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Arianna Agosto
(Università degli Studi di Pavia)

Alessandro Bitetto
(Carlo Cattaneo University - LIUC, Italy)

Paola Cerchiello
(Università degli Studi di Pavia)

Yana Kostiuk
(IUSS - School for Advanced Studies Pavia, Italy)

Alessandra Tanda
(Università degli Studi di Pavia)

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Via San Felice, 5
I-27100 Pavia

https://economiaemanagement.dip.unipv.it/it

How to measure environmental performance: a new data-driven index

Arianna Agosto[a], Alessandro Bitetto[b,*], Paola Cerchiello[a], Yana Kostiuk[c], Alessandra Tanda[a]

[a] *University of Pavia, Italy*
[b] *Carlo Cattaneo University - LIUC, Italy*
[c] *IUSS - School for Advanced Studies Pavia, Italy*

Abstract

In this paper, we propose a new, entirely data-driven, and time-consistent index of environmental performance that relies on a reliable statistical technique to objectively assess environmental sustainability. While most indices depend on expert-based or equally distributed weights, the proposed index — the Data-Driven Environmental Performance Index (DDEPI) — is built on empirical data, focusing on variables that account for the largest share of variance in the data over time. To construct the proposed index, we apply a dimensionality reduction technique, such as Robust Principal Component Analysis (Robust PCA), which captures the relationship between variables and countries for each year. The DDEPI is primarily driven by indicators related to air quality, drinking water quality, and biodiversity. An analysis of the causal relationships between the proposed index and country-specific dimensions highlights the critical role of institutional quality and natural

*Corresponding author

Email addresses: arianna.agosto@unipv.it (Arianna Agosto), abitetto@liuc.it (Alessandro Bitetto), paola.cerchiello@unipv.it (Paola Cerchiello), yana.kostiuk@iusspavia.it (Yana Kostiuk), alessandra.tanda@unipv.it (Alessandra Tanda)

resource management in achieving sustainability goals.
Keywords: Environmental Performance, Sustainability Index, Data-Driven, Policy Planning, Country Ranking, Robust Statistics

1. Introduction

In the face of growing environmental concerns, geopolitical tensions, economic challenges, and social inequalities, sustainable development has become increasingly significant for nations worldwide. While there are numerous conceptualizations of sustainable development in the literature, the most commonly accepted and widespread is based on the 'three pillars' concept: environmental, economic, and social sustainability (Purvis et al., 2019). Traditional metrics such as Gross Domestic Product (GDP) have long been used to gauge the economic strength of a country, but they fail to account for the environmental dimension that is critical to the well-being of both current and future generations. Indeed, as stated by Liberatore (1997), long-term sustainable development can not be achieved without integrating environmental factors in the formulation and implementation of economic policies. The importance of a well-constructed environmental measure became especially evident with the adoption of frameworks like the United Nations' Sustainable Development Goals (SDGs) and international climate agreements such as the Paris Agreement, which challenges nations to take decisive action in reducing greenhouse gas emissions and capping global temperature rise to well below 2°C above pre-industrial levels. These frameworks demand that countries not only focus on economic growth, but also prioritize environmental protection and social equity.

Composite indices are widely used tools for providing clear, measurable means of assessing and demonstrating environmental sustainability. They play an important role for policymakers and national governments in evaluating implemented policies and progress toward defined goals. Moreover, they may be useful in decision-making and encouraging public engagement and awareness (Cook et al., 2017). However, the development of a consistent methodology faces several challenges, including data availability and accuracy, variable selection, and the choice of aggregation and weighting methods (Giannetti et al., 2009). The sensitivity of the composite index to the chosen weighting method can result in varying outcomes, potentially undermining the indicator's accuracy and comparability (Foster et al., 2013; Greco et al., 2019).

