Journal of New Theory
ISSN: 2149-1402

36 (2021) 117-126
Journal of New Theory
https://dergipark.org.tr/en/pub/jnt
Open Access

A Robust Alternative to Environmental Performance Index

Hasan Bulut[1]

Article History
Received: 01 Sep 2021
Accepted: 22 Sep 2021
Published: 30 Sep 2021
10.53570/jnt.989890
Research Article

Abstract − A composite index called the Environmental Performance Index (EPI) was obtained to evaluate countries' environmental performance. This index was calculated for 180 countries concerning 24 environmental indicators. However, it is well known that there are huge differences between countries regarding environmental factors besides social, economic, and cultural factors. This case aggravates the doubt that the data set has outliers. Therefore, the index values should be obtained such that they are unsensitive to outliers. This study aims to generate a composite index, which is a robust alternative to EPI. For this aim, we use the Robust Principal Component Analysis (ROBPCA) and the Technique for Order Preferences by Similarity to an Ideal Solution (TOPSIS), which is a multi-criteria decision-making method.

Keywords − *Environmental performance index (EPI), robust EPI, ROBPCA, TOPSIS, composite index*

Mathematics Subject Classification (2020) − 62P12, 62H25

1. Introduction

Rapid industrialization and population growth cause harmful effects on the environment. In recent years, even ordinary people have realized this fact because of global warming and climate change. Therefore, we need evaluation and comparing countries concerning environmental factors. For this aim, a composite index called EPI was defined to measure the environmental performance of countries. This index was obtained with the collaboration of the Yale Center for Environmental Law and Policy (YCELP), Yale University, Columbia University Center for International Earth Science Information Network (CIESIN), and the World Economic Forum (WEF). The result of this index was released in Davos, Switzerland, at the annual meeting of the World Economic Forum in 2018. According to this report, 180 countries were sorted according to their EPI values, calculated from 24 environmental indicators [1].

In the literature, there are many studies related to environmental factors. In some of these studies, researchers investigated the relationship between the environmental performance of counties and different factors, such as socioeconomic, cultural, financial, ideological, economic growth [2-7]. In other studies, authors focused on obtaining a new composite index, which measures the environmental performance of countries, by using data envelopment analysis and Malmquist approaches [8-13].

Also, the principal components analysis (PCA) is one of the valuable methods to obtain a composite index [14]. Generally, researchers are interested in topics on human development, quality of life, and economic development in the studies that purpose a composite index using PCA [15-19]. Moreover, Bulut and Öner used robust PCA to obtain a composite index that is not sensitive to outliers. Thus, they evaluated the regions

[1]hasan.bulut@omu.edu.tr (Corresponding Author)
Department of Statistics, Faculty of Science and Letter, Ondokuz Mayıs University, Samsun, Turkey

robustly in Turkey about their socioeconomic development [20]. Also, Alpaykut investigated the well-being of cities in Turkey by using classical PCA, which is sensitive to outliers, and TOPSIS methods [21].

It is well known that the economic and cultural features of countries may affect environmental factors. For example, companies may call in their top model cars because of unsuitable emissions in a developed country, while old vehicles may be on the roads by polluting the environment in an undeveloped country. Because of similar reasons, when countries' environmental performance is evaluated, it should not forget that the data sets consist of countries having different development levels. This case may cause the data set to include outliers. Hence, a robust approach is needed to obtain a composite index from like data.

This study purposes construction of a composite index, which is not sensitive to outliers, to evaluate countries' environmental performance. For this purpose, we use the ROBPCA method, which is a robust principal component analysis algorithm, and the TOPSIS algorithm, which is a multi-criteria decision method. In this way, we have robustly constructed a composite index measuring the environmental performances of countries and sort countries according to these values.

The remainder of the paper is organized as follows. The principal component analysis and TOPSIS methods are introduced in Section 2. In Section 3, a robust alternative to the EPI is constructed called the robust EPI (REPI). The REPI values of countries are obtained, and the countries are ordered according to these values. Finally, we conclude from the obtained results in the last section.

2. Materials and methods

In this section, we introduce the principal component analysis and TOPSIS methods used to construct a composite index called robust environmental performance index.

2.1. Principal Component Analysis

The principal component analysis is one of the most popular multivariate statistical methods. The PCA aims to obtain the new variables, which are the linear combinations of variables that are correlated with each other, and components number is less than the number of the original variables (p). These new variables are called principal components. However, it is well known that classical PCA is sensitive to outliers [20]. A robust principal component analysis method called ROBPCA was developed [22].

The ROBPCA algorithm consists of three stages which are given below.

