5828) has more weight and importance in constructing the composite environmental quality index. Each of the indicators including environmental sustainability and adjusted net saving (with the weight values of 0.4410 and 0.3852, respectively) have gained less weight and importance. Finally, the pressure on nature has the lowest weight and importance in explaining the quality of environment with the weight value of 0.3255) compared to other indicators. In the case of selected OECD countries, the index of environmental sustainability (with the weight value of 0.7576) has the greatest weight and importance in explaining the quality of the environment compared to other indicators. After that, each of the environmental vulnerability and ecological footprint indices (with the weight values of 0.6219 and 0.5496, respectively) has higher importance. Finally, adjusted net saving, pressure on nature and environmental performance indices with the weight values of 0.4718, 0.4045 and 0.4021 respectively has the lowest role in explaining the quality of environment and constructing the composite environmental quality index.

According to the results of the ANN method related to environmental quality indicators, the composite environmental quality index, as the weight average of the six indicators (multiplying each of the environmental indicators in their weights and their significance in total variations), can be calculated for each of the two groups of OPEC and OECD countries. Before calculating this composite index, it is necessary to ensure that the sum of the weights is equal to one. In order to the sum of the weights to be equal to one, first the absolute values of selected indicators' weights are added up together. Then the values related to each individual index is divided by this obtained sum total value. The weights related to each of environmental indicators are illustrated in figure 14.

Based on the coefficients presented in figure 14, the mathematical equations of the composite environmental quality index related to each of the two groups of OPEC and OECD countries are shown in table 12.



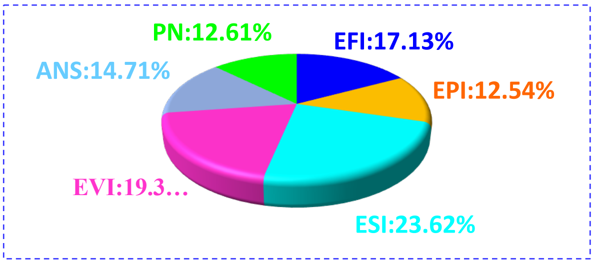


Figure 14. (a) The weights of indicators related to OPEC (b) The weights of indicators related to OECD

Table 12. Calculation of composite environmental quality index

OPEC countries
$\mathbf{CEQI} = 0.1996\mathbf{EFI} + 0.2126\ \mathbf{EPI} + 0.1495\ \mathbf{ESI} + 0.1975\ \mathbf{EVI} + 0.1305\ \mathbf{ANS} + 0.1103\ \mathbf{PN}$
OECD countries
$\mathbf{CEQI} = 0.1713\ \mathbf{EFI} + 0.1254\ \mathbf{EPI} + 0.2362\ \mathbf{ESI} + 0.1939\ \mathbf{EVI} + 0.1471\ \mathbf{ANS} + 0.1261\ \mathbf{PN}$

Therefore, using the above equations (in the red dotted-line boxes in table 12, the composite environmental quality index can be calculated for each of the two groups and used in the estimation regressions.

Analyzing the trend of composite index and economic growth simultaneously

In accordance with the economic realities of the two groups of countries, the trend of composite environmental quality index and the trend of GDP (as one of the most important indicators of economic growth) is analyzed simultaneously which are presented in figures 15 and 16.

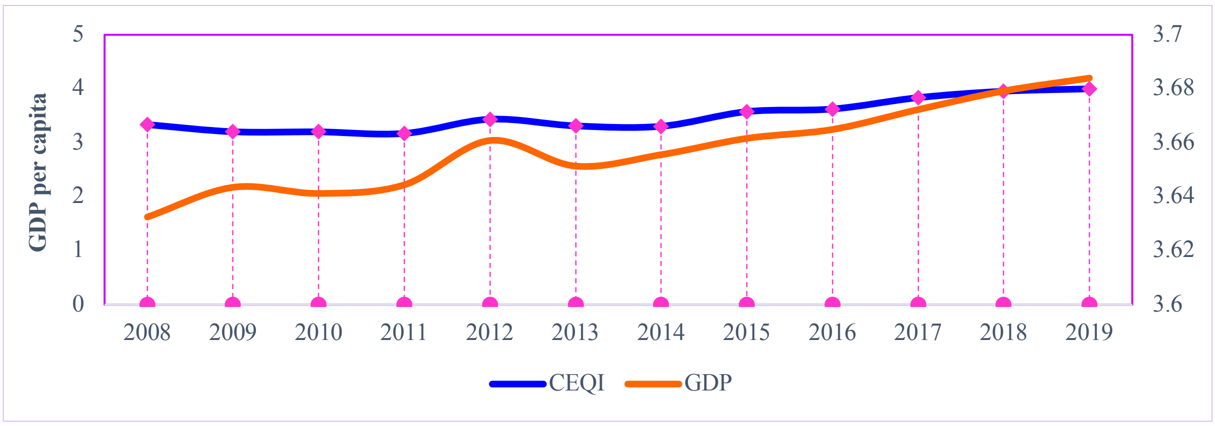


Figure 15. Interaction between economic growth and environmental quality in selected OECD countries.

As shown in figure 15, the relationship between economic growth and composite environmental quality index follows a direct relationship; so that, along with economic growth, environmental quality has increased and we are not dealing with environmental degradation. It can be stated that according to the environmental laws governing the production process and the appropriate environmental incentives in the processes related to the production of goods as well as the provision of services, producers have been tended to the efficient use of natural resources and energy. This has led to a reduction in environmental degradation.