Data-driven approaches provide potential solutions to the aforementioned issues encountered when creating an explainable index for assessing the environmental performance of countries. These approaches are similar to the epidemiologic preparedness index introduced by Bitetto et al. (2021) and the financial soundness index outlined by Bitetto et al. (2023). One key advantage of data-driven approaches is their ability to integrate and analyze multi-dimensional datasets, capturing the intricate relationships between different environmental variables. For example, machine learning algorithms can process large volumes of climate data to predict future environmental conditions with greater accuracy, helping policymakers make informed decisions (Li and Huang, 2023). Additionally, these methods are particularly adept at handling unbalanced datasets and missing information, a common challenge in environmental data collection. Moreover, data-driven methods do not rely on predefined modelling assumptions, allowing for more flexibility. Finally, when it comes to assigning weights to the selected indicators, the data-driven methods are not biased by the subjective nature of judgments, as in the case of the opinion-based models. Given their robustness, data-driven models are widely utilized in environmental data science, not only for the development of composite indexes but also for applications such as addressing water resource challenges (Dalla Torre et al. (2023)), forecasting emissions (Yang et al. (2024)), and analyzing energy flows (Elomari et al. (2024)), among others.

Our paper contributes to the literature on sustainable performance and, in particular, on the development of composite indexes in the following ways. We propose a new, entirely data-driven, and time-consistent index of environmental performance that relies on a robust statistical technique to objectively assess environmental sustainability. Unlike traditional indices that rely on expert-defined weights, the proposed index — the Data-Driven Environmental Performance Index (DDEPI) — is built on empirical data, focusing on variables that account for the largest share of variance in the data. In order to create the proposed index, we apply a dimensionality reduction technique that captures the relationship between variables and countries every single year, such as Robust Principal Component Analysis (RobPCA). We utilize the Environmental Performance Index (EPI) historical time series from the Yale Center for Environmental Law and Policy[1], complemented by a set of mitigation indicators published by the International Monetary Fund (IMF)[2] and a dataset on changes in operating capacities provided by the Global Energy Monitor[3] and Ember[4]. The index consists of 32 variables grouped into four policy objectives, which are then integrated to develop the final composite index. The DDEPI is computed annually for 167 countries over the period from 2015 to 2022.

Such an index could become an essential tool not only to monitor and compare the different countries but also to be included in further analyses as a predictor. In

[1]https://epi.yale.edu/

[2]https://prosperitydata360.worldbank.org/en/dataset/IMF+FFS

[3]https://globalenergymonitor.org/

[4]https://ember-energy.org/

particular, we construct the index with a methodology that is consistent throughout the years, taking advantage of the entire time series as a whole. Moreover, our approach relies only on the intrinsic information of the data, without the intervention of expert judgment or subjective assumptions, providing a clear and intuitive explanation of the contribution of each input variable. Furthermore, our methodology can be used to forecast the evolution of the index over the years, including confidence intervals and allowing for scenario analysis.

Moreover, to better understand the multifaceted drivers of sustainability, we analyze the relationship of the DDEPI with broad-scale aspects specific to every country, such as institutional quality, state of democracy, and natural resources management. These dimensions are essential for achieving sustainability goals and enabling and monitoring environmental policies. This analysis may help identify challenges and opportunities, allowing policymakers to develop more targeted and impactful strategies to improve environmental performance at the national level.

The paper is organized as follows: in Section 2, we discuss the relevant literature; in Sections 3 and 4, we explain the data and the relevant methodology, respectively. Section 5 presents empirical evidence, and Section 6 discusses conclusions.

2. Literature review

As a concept, sustainable development gained international prominence with the publication of the Brundtland Report in 1987[5], which defined it as "devel-

[5] Brundtland, G.H. and Khalid, M. (1987) World Commission on Environment and Development: Our Common Future. Oxford University Press, New York

opment that meets the needs of the present without compromising the ability of future generations to meet their own needs." The core idea behind sustainable development is the recognition that long-term economic development must consider environmental limits and social well-being to ensure that human progress is both inclusive and enduring. Over the years, the concept has expanded, incorporating broader dimensions like governance, institutional resilience, and climate change mitigation. This has led to diverse frameworks and theories guiding the global discourse on sustainability, from ecological economics to environmental justice.

In parallel, the concept of sustainability has gained critical importance in global policy discussion and, consequently, in academic literature. The need to quantify and track sustainable development gave rise to various sustainability indexes, each aiming to assess and compare countries' performance in different areas of sustainability, facilitate comparisons and policymaking, and monitor performance progression over time.