- **Stage 1:** The data is reduced to space that has maximum $(n-1)$ dimension using the projection pursuit approach.
- **Stage 2:** The initial covariance matrix Σ_0 is obtained, and q, which is the number of important components, is determined.
- **Stage 3:** The data points are projected on this subspace where their location and scatter matrix are robustly estimated, from which its k nonzero eigenvalues $\lambda_1, \lambda_2, \dots, \lambda_q$ are computed. The corresponding eigenvectors are the q robust principal components [20,22]

Principal component scores are obtained from (1):

$$T_{n,q} = \left(X_{n,p} - 1_n\, \widehat{\mu}^T\right) P_{p,q} \tag{1}$$

where $X: n \times p$ is data matrix, n is observation number, p is the variable number, $P: p \times q$ is eigenvectors matrix, $\widehat{\mu}$ which is called a robust location estimation is a column vector with p-dimension 1_n is the column vector with all n components equal to 1, and $(.)^T$ is the transpose operator. The robust scatter matrix is also calculated using spectral demonstration, as below

$$\Sigma_{p,p} = P_{p,q} L_{q,q} P'_{q,p} \tag{2}$$

where $L_{q,q}$ is eigenvalues matrix [22].

An essential advantage of the ROBPCA algorithm is that it detects outliers by calculating orthogonal and score distances and using critical values for these distances. The critical value of score distance is $\sqrt{\chi^2_{q,0.975}}$ and the critical value of the orthogonal distance is $(\hat{\mu} + \hat{\sigma} Z_{0.975})^2$, where g_1 and g_2 are unknown parameters, $\hat{\mu} = (g_1 g_2)^{\frac{1}{3}}\left(1 - \frac{2}{9g_2}\right)$ and $\hat{\sigma}^2 = \frac{2g_1^{\frac{2}{3}}}{9g_2^{\frac{1}{3}}}$. Score and orthogonal distances are calculated as below, respectively:

$$SD_i = \sqrt{\sum_{j=1}^{q} \frac{t_{ij}^2}{\lambda_j}}\ , (i = 1,2, \dots, n) \tag{3}$$

$$OD_i = \left\| x_i - \hat{\mu} - P_{p,q} t_i' \right\|\ , (i = 1,2, \dots, n) \tag{4}$$

where t_{ij} is a member in i_{th} row and j_{th} column of $T_{n,q}$ matrix, which is defined in (1). t_i is also i_{th} row vector of $T_{n,q}$ matrix [22].

In this study, "rrcov" package in the R programming language has been used for calculations regarding the ROBPCA algorithm [23].

2.2. The technique for Order Preferences by Similarity to an Ideal Solution (TOPSIS)

Hwang and Yoon [24] suggested the TOPSIS method. In the TOPSIS method, the aim is to select the best solution between different alternatives. The main idea of the TOPSIS method is based on the selection of a solution, which is the nearest to the positive ideal solution and is the farthest to the negative ideal solution. Thus, the TOPSIS method obtains the best sorting [21].

In the TOPSIS method, one needs a decision matrix and a weights vector. Criteria are in rows of the decision matrix, and alternative values are in columns of the decision matrix. Weight vector consists of weights of alternative solutions.

In this study, "topsis" package in the R programming language has been used for calculations regarding the TOPSIS algorithm [25].

3. Construction of Robust Environmental Performance Index

This study uses the data set consisted of the values of 180 countries' 24 environmental indicators. These indicators are given in Table 1. We have downloaded the data set from web site EPI 2018 [26].

Table 1. The environmental indicators used in this study

Indicator	Code	Indicator	Code
Household Solid Fuels	HAD	Marine Protected Areas	MPA
$PM_{2.5}$ Exposure	PME	Biome Protection (National)	TBN
$PM_{2.5}$ Exceedance	PMW	Biome Protection (Global)	TBG
Drinking-Water	UWD	Species Protection Index	SPI
Sanitation	USD	Representativeness Index	PAR
Lead Exposure	PBD	Species Habitat Index	SHI
Tree Cover Loss	TCL	Methane Emissions	DMT
Fish Stock Status	FSS	N_2O Emissions	DNT
Regional Marine Trophic Index	MTR	Black Carbon Emissions	DBT
CO_2 Emissions – Total	DCT	SO_2 Emissions	DST
CO_2 Emissions – Power	DPT	NO_X Emissions	DXT
Sustainable Nitrogen Management	SNM	Wastewater Treatment	WWT

Firstly, we investigate whether the data set has outliers by using both classical Mahalanobis distances and the ROBPCA algorithm. While we cannot determine outliers in the classical approach, we determine outliers in the data set via the ROBPCA algorithm. Because classical Mahalanobis distances are based on classical mean vector and sample covariance matrix, which are sensitive to outliers, they may fail to determine outliers. In the robust literature, this case is called masking. The results of outlier detection are given in Table A in the Appendix.

Moreover, we investigate the relationship between 24 environmental indicators and give the graph of the obtained correlation matrix in Figure A in the Appendix. The X icon of this graph means that the relationship is statistically unimportant. According to the graphic, we decide to use PCA for dimension reduction because there are many statistically important correlations.