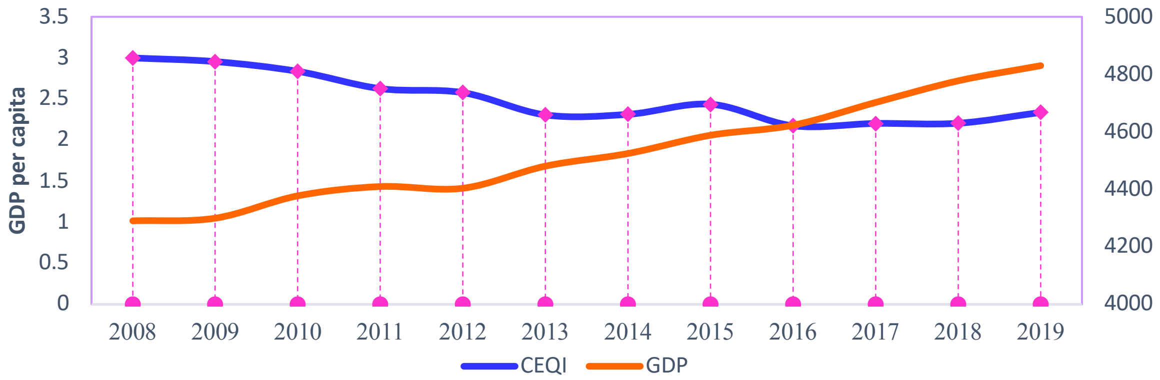


Figure 16. Interaction between economic growth and environmental quality in selected OPEC countries.

The trend of composite environmental quality index and economic growth for the selected OPEC countries is presented in figure 16. As can be seen in this figure, the relationship between economic growth and the composite index of environmental quality follows an inverse relationship; so that, along with economic growth, environmental quality reduces and we are faced with environmental degradation. In the analysis of this result, it can be stated that in the early stages of economic growth, due to the high priority of production and employment over a clean environment in this group of countries, the use of natural resources and energy consumption has increased and this leads to environmental degradation. In the following, due to environmental laws, they have tended towards the efficient consumption of natural resources and energy, and this has led to a reduction in environmental degradation. However, due to the weakness of environmental laws and the lack of incentives to comply with environmental laws, the motivations have decreased and the quality of environment has lost its priority and has given way to production and employment. Following that, we are witnessing an increase in environmental degradation.

Conclusions and policy implications

Regarding the lack of research on the feasibility and application of the PCA and ANN techniques in calculating the composite environmental quality index, this study aimed to test the applicability of these techniques for the environmental indicators that represent the environmental quality and provide the future researchers with findings to be used in further research on environmental quality. This study sought to find out which of them can be used to develop a composite environmental quality index in two groups of the selected OPEC and OECD countries with regard to appropriate statistical criteria and how their estimation equation is. Accordingly, this study investigates the efficiency of PCA and ANN methods in order to construct a composite environmental quality index in two groups of selected countries to test environmental indicators that are representative and indicators of environmental quality. To this end, this study uses panel data for the period of 2008-2019.

The results are presented for the two PCA and ANN methods in calculating the composite environmental quality index, and the performance of these two methods are evaluated to calculate the weight of the indices using the performance evaluation criteria of the methods. According to the estimated error of the two methods, the ANN method was used to calculate the weight of environmental indices as it had the smallest error. Since the ANN method has the smallest error, the results of this method are more reliable. The results extracted from the ANN method indicate that environmental performance index, ecological footprint index, and environmental vulnerability index are the main indices in explaining the environmental quality and play the most prominent role in creating a composite environmental quality index in the selected OPEC countries. Accordingly, these three indices in the selected OPEC countries should be further considered. However, in the selected OECD countries, the environmental sustainability index, the environmental vulnerability index and the ecological footprint index had the largest weight and significance in explaining the environmental status. Therefore, it is recommended to pay more attention to these three indicators in selected OECD countries. It is worth mentioning that the ecological footprint and environmental vulnerability indices in both OPEC and OECD selected countries, had greater contribution in explaining environmental quality and creating a composite environmental quality index.

Limitations and future recommendations

Considering the research findings, some suggestions are provided for future researchers. It is suggested that other methods such as Fuzzy Robust Principal Component Analysis (FRPCA), Kernel Principal Component Analysis (KPCA), the CRiteria Importance Through Intercriteria Correlation (CRITIC) method and analytic hierarchy process (AHP) method can be used for index weighting and developing a composite environmental quality index. Moreover, better output and analysis can be provided by comparing these methods with the aim of determining the best method to weight the environmental quality indicators. Finally, the application of the PCA approach also has shortcomings to be considered by researchers. The main limitation with this approach is the difficulty of interpreting the extracted components. Given that these components are composite, it is difficult to extract their meaning. Furthermore, this method can be time consuming since it does not delete the variables and only changes their application. It also should be noted that the findings of the present study are valid only for the concerned time period, and the findings should be retested and reanalyzed to be used in other time periods.

Credit Author Statement

Hossein Ali Fakher: Data curation, Conceptualization, Investigation, Methodology, Software, Formal analysis, Writing – original draft, Visualization. **Mostafa Panahi:** Supervision, Investigation, Formal analysis, Writing – review & editing, Validation. **Karim Emami:** Methodology, Software. **Kambiz Peykarjou:** Writing – review & editing. **Seyed Yaghoub Zeraatkish:** Conceptualization, Writing – review & editing.

Conflict of Interest

The authors declare that there is not any conflict of interests regarding the publication of this manuscript. In addition, the ethical issues, including plagiarism, informed consent, misconduct, data fabrication and/ or falsification, double publication and/or submission, and redundancy has been completely observed by the authors.

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