In line with the three-pillar conceptualization of sustainable development, the sustainability indexes can focus on economic, societal, and environmental dimensions, either individually or in combination (Purvis et al., 2019). In 2017, there were already more than 90 indexes focused on different dimensions of sustainability according to the review provided by Gan et al. (2017). For instance, the societal and economic dimensions are the core aspects of the Human Development Index (HDI). On the other hand, the environmental dimension is the primary focus of indexes such as the Living Planet Index (LPI), Composite Index of Environmental Performance (CIEP), Environmental Vulnerability Index (EVI), Environmental Performance Index (EPI), and others. Finally, indexes such as the Sustainable Society Index (SSI), Sustainable Development Goals (SDG) Index, and FEEM Sustainability Index attempt to balance all three pillars, providing a holistic measure by tracking progress across multiple indicators that span human well-being, economic stability, and environmental preservation.

One of the most challenging methodological choices for the construction of composite indexes is the selection of weighting and aggregation procedures, which can influence the final ranking. A study by Pinar (2022) reveals significant differences in environmental performance depending on the choice of weights for the EPI indicators. In particular, when using Stochastic Dominance criteria to determine weights, 67 countries would have experienced a ranking shift of 30 or more positions. Similarly, the uncertainty analysis of the JRC audit of the EPI 2022 reveals how the weighting method was almost entirely responsible for the shifts in rankings (Smallenbroek et al., 2023).

The literature identifies indexes that utilize equal weighting, participatory-based weighting, and statistic-based weighting approaches. Out of the 96 sustainability indexes analyzed by Gan et al. (2017), 46.88% applied equal weighting techniques, 23.95% relied on participatory-based (including expert/public opinion) approaches, while the remaining 21.88% used statistical-based methods. In the case of equal weighting, all variables are considered equally important. While allowing for straightforward comparisons, this approach can cause issues related to the double counting of variables and the unbalanced index structure (OECD, 2008). This type of weighting has been used in the construction of indexes such as HDI and LPI. In contrast, opinion/expert-based methods rely on the degree of concern perceived by the stakeholders regarding the provided issues. Although transparent, this method involves subjective judgments and opinions, which may lead to an overemphasis on public concerns, underestimating the actual importance of variables (Nardo et al. (2005)). A well-known index that relies on expert-based weighting is the EPI, developed by the Yale Center for Environmental Law & Policy (YCELP).

The EPI is among the most widely recognized indices worldwide. It is updated biennially and is frequently used by governments, researchers, and NGOs to measure progress towards global targets like the Sustainable Development Goals (SDGs). Several limitations of the EPI have been discussed in the literature. For instance, Burgass et al. (2017) find that data quality and availability prevail over the relevance of the indicators for the system in the selection of variables. The 2022 EPI audit conducted by the Joint Research Centre (JRC) highlights concerns regarding negative correlations and suggests revising specific indicators to improve the statistical robustness of the index (Smallenbroek et al., 2023). Several studies highlight the limitations of the weighting procedure of the index. das Neves Almeida and García-Sánchez (2016) highlight the subjectivity in the assignment of weights, noting that they are determined based on data quality and the relevance of variables to specific policies. Similarly, Athanasoglou et al. (2014) show how expert weighting results in a situation where the influence of certain key environmental variables on the overall index variation becomes minimal.

Finally, data-driven approaches allocate weights based on statistical relationships, ensuring objectivity by emphasizing indicators that explain the most variance. Additionally, data-driven methods are particularly valuable in selecting and aggregating indicators. For example, machine learning algorithms can identify which indicators are most predictive of sustainability outcomes, helping to fine-tune the weighting process and minimize bias.

Scholars have proposed diverse data-driven solutions for the construction of composite indexes. One of them is the Data Envelopment Analysis (DEA), which is an effective method for synthesizing various performance indicators into a single efficiency score. By considering the proportional relationship between inputs—such as resource consumption or investment—and outputs, like environmental quality or economic growth, DEA enables researchers to identify best practices and benchmark performance. For instance, Zanella et al. (2013) introduced an improved Data Envelopment Analysis (DEA) model that offers a comprehensive summary metric of countries' environmental performance using the indicators from the EPI. Similarly, Caravaggio et al. (2019) employed DEA to develop a tool for air quality measurement. In contrast to other methods, the weights generated by DEA change from one country to another. Assigning varying weights to different indicators for each country results in outcomes that are often incomparable, as a country's performance can be influenced by allocating maximum weight to an indicator where it excels or struggles the most Rogge (2012).