Table 2. The proportion of explained variance

Method	**Values**	PC_1	PC_2	PC_3	PC_4	PC_5	PC_6	PC_7	PC_8
	Standard deviation	73.27	55.87	52.17	35.90	33.31	29.13	25.86	24.87
CPCA	Proportion of Variance	0.28	0.16	0.14	0.07	0.06	0.04	0.03	0.03
	Cumulative Proportion	0.275	0.436	0.575	0.641	0.698	0.742	0.776	**0.808**
	Standard deviation	79.59	57.43	56.32	35.42	31.37	26.23	24.48	22.92
ROBPCA	Proportion of Variance	0.36	0.19	0.18	0.07	0.06	0.04	0.03	0.03
	Cumulative Proportion	0.358	0.545	0.724	0.795	**0.851**	0.890	0.924	0.953

Also, we decide to use robust principal component analysis because the data set has outliers. Table 2 gives the explained variance's proportions obtained from classical PCA (CPCA) and robust PCA (ROBPCA). According to Table 2, 8 components explain 80.8% of the variance in CPCA, while only 5 components explain 85.1% of the variance in ROBPCA. Therefore, we use the scores obtained from the ROBPCA, which the number of important components is 5.

To obtain only a composite index by basing five principal components, we use the TOPSIS method. In the TOPSIS method, we take countries as criteria and the important components as alternative values. We also take the marginal proportions of explained variance as weights for each alternative. Therefore, the first principal component, which explains the biggest proportion of variance, has the biggest weight on the composite index. In this way, the obtained composite index is called the Robust Environmental Performance Index (REPI) because it is not sensitive to outliers. The EPI and the REPI values and the ranks of countries according to these values are given in Table 3. We show these values of indexes on the world map in Figure 1.

According to Table 3, there are dramatic differences in the results of the REPI and the EPI. The performance rankings of some countries (Armenia, Azerbaijan, Bolivia, Hungary, Czech Republic, Turkmenistan, Makedonia, etc.) decrease, while the performance rankings of other countries (Bahrain, Bangladesh, Chile, China, Malaysia, Maldives, etc.) increase. We detect an essential difference for top countries. Accordingly, the rank of Malta is 1 instead of 4, the rank of Israel is 2 instead of 19, the rank of Sweden is 3 instead of 5, the rank of Finland is 4 instead of 10, the rank of Holland is 5 instead of 18, the rank of South Korea is 6 instead of 60, the rank of Singapore is 7 instead of 49, and the rank of Japan is 8 instea of 20. On the contrary, the rank of Switzerland decreases from 1 to 52, the rank of France decreases from 2 to 10, the rank of Denmark decreases from 3 to 17, the rank of Luxembourg decreases from 7 to 69 and the rank of United Kingdom decreases from 6 to 12.

Table 3. The Index Values and Ranking of Countries According to EPI2018 and REPI

Country	EPI 2018		REPI		Country	EPI 2018		REPI	
	Value	Rank	Value	Ran		Value	Ran	Value	Ran
Afghanistan	37.74	168	31.46	161	Djibouti	40.04	163	40.05	136
Albania	65.46	40	62.83	34	Dominica	59.38	73	49.01	98
Algeria	57.18	88	51.49	88	Dominican Republic	64.71	46	60.23	46
Angola	37.44	170	37.27	146	Ecuador	57.42	87	53.47	75
Antigua and Barbuda	59.18	76	55.08	67	Egypt	61.21	66	55.77	61
Argentina	59.3	74	60.03	48	El Salvador	53.91	106	43.58	118
Armenia	62.07	63	43.07	123	Equatorial Guinea	60.4	71	54.62	70
Australia	74.12	21	67.89	19	Eritrea	39.34	165	35.34	153
Austria	78.97	8	54.89	68	Estonia	64.31	48	61.41	41
Azerbaijan	62.33	59	44.04	115	Ethiopia	44.78	141	21.88	175
Bahamas	54.99	98	52.36	81	Fiji	53.09	107	49.77	93
Bahrain	55.15	96	63.54	29	Finland	78.64	10	71.26	4
Bangladesh	29.56	179	43.44	121	France	83.95	2	70.12	10
Barbados	55.76	93	53.09	78	Gabon	45.05	140	42.36	126
Belarus	64.98	44	48.58	101	The Gambia	42.42	156	37.14	147
Belgium	77.38	15	68.68	15	Georgia	55.69	94	53.22	77
Belize	57.79	81	50.71	90	Germany	78.37	13	68.89	14
Benin	38.17	167	30.50	162	Ghana	49.66	124	46.60	111
Bhutan	47.22	131	30.42	164	Greece	73.6	22	64.21	26
Bolivia	55.98	92	35.66	152	Grenada	50.93	118	48.05	102
Bosnia and Herzegovina	41.84	158	34.23	155	Guatemala	52.33	110	51.51	86
Botswana	51.7	113	32.82	156	Guinea	46.62	134	38.58	140
Brazil	60.7	69	58.08	55	Guinea-Bissau	44.67	143	36.48	149
Brunei Darussalam	63.57	53	61.78	39	Guyana	47.93	128	38.52	141
Bulgaria	67.85	30	59.87	49	Haiti	33.74	174	35.17	154
Burkina Faso	42.83	154	20.97	176	Honduras	51.51	114	48.60	100
Burundi	27.43	180	19.91	178	Hungary	65.01	43	46.84	110
Cabo Verde	56.94	89	47.64	107	Iceland	78.57	11	66.54	22
Côte d’Ivoire	45.25	139	42.52	125	India	30.57	177	43.65	117
Cambodia	43.23	150	43.45	120	Indonesia	46.92	133	49.08	97
Cameroon	40.81	161	31.50	160	Iran	58.16	80	52.62	80
Canada	72.18	25	62.99	32	Iraq	43.2	152	36.11	150
The central African	36.42	171	17.29	180	Ireland	78.77	9	69.63	11
Chad	45.34	137	23.55	171	Israel	75.01	19	73.86	2
Chile	57.49	84	61.92	37	Italy	76.96	16	67.06	21
China	50.74	120	61.79	38	Jamaica	58.58	78	48.98	99
Colombia	65.22	42	63.28	30	Japan	74.69	20	70.14	8
Comoros	44.24	146	38.16	143	Jordan	62.2	62	49.54	95
Costa Rica	67.85	31	57.47	57	Kazakhstan	54.56	101	40.65	132
Croatia	65.45	41	59.02	53	Kenya	47.25	130	40.37	134
Cuba	63.42	55	61.24	42	Kiribati	55.26	95	49.37	96
Cyprus	72.6	24	66.45	24	Kuwait	62.28	61	64.25	25
Czech Republic	67.68	33	47.79	104	Kyrgyzstan	54.86	99	32.61	157
Dem. Rep. Congo	30.41	178	20.35	177	Laos	42.94	153	30.20	166
Denmark	81.6	3	68.32	17	Latvia	66.12	37	59.67	50
Lebanon	61.08	67	60.47	44	São Tomé and Príncipe	54.01	104	44.69	114
Lesotho	33.78	173	29.86	167	Saint Lucia	56.18	91	51.80	85
Liberia	41.62	160	40.06	135	Saint Vincent and the	66.48	36	55.33	63
Libya	49.79	123	46.55	112	Samoa	54.5	102	49.74	94
Lithuania	69.33	29	63.64	28	Saudi Arabia	57.47	86	61.44	40
Luxembourg	79.12	7	54.85	69	Senegal	49.52	126	43.21	122
Macedonia	61.06	68	41.56	129	Serbia	57.49	85	41.36	130
Madagascar	33.73	175	39.23	137	Seychelles	66.02	39	52.21	83
Malawi	49.21	127	22.76	172	Sierra Leone	42.54	155	37.50	145
Malaysia	59.22	75	64.12	27	Singapore	64.23	49	70.22	7
Maldives	52.14	111	55.57	62	Slovakia	70.6	28	51.88	84
Mali	43.71	147	22.22	173	Slovenia	67.57	34	47.03	109