One of the most commonly employed data-driven methods that address the subjective aspects of weight selection is Principal Component Analysis (PCA) and Factor Analysis (FA). Both techniques aim to reduce data dimensionality through linear transformation while preserving critical information. These methodologies are especially beneficial when a large number of indicators need to be considered Gan et al. (2017). However, despite their reliance on data, these methods can introduce a degree of uncertainty, primarily due to the necessity of determining the number of components or selecting the rotation method. For instance, Oţoiu and Grădinaru (2018) produces an alternative version of the EPI - the Environmental State and Sustainability Index (EESI) - deriving weights from FA. On the other hand, PCA has been used by Smits and Steendijk (2015) for the construction of the International Wealth Index. Radovanović et al. (2018) relied on PCA for the development of the Geo-economic Index of Energy Security. Similarly, Salvati and Carlucci (2014) propose an index of sustainable development of Italian municipalities using weights obtained from PCA.

Overall, the literature on sustainable indexes, and, in particular, on those evaluating the environmental dimension, reveals numerous methodologies for evaluating environmental performance, with varying approaches to selecting indicators, weighing them, and aggregating results. While some studies advocate for equal or expert-based weighting, others emphasize more nuanced statistic-based methods. Despite these differences, the overarching challenge remains: developing a data-driven approach that accurately reflects the complex nature of sustainability. This review underscores the need for continued refinement of these indexes to enhance their robustness and relevance.

In developing environmental composite indexes, researchers also emphasize the importance of exploring their relationship with broader contextual factors related to governance and institutional quality, whose effectiveness is essential for achieving sustainability goals across all three dimensions (Silva et al., 2022). Moreover, as evidenced by Lovei and Weiss (1996), the institutional framework is a key part of managing the environment as it helps create environmental policies and makes sure they are put into action and monitored.

The literature on the relationship between environmental performance and institutional quality is still limited, though it is expanding rapidly (Azam et al., 2021). While there is no consensus in the literature on the specific types of indicators to be used, a significant body of research relies on the Worldwide Governance Indicators (WGI) developed by the World Bank. These indicators cover six key dimensions of governance: government effectiveness, political stability and absence of violence, voice and accountability, control of corruption, regulatory quality, and the rule of law (Kaufmann et al., 2010).

Concerning each individual dimension, the literature presents significant, although sometimes contradicting, evidence. Government effectiveness has been found to be significantly correlated with reduced CO_2 (Zhang et al., 2024) while playing a crucial role in reducing the ecological footprint (Wang et al., 2024). Another important aspect is political stability and the absence of violence, which are essential for sustainable development as they may facilitate efforts that promote environmental sustainability and development (of Experts, 2015) and enable the implementation of green growth strategies that balance economic progress with environmental sustainability (Adebayo et al., 2022). Indeed, as evidenced by Cairns (2000), peace and sustainability are deeply interconnected. However, conflicting findings are reported in the literature. For instance, Simionescu et al. (2023), focusing on Central and Eastern European (CEE) countries, which are in close proximity to Ukraine and therefore near the war zone, found a positive relationship between political stability and CO_2 emissions. In contrast, findings by Kirikkaleli and Osmanlı (2023) indicate that political stability in Turkey helps curb environmental deregulation by lowering CO_2 emissions. Notably, political stability emerged as the only governance indicator influencing emissions for India, Russia, South Africa, and Turkey (Halkos and Tzeremes, 2013). Moreover, according to Al-Mulali and Ozturk (2015), political stability contributes to a decrease in environmental damage in the long run and the short-term ecological footprint in the MENA region. Similarly, political stability was found to have a mitigation impact on environmental degradation in both the short and long term in the

United States (Hacıimamoğlu and Sungur, 2024). Voice and accountability have been shown to improve national environmental performance (Handoyo, 2024) and to be negatively correlated with CO_2 emissions in the five countries responsible for about 60% of global CO_2 emissions. Similarly, regulatory quality and the rule of law have positive links with the national environmental performance (Handoyo, 2024). When it comes to corruption, the literature agrees on its negative impact on environmental performance. For instance, Lisciandra and Migliardo (2017) evidenced how corruption undermines environmental quality, while Sekrafi and Sghaier (2018) showed the direct effect of corruption on economic growth, environmental quality, and energy consumption in the MENA region. Focusing on the enlarged EU, Pellegrini and Gerlagh (2006) identified corruption levels as the key factor in explaining the variation in environmental policies among member states.

Another strand of research focuses on the impact of democracies on diverse aspects of environmental performance. In particular, an increase in democracy has been found to reduce environmental degradation and enhance environmental performance Li and Reuveny (2006); Adams and Klobodu (2017). Moreover, the results by Bättig and Bernauer (2009) indicate that democracy has a positive effect on the political commitment to climate change mitigation. In contrast, its effect on policy outcomes, measured by emission levels and trends, is unclear.

Natural resource rent is another important factor examined in relation to environmental performance, mainly due to its economic relevance in developing nations and those heavily dependent on fossil fuels. Still, there is no consensus regarding its impact on national environmental performance. For instance, according to (Balsalobre-Lorente et al., 2018), the abundance of natural resources can help reduce CO_2 emissions in an economy by reducing the reliance on imported fossil energy sources and improving energy consumption efficiency. On the other hand, in the long run, the misusage of natural resources can lead to environmental damage (Kwakwa et al., 2019) and to the "resource curse", where over-reliance on resource extraction undermines economic diversification and sustainability efforts.

The analyzed literature highlights the importance of diverse dimensions of governance and natural resource rents in shaping environmental performance. However, while most research focuses on specific aspects of environmental performance, such as CO_2 emissions or ecological footprints, relatively few studies (Nguyen et al., 2024; Dkhili, 2018) adopt a holistic approach using comprehensive measures of environmental performance, typically represented by composite indexes. Examining the connections between the above-mentioned factors and the indexes measuring environmental performance is crucial for understanding the multifaceted drivers of sustainability. This approach helps identify challenges and opportunities, allowing policymakers to develop more targeted and impactful strategies to improve environmental performance at the national level.

3. Data

3.1. Collection of variables

To build the proposed index, we collected data from several open-source databases. A significant portion of the data is drawn from the Environmental Performance Index (EPI) 2024 dataset [6], including in total 55 indicators grouped under three policy objectives: Environmental Health, Ecosystem Vitality, and Climate Change,

[6] https://epi.yale.edu/

spanning the years 1995 to 2022. It is important to notice that despite the name, EPI 2024, the last considered year is 2022. For this reason, to avoid confusion, in the following we denote such index as EPI 2022. To account for additional important dimensions that can help evaluate government actions in combating climate change, we enrich the EPI dataset, particularly the Climate Change policy objective, with several additional variables. Specifically, we add variables representing the estimated value of explicit and implicit government subsidies related to fossil fuels, sourced from the IMF Climate Change Dashboard[7], in the period 2015 to 2022. While intended to protect consumers, fossil fuel subsidies promote inefficient resource allocation, encourage pollution, and increase inequality by disproportionately benefiting the wealthiest members of society Whitley and van der Burg (2015). Continuing to promote fossil fuel subsidies sends mixed signals, hindering global efforts to decarbonize energy systems and jeopardizing climate goals.

To reflect the critical role that the shift toward sustainable and low-carbon energy systems plays in addressing global environmental challenges, we include variables measuring the change in operating coal-fired, gas, oil, solar, and wind capacities, provided by the Global Energy Monitor[8] (GEM) for the period 2015-2022. These variables are essential for assessing the ongoing energy transition, as shifts in energy generation capacity are directly linked to a country's ability to reduce carbon emissions and meet sustainability targets. By tracking the expansion of renewable energy sources like solar and wind alongside the decline in fossil fuel-based capacities, this index offers a more comprehensive view of a

[7]https://prosperitydata360.worldbank.org/en/dataset/IMF+FFS
[8]https://globalenergymonitor.org/

nation's progress toward a low-carbon future. Moreover, using data from Ember[9] from 2000 to 2022, we account for the share of electricity generated by renewables, one of the key indicators of a country's commitment to sustainable energy practices. By tracking the proportion of electricity derived from renewables, the index provides insight into the transition away from fossil fuels and the level of investment in cleaner energy technologies. Overall, we collect 65 variables: 58 from EPI, two from IMF, 4 from GEM, and 1 from Ember. Following the classification of the EPI policy objectives, we divide our variables into four groups: Ecosystem Vitality (EV), Environmental Health (EH), Climate Change (CC), and an additional dimension called Energy Transition (ET).