Table 3. (Continued) The Index Values and Ranking of Countries According to EPI2018 and REPI

Country	EPI 2018		REPI		Country	EPI 2018		REPI	
	Values	**Rank**	**Values**	**Rank**		**Values**	**Rank**	**Values**	**Rank**
Malta	80.9	4	74.24	1	Solomon Islands	43.22	151	41.61	128
Mauritania	39.24	166	40.77	131	South Africa	44.73	142	50.35	91
Mauritius	56.63	90	52.33	82	South Korea	62.3	60	71.05	6
Mexico	59.69	72	56.71	59	Spain	78.39	12	66.52	23
Micronesia	49.8	122	47.49	108	Sri Lanka	60.61	70	52.64	79
Moldova	51.97	112	42.64	124	Sudan	51.49	115	47.77	105
Mongolia	57.51	83	38.09	144	Suriname	54.2	103	50.92	89
Montenegro	61.33	65	54.14	73	Swaziland	40.32	162	30.22	165
Morocco	63.47	54	55.78	60	Sweden	80.51	5	72.45	3
Mozambique	46.37	135	39.16	138	Switzerland	87.42	1	59.11	52
Myanmar	45.32	138	47.66	106	Taiwan	72.84	23	67.81	20
Namibia	58.46	79	49.94	92	Tajikistan	47.85	129	31.70	159
Nepal	31.44	176	22.16	174	Tanzania	50.83	119	43.46	119
Netherlands	75.46	18	71.23	5	Thailand	49.88	121	55.21	65
New Zealand	75.96	17	67.92	18	Timor-Leste	49.54	125	43.84	116
Nicaragua	55.04	97	51.49	87	Togo	41.78	159	31.78	158
Niger	35.74	172	19.09	179	Tonga	62.49	57	54.59	71
Nigeria	54.76	100	45.45	113	Trinidad and Tobago	67.36	35	59.53	51
Norway	77.49	14	68.60	16	Tunisia	62.35	58	61.23	43
Oman	51.32	116	54.41	72	Turkey	52.96	108	53.94	74
Pakistan	37.5	169	38.94	139	Turkmenistan	66.1	38	48.00	103
Panama	62.71	56	58.57	54	Uganda	44.28	145	24.77	170
Papua New Guinea	39.35	164	36.94	148	Ukraine	52.87	109	56.99	58
Paraguay	53.93	105	36.04	151	United Arab Emirates	58.9	77	63.07	31
Peru	61.92	64	60.35	45	United Kingdom	79.89	6	69.37	12
Philippines	57.65	82	55.32	64	United States of America	71.19	27	68.92	13
Poland	64.11	50	60.10	47	Uruguay	64.65	47	62.15	36
Portugal	71.91	26	62.86	33	Uzbekistan	45.88	136	38.42	142
Qatar	67.8	32	70.13	9	Vanuatu	44.55	144	41.69	127
Republic of Congo	42.39	157	40.45	133	Venezuela	63.89	51	55.21	66
Romania	64.78	45	57.82	56	Viet Nam	46.96	132	53.24	76
Russia	63.79	52	62.32	35	Zambia	50.97	117	30.48	163
Rwanda	43.68	148	25.42	168	Zimbabwe	43.41	149	25.04	169

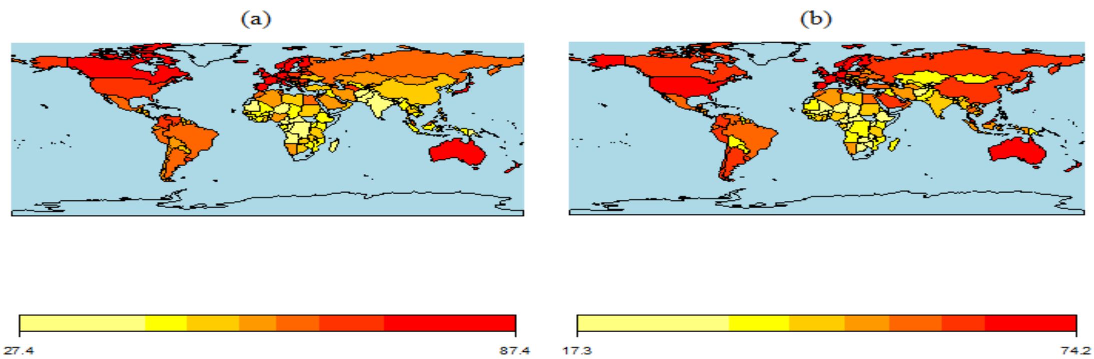

Fig. 1. The world maps according to environmental performance indexes (a) EPI2018 (b) REPI

These results based on the REPI are more confidential than those based on the EPI because the REPI is not sensitive to outliers in the data set. Moreover, it is seen that African countries have poorer environmental performances than American and European countries, according to both the EPI and the REPI, when maps given in Figure 1 are investigated.

4. Conclusion

This study aims to construct a robust composite index, an alternative to the EPI. For this aim, firstly, we have investigated whether the data set has outliers or not and decided the data set has outliers. Therefore, we used the ROBPCA algorithm, a robust principal component analysis, for dimension reduction and obtained five important principal components scores for each country. We have used the TOPSIS method to construct a composite index from five principal components scores. Finally, we have obtained the REPI values, which are not sensitive to outliers in the data set, for each country and have ranked countries according to these index values. When they are compared with the EPI results, the REPI results have dramatic differences. The reason for these differences is the impact of outliers in data sets. Therefore, we suggest using methods that are not sensitive to outliers when constructing a composite index.

Author Contributions

The author read and approved the last version of the manuscript.

Conflict of Interest

The author declares no conflict of interest.

References

[1] E. P. Index, *Environmental Performance Index*, Yale University and Columbia University: NewHaven, CT, USA.

[2] P. A. Stanwick, S. D. Stanwick, *The Relationship between Corporate Social Performance, and Organizational Size, Financial Performance, and Environmental Performance: An Empirical Examination*, Journal of Business Ethics 17(2) (1998) 195–204.

[3] D. M. Patten, *The Relation between Environmental Performance and Environmental Disclosure: A Research Note*, Accounting, Organizations and Society 27(8) (2002) 763–773.

[4] S. A. Al-Tuwaijri, T. E. Christensen, K. E. Hughes, *The Relations among Environmental Disclosure, Environmental Performance, and Economic Performance: A Simultaneous Equations Approach*, Accounting, Organizations and Society 29(5-6) (2004) 447–471.

[5] P. M. Clarkson, Y. Li, G. D. Richardson, F. P. Vasvari, *Revisiting the Relation between Environmental Performance and Environmental Disclosure: An Empirical Analysis*, Accounting, Organizations and Society 33(4-5) (2008) 303–327.

[6] J. Wen, Y. Hao, G.-F. Feng, C.-P. Chang, *Does Government Ideology Influence Environmentalperformance? Evidence Based on a New Dataset*, Economic Systems 40(2) (2016) 232–246.

[7] G. Halkos, A. Zisiadou, *Relating Environmental Performance with Socioeconomic and Culturalfactors*, Environmental Economics and Policy Studies 20(1) (2018) 69–88.

[8] R. F¨are, S. Grosskopf, F. Hernandez-Sancho, *Environmental Performance: An Index Number Approach*, Resource and Energy Economics 26(4) (2004) 343–352.

[9] P. Zhou, B. Ang, K. Poh, *Slacks-based Efficiency Measures for Modeling Environmental Performance*, Ecological Economics 60(1) (2006) 111–118.