Finally, we collected supplementary data from the World Bank to examine the relationship between the constructed index and dimensions related to governance and resource management. Specifically, we used the World Governance Indicators[10] dataset, which assesses six key dimensions of governance: government effectiveness (GOV), political stability, and absence of violence (POL), voice and accountability (VAC), control of corruption (COR), regulatory quality (REG), and the rule of law (LAW). Additionally, we incorporated data from the EUI-Democracy Index[11], which provides insights into the state of democracy in the analyzed countries. Resource management data are represented by the Total Natural Resource Rent (RNT)[12] indicator, calculated as the sum of rents from oil, natural gas, coal (hard and soft), minerals, and forests. For a detailed list of the

[9] https://ember-energy.org/

[10] www.govindicators.org

[11] https://prosperitydata360.worldbank.org/en/dataset/EIU+DI

[12] https://prosperitydata360.worldbank.org/en/indicator/UN+SDG+NY+GDP+TOTL+RT+ZS

supplementary variables, along with their descriptions and sources, please refer to Table .6 in the Appendix.

3.2. Processing of variables

The variables in the EPI are expressed in the 0-100 range, where 100 represents the best positive effect of policies on the environment. Similarly, the share of electricity provided by Ember is already in the 0-100 range, where higher values imply benefits for the environment. Explicit and implicit subsidies are provided as a percentage of GDP in the 0-100 range. However, as a higher value implies strong intervention from the government to mitigate the negative effects of fossil fuels, we transformed the variable as the complementary of 100 to its original value to align its interpretation with the other constituents of the proposed index. Raw variables from the GEM dataset report the capacity of both retired and newly opened powerplants, so we first evaluate the yearly change in net capacity of the current year (retired minus new) over the total capacity of the previous year. The results were wonorized, with extreme values removed and then rescaled to the 0-100 range. As for previous variables, in order to have the interpretation of the input aligned, we keep the evaluated share for wind and solar powerplants (having a positive effect on the environment), and we take the complementary to 100 for coal and gas and oil powerplants.

In order to have reliable results, the processed constituents have been skimmed according to the following criteria. First, we removed variables that have no variation over the years for every country, such as those coming from the EPI, for which only the last available detection is retained and set equal for all years. Second, we remove variables with a percentage of missing greater than 25%. Third, we remove variables with either absolute correlation or absolute partial correlation greater than 80%. Therefore, we restricted the number of variables to 32: 10 for EV, 8 for EH, 9 for CC, and 5 for ET. Finally, we will keep the commonly available time span from 2015 to 2022.

Table 1 reports the descriptive statistics for the final 32 variables. For a detailed list of the constituent variables, along with their descriptions and sources, please refer to Table .5 in the Appendix. Additionally, Figure .5 in the Appendix reports the partial correlation of the final 32 variables.

Table 1: List of variables used to build the Environmental Sustainability Index, with macro policy level, sources, total number of non-missing observations, total number of countries, and descriptive summary statistics.