[10] P. Zhou, K. L. Poh, B. W. Ang, *A Non-Radial DEA Approach to Measuring Environmental Performance*, European Journal of Operational Research 178(1) (2007) 1–9.

[11] M. Kortelainen, *Dynamic Environmental Performance Analysis: A Malmquist Index Approach*, Ecological Economics 64(4) (2008) 701–715.

[12] P. Zhou, B. W. Ang, K. L. Poh, *Measuring Environmental Performance under Different Environmental DEA Technologies*, Energy Economics 30(1) (2008) 1–14.

[13] W. Liu, J. Tian, L. Chen, W. Lu, Y. Gao, *Environmental Performance Analysis of Eco-Industrial Parks in China: A Data Envelopment Analysis Approach*, Journal of Industrial Ecology 19(6) (2015) 1070–1081.

[14] J. R. C.-E. Commission, et al., *Handbook on Constructing Composite Indicators: Methodology and User Quide*, OECD Publishing, 2008.

[15] R. Ram, *Composite Indices of Physical Quality of Life, Basic Needs Fulfilment, and Income: A 'Principal Component' Representation*, Journal of Development Economics 11(2) (1982) 227–247.

[16] D. J. Slottje, *Measuring the Quality of Life Across Countries*, The Review of Economics and Statistics (1991) 684–693.

[17] B. Biswas, F. Caliendo, *A Multivariate Analysis of the Human Development Index*, Economics Research Institute Study Paper 11 (2002) 1.

[18] D. Lai, *Principal Component Analysis on Human Development Indicators of China*, Social Indicatorsresearch 61(3) (2003) 319–330.

[19] K. M. Wong, *Well-being and Economic Development: A Principal Components Analysis*, International Journal of Happiness and Development 1(2) (2013) 131–141.

[20] H. Bulut, Y. Öner, *The Evaluation of Socioeconomic Development of Development Agency Regions in Turkey using Classical and Robust Principal Component Analyses*, Journal of Applied Statistics 44(16) (2017) 2936–2948.

[21] S. Alpaykut, *A Study for Analysing Well-Being for Provinces in Turkey by Using Principal Component Analysis and TOPSIS*, Journal of Suleyman Demirel University Institute of Social Sciences 29(4) (2017) 367–395.

[22] M. Hubert, P. J. Rousseeuw, K. Vanden Branden, *ROBPCA: A New Approach to robust principal component analysis*, Technometrics 47(1) (2005) 64–79.

[23] V. Todorov, P. Filzmoser, *An Object-Oriented Framework for Robust Multivariate Analysis*, Journal of Statistical Software 32(1) (2009) 1–47.

[24] C.-L. Hwang, K. Yoon, *Methods for Multiple Attribute Decision Making, in: Multiple Attribute Decision Making*, Springer (1981) 58–191.

[25] B. A. C. Martin, *MCDM: Multi-Criteria Decision Making Methods for Crisp Data*, r package version 1.2 (2016) .URL https://CRAN.R-project.org/package=MCDM

[26] Y. University, *Environmental Performance Index* (2018) .URL:https://epi.yale.edu