Variable	Policy Level	Source	Description	Obs	Countries	Full missing countries	Partial missing countries	Missing	Mean	S.D.	Min	25th	Median	75th	Max
1 - NXA	EV	YALE[1]	Adjusted emissions growth rate for nitrous oxides	1,336	167	0	0	0 (0%)	58.68	31.86	0	32.65	59.4	91.6	100
2 - OEB			Ozone exposure KBAs	1,336	167	0	0	0 (0%)	50.43	27.09	0	30.75	51.1	70.3	100
3 - PSU			Phosphorus Surplus	1,336	167	0	0	0 (0%)	61.02	27.64	0	40	54.7	94.85	100
4 - RLI			Red List Index	1,328	167	1	0	8 (0.6%)	54.42	29.72	0	30.85	60.2	79.1	97.7
5 - SDA			Adjusted emissions growth rate for sulfur dioxide	1,336	167	0	0	0 (0%)	72.95	29.24	0	51.95	80.35	100	100
6 - SHI			Species Habitat Index	1,240	167	12	0	96 (7.2%)	58.24	29.23	0	40.25	67.5	80.4	100
7 - SNM			Sustainable Nitrogen Management Index	1,336	167	0	0	0 (0%)	42.05	18.95	0	29.8	43.6	54.75	93
8 - SPI			Species Protection Index	1,336	167	0	0	0 (0%)	45.85	27.69	0	22.5	44.5	69.1	100
9 - TBN			Terrestrial Biome Protection (national weights)	1,336	167	0	0	0 (0%)	52.08	29.95	0	27.8	51.6	76.6	100
10 - TKP			Terrestrial KBA Protection	1,336	167	0	0	0 (0%)	54.51	29.26	0	29.9	57.7	80	100
1 - COE	EH	YALE[1]	CO exposure	1,336	167	0	0	0 (0%)	53.64	19.41	0	41.8	56.2	63.85	99.2
2 - HPE			Anthropogenic PM2.5 exposure	1,336	167	0	0	0 (0%)	42.87	29.24	0	19.9	37.2	62.2	100
3 - LED			Lead exposure	1,336	167	0	0	0 (0%)	52.06	23.48	0	32.7	47.5	67.9	100
4 - NOD			NOx exposure	1,336	167	0	0	0 (0%)	36.78	18.99	0	23.15	33.9	46.9	100
5 - OZD			Ozone exposure	1,336	167	0	0	0 (0%)	46.05	21.84	0	31.8	42.2	58.8	100
6 - SOE			SO2 exposure	1,336	167	0	0	0 (0%)	46.95	25.05	0	30.05	46.65	66.35	99.3
7 - UWD			Unsafe drinking water	1,336	167	0	0	0 (0%)	53.95	27.47	6.3	26.95	54.35	76.25	100
8 - VOE			VOC exposure	1,336	167	0	0	0 (0%)	34.97	25.43	0	15.3	30.8	48.95	100
1 - BCA	CC	YALE[1]	Adjusted emissions growth rate for black carbon	1,336	167	0	0	0 (0%)	58.58	29.25	0	35.05	56	85.85	100
2 - CDA			Adjusted emissions growth rate for carbon dioxide	1,336	167	0	0	0 (0%)	42.07	16.78	0	31.95	44.2	52.2	100
3 - CDF			Adjusted emissions growth rate for carbon dioxide (country-specific targets)	1,336	167	0	0	0 (0%)	52.75	28.82	0	32.45	48.4	73.45	100
4 - CHA			Adjusted emissions growth rate for methane	1,336	167	0	0	0 (0%)	45.07	23.39	0	30	43.7	57.45	100
5 - FGA			Adjusted emissions growth rate for F-gases	1,152	167	23	0	184 (13.8%)	29.03	22.69	0	12.75	26.9	37.6	100
6 - GHN			Projected GHG Emissions in 2050	1,336	167	0	0	0 (0%)	25.14	19.42	0	13.1	21.3	33.3	100
7 - GTP			GHG growth rate adjusted by per capita emissions	1,336	167	0	0	0 (0%)	38.03	12.49	0	31.7	38.9	45.55	82.8
8 - LUF			Net carbon fluxes due to land cover change	1,288	167	6	0	48 (3.6%)	44.78	16.29	0	46.4	48.9	50.2	100
9 - NDA			Adjusted emissions growth rate for nitrous oxide	1,336	167	0	0	0 (0%)	42.26	21.03	0	30	41.6	52.1	100
1 - EXS	ET	IMF[2]	Explicit subsidies reflect underpricing due to supply costs being greater than prices paid by users	1,336	167	0	0	0 (0%)	98.74	2.25	71.2	98.57	99.62	99.99	100
2 - IMS			Implicit subsidies reflect the difference between supply costs and socially efficient prices	1,336	167	0	0	0 (0%)	95.56	5.05	65.4	93.99	97.43	98.95	100
3 - CGC		GEM[3]	Change in gas and oil capacity	1,160	167	22	0	176 (13.2%)	15.94	5.21	0	14.92	14.92	14.92	100
4 - CSC			Change in solar capacity	1,024	167	39	0	312 (23.4%)	4.7	16.73	0	0	0	1.45	100
5 - RSE		EMBER[4]	Share of electricity generated by renewables	1,336	167	0	0	0 (0%)	36.55	32.32	0	8.09	26.33	61.8	100

[1] https://epi.yale.edu/

[2] https://prosperitydata360.worldbank.org/en/dataset/IMF+FFS

[3] https://globalenergymonitor.org/

[4] https://ember-energy.org/

Despite screening the variables, approximately 2% of the data presents missing values, so we decided to impute the missing entries. The method used to impute missing data can significantly affect the outcome of an analysis. As demonstrated by Freyberger et al. (2021), the commonly used approaches, such as imputing the mean or median, can introduce bias into the results. For this reason, we use the Bayesian Tensor Factorization (BTF) imputation method Khan and Ammad-ud din (2016), that allows us to extrapolate the missing values using a tensorial decomposition of the 3-dimensional tensor. In our case, the three dimensions are the countries, the variables, and the year. In this way, the algorithm can leverage information from country-variable dependence and temporal evolution.