Appendix

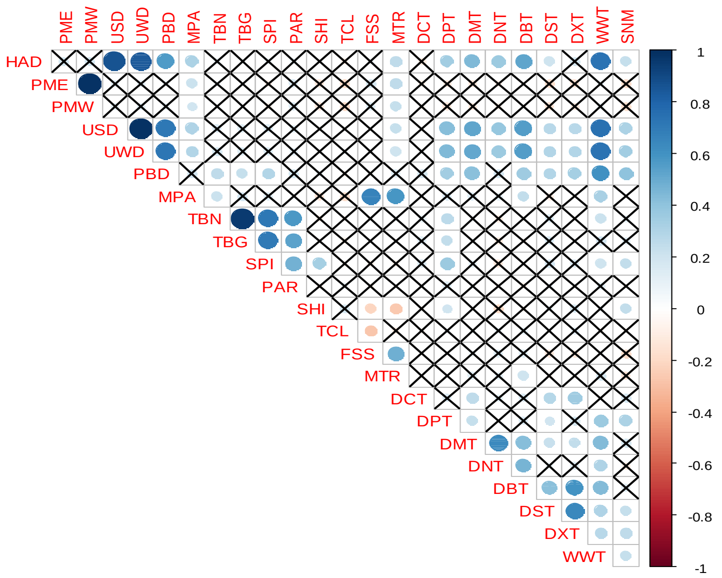

Fig. A. Correlation matrix for environmental indicators

Table A. Outlier Detection

Country	Mah_C	SD	OD	Decision	Country	Mah_C	SD	OD	Decision
Afghanistan	37.14	4.84	82.58	FALSE	Djibouti	14.00	2.54	45.46	TRUE
Albania	31.39	2.56	76.74	TRUE	Dominica	23.77	2.55	111.72	FALSE
Algeria	28.21	3.10	67.56	TRUE	Dominican Republic	15.97	2.19	46.18	TRUE
Angola	16.41	3.00	46.30	TRUE	Ecuador	21.97	2.58	50.36	TRUE
Antigua and Barbuda	34.28	3.03	116.98	FALSE	Egypt	42.66	3.35	66.42	TRUE
Argentina	29.78	2.30	64.39	TRUE	El Salvador	21.67	2.88	61.76	TRUE
Armenia	29.15	2.63	71.40	TRUE	Equatorial Guinea	21.17	3.89	29.69	TRUE
Australia	18.79	3.26	37.74	TRUE	Eritrea	32.78	4.70	52.54	FALSE
Austria	21.72	2.96	47.66	TRUE	Estonia	13.61	2.42	40.73	TRUE
Azerbaijan	38.94	3.88	63.17	TRUE	Ethiopia	22.20	4.49	37.21	TRUE
Bahamas	23.19	3.84	45.33	TRUE	Fiji	19.64	2.14	58.48	TRUE
Bahrain	31.74	4.37	64.33	TRUE	Finland	17.35	2.46	50.94	TRUE
Bangladesh	67.70	5.74	79.49	FALSE	France	17.38	2.71	39.51	TRUE
Barbados	30.74	3.52	93.33	FALSE	Gabon	31.01	3.27	52.13	TRUE
Belarus	13.16	2.18	32.26	TRUE	Gambia	15.03	2.38	40.92	TRUE
Belgium	19.76	1.86	48.80	TRUE	Georgia	34.73	4.27	60.79	TRUE
Belize	16.34	2.55	57.53	TRUE	Germany	16.39	2.48	45.88	TRUE
Benin	16.56	2.63	51.72	TRUE	Ghana	9.53	1.82	37.38	TRUE
Bhutan	22.49	4.07	44.86	TRUE	Greece	23.74	3.08	44.66	TRUE
Bolivia	16.00	2.46	35.63	TRUE	Grenada	29.50	2.51	113.88	FALSE
Bosnia and Herzegovina	31.18	3.24	84.71	FALSE	Guatemala	28.83	2.96	58.94	TRUE
Botswana	20.72	3.43	38.51	TRUE	Guinea	18.98	3.12	39.70	TRUE
Brazil	31.14	2.82	49.21	TRUE	Guinea-Bissau	15.60	2.91	34.90	TRUE
Brunei Darussalam	49.77	3.27	109.83	FALSE	Guyana	26.52	2.39	88.64	FALSE
Bulgaria	22.03	2.10	49.47	TRUE	Haiti	27.84	3.24	52.89	TRUE
Burkina Faso	13.05	2.86	28.12	TRUE	Honduras	17.65	2.50	41.55	TRUE
Burundi	12.82	2.86	31.44	TRUE	Hungary	19.46	2.82	37.60	TRUE
Cabo Verde	18.89	3.70	35.28	TRUE	Iceland	33.92	2.75	81.39	FALSE
Côte d'Ivoire	17.71	2.20	56.14	TRUE	India	28.61	5.67	30.80	FALSE
Cambodia	21.54	2.89	41.71	TRUE	Indonesia	8.35	2.38	22.62	TRUE
Cameroon	25.38	4.04	39.14	TRUE	Iran	36.01	4.35	62.79	TRUE
Canada	14.87	3.27	32.86	TRUE	Iraq	31.83	3.09	46.05	TRUE
Central African Republic	16.02	3.16	26.76	TRUE	Ireland	21.01	2.83	45.92	TRUE
Chad	28.70	3.34	57.87	TRUE	Israel	30.45	2.75	55.63	TRUE
Chile	32.27	5.22	43.99	FALSE	Italy	14.75	2.31	36.99	TRUE
China	12.21	2.84	28.80	TRUE	Jamaica	21.99	1.85	56.78	TRUE
Colombia	10.73	1.53	36.14	TRUE	Japan	23.19	3.54	36.47	TRUE
Comoros	25.72	2.78	49.65	TRUE	Jordan	31.61	3.23	65.28	TRUE
Costa Rica	14.34	2.38	43.09	TRUE	Kazakhstan	33.83	2.96	65.89	TRUE
Croatia	20.06	2.64	45.38	TRUE	Kenya	17.69	2.26	40.71	TRUE
Cuba	15.07	2.41	51.40	TRUE	Kiribati	29.31	3.11	103.39	FALSE
Cyprus	27.11	2.86	57.96	TRUE	Kuwait	34.25	2.94	89.96	FALSE
Czech Republic	19.39	2.85	37.06	TRUE	Kyrgyzstan	30.46	3.88	61.15	TRUE
Dem. Rep. Congo	28.54	5.11	51.21	FALSE	Laos	28.66	5.02	29.13	FALSE
Denmark	16.64	2.21	46.20	TRUE	Latvia	14.64	2.67	40.76	TRUE
Critical Values	39.36	4.53	77.28			39.36	4.53	77.28	

Table A. Outlier Detection (Continue)

Country	Mah_C	SD	OD	Decision	Country	Mah_C	SD	OD	Decision
Lebanon	26.37	3.72	46.77	TRUE	São Tomé and Príncipe	28.93	2.12	117.10	FALSE
Lesotho	17.64	2.98	38.86	TRUE	Saint Lucia	43.98	3.52	135.91	FALSE
Liberia	22.94	2.67	55.91	TRUE	Saint Vincent and the Grenadines	18.44	2.71	40.96	TRUE
Libya	31.52	4.99	41.92	FALSE	Samoa	25.84	2.92	94.54	FALSE
Lithuania	15.54	1.43	49.76	TRUE	Saudi Arabia	15.70	2.83	49.83	TRUE
Luxembourg	26.27	3.52	46.70	TRUE	Senegal	8.55	2.34	26.51	TRUE
Macedonia	18.12	2.10	46.99	TRUE	Serbia	15.64	2.11	46.85	TRUE
Madagascar	33.00	3.16	60.31	TRUE	Seychelles	41.32	3.70	101.34	FALSE
Malawi	13.56	2.65	36.08	TRUE	Sierra Leone	22.62	2.60	39.06	TRUE
Malaysia	28.60	3.35	59.82	TRUE	Singapore	48.81	5.70	79.33	FALSE
Maldives	21.10	3.59	35.72	TRUE	Slovakia	22.53	2.91	43.10	TRUE
Mali	20.18	3.05	34.34	TRUE	Slovenia	15.98	2.45	32.93	TRUE
Malta	32.86	3.80	92.14	FALSE	Solomon Islands	15.89	2.78	38.75	TRUE
Mauritania	23.90	3.17	51.35	TRUE	South Africa	18.17	3.41	43.32	TRUE
Mauritius	20.15	1.88	47.33	TRUE	South Korea	32.02	3.99	61.69	TRUE
Mexico	11.16	1.63	48.37	TRUE	Spain	15.45	2.17	41.29	TRUE
Micronesia	43.49	4.89	105.69	FALSE	Sri Lanka	17.57	2.94	48.24	TRUE
Moldova	9.65	2.61	23.11	TRUE	Sudan	36.42	6.47	41.20	FALSE
Mongolia	26.61	2.46	48.52	TRUE	Suriname	29.89	2.90	88.79	FALSE
Montenegro	31.79	2.01	61.92	TRUE	Swaziland	19.40	2.68	53.63	TRUE
Morocco	17.21	2.48	42.77	TRUE	Sweden	17.03	2.58	48.08	TRUE
Mozambique	16.42	2.87	36.38	TRUE	Switzerland	27.22	4.03	34.05	TRUE
Myanmar	29.86	4.57	31.48	FALSE	Taiwan	21.27	3.21	40.95	TRUE
Namibia	27.95	3.47	57.82	TRUE	Tajikistan	29.09	5.36	37.50	FALSE
Nepal	47.19	5.75	46.73	FALSE	Tanzania	17.30	2.71	33.99	TRUE
Netherlands	17.13	2.65	47.59	TRUE	Thailand	37.07	3.49	40.67	TRUE
New Zealand	11.06	2.10	38.00	TRUE	Timor-Leste	13.35	2.68	37.02	TRUE
Nicaragua	24.34	3.84	40.99	TRUE	Togo	30.06	4.08	72.13	TRUE
Niger	18.44	3.23	47.25	TRUE	Tonga	35.89	3.99	105.62	FALSE
Nigeria	17.93	3.31	28.50	TRUE	Trinidad and Tobago	28.69	2.80	59.20	TRUE
Norway	18.24	3.18	41.76	TRUE	Tunisia	20.85	2.62	46.97	TRUE
Oman	29.00	3.98	58.47	TRUE	Turkey	16.85	3.14	45.37	TRUE
Pakistan	31.09	6.07	37.91	FALSE	Turkmenistan	33.01	3.22	60.17	TRUE
Panama	13.20	2.78	27.65	TRUE	Uganda	10.67	2.67	17.03	TRUE
Papua New Guinea	20.58	2.76	55.59	TRUE	Ukraine	20.87	2.81	47.67	TRUE
Paraguay	31.18	4.66	43.90	FALSE	United Arab Emirates	41.79	2.24	100.27	FALSE
Peru	15.63	2.66	30.39	TRUE	United Kingdom	18.76	3.07	45.88	TRUE
Philippines	19.86	1.95	44.49	TRUE	United States of America	31.40	2.39	40.21	TRUE
Poland	22.87	2.54	57.67	TRUE	Uruguay	38.47	3.59	87.97	FALSE
Portugal	30.64	2.13	60.00	TRUE	Uzbekistan	29.48	4.94	48.61	FALSE
Qatar	20.21	3.10	51.45	TRUE	Vanuatu	18.73	2.99	57.38	TRUE
Republic of Congo	26.25	3.89	45.24	TRUE	Venezuela	23.42	3.75	49.59	TRUE
Romania	12.15	1.82	43.08	TRUE	Viet Nam	18.87	3.33	40.50	TRUE
Russia	13.55	2.17	30.24	TRUE	Zambia	17.62	2.76	50.04	TRUE
Rwanda	19.20	2.59	39.96	TRUE	Zimbabwe	20.56	3.46	38.00	TRUE
	39.36	4.53	77.28			39.36	4.53	77.28	