The final dataset of the index constituents consists of 32 variables for 167 countries over the period 2015-2022.

4. Methodology

4.1. Principal Component Analysis

To build the proposed data-driven index for measuring countries' environmental performance, we employ Principal Component Analysis (PCA), a dimensionality reduction technique that captures the most significant patterns in complex, multidimensional datasets by maximizing the explained variance. Specifically, PCA transforms a larger set of variables into a smaller number of components, each representing a linear combination of the original variables. The resulting combinations are mutually orthogonal.

The model is defined as follows:

$$C_1 = w_1 Y_1 + ... + w_n Y_n, \tag{1}$$

where C_1 is the principal component defined as a linear combination of original variables Y_i and w_i are the weights.

Given a $n \times p$ matrix $\mathbf{X}$, where n and p denote the number of observations and variables, respectively, the goal is to identify a $k \times p$ matrix of principal components C, with $k \leq p$, such that the scores matrix, defined as $W = XC^T$, has the $n \times k$ dimension.

The problem can be defined as:

$$\begin{aligned} \underset{\mathbf{C}}{\text{minimize}} \quad & \|\mathbf{X} - \mathbf{X}\mathbf{C}\mathbf{C}^T\|_F^2 \\ \text{subject to} \quad & \mathbf{C}^T\mathbf{C} = \mathbf{I}, \end{aligned} \tag{2}$$

where $\|\cdot\|_F$ is the Frobenius norm.

To obtain a robust estimation of the Principal Components, we can decompose the data matrix $\mathbf{X}$ into two components: a low-rank component L that captures the inherent low-dimensional structure and an outlier component S that identifies anomalies in the data. The problem can then be formulated and solved as follows:

$$\begin{aligned} \underset{\mathbf{L},\mathbf{S}}{\text{minimize}} \quad & \|\mathbf{L}\|_* + \lambda\|\mathbf{S}\|_1 \\ \text{subject to} \quad & \mathbf{L} + \mathbf{S} = \mathbf{X}, \end{aligned} \tag{3}$$

where $\|\mathbf{L}\|_*$ denotes the nuclear norm and λ is a penalization term.

4.2. Granger Causality

In order to understand the causal relationship between the proposed index and dimensions related to governance and resource management, we test the Granger Causality. Granger causality is a statistical concept used to determine whether one time series can predict another. Formally, a time series X_t is said to Granger-cause Y_t if the past values of X_t provide statistically significant information about Y_t beyond the information contained in the past values of Y_t alone.

Consider the following models:

$$Y_t = \alpha + \sum_{i=1}^{p} \beta_i Y_{t-i} + \varepsilon_t, \tag{4}$$

$$Y_t = \alpha + \sum_{i=1}^{p} \beta_i Y_{t-i} + \sum_{i=1}^{p} \gamma_i X_{t-i} + \varepsilon_t, \tag{5}$$

where ε_t is a white noise error term, and p is the lag order.

The null hypothesis for Granger causality is:

$$H_0 : \gamma_1 = \gamma_2 = \cdots = \gamma_p = 0,$$

which states that X_t does not Granger-cause Y_t. Rejection of H_0 indicates that X_t contains predictive information about Y_t.

Therefore, testing Granger causality is performed by evaluating an F-test to compare the restricted model (without X_t) and the unrestricted model (with X_t).

4.3. Panel Vector Autoregressive Model and Impulse Response Function

After assessing if there is a causal relationship between the DDEPI and dimensions related to governance and resource management, we want to quantify the strength of such causality. So, we evaluate a Panel Vector Autoregressive (PVAR) model, and we compute the Generalized Impulse Response Function.

The Panel Vector Autoregressive (PVAR) model extends the vector autoregressive framework to panel data, enabling the analysis of dynamic interactions among multiple variables across entities (i.e., countries) over time. The PVAR model is expressed as:

$$\mathbf{y}_{i,t} = \sum_{p=1}^{P} \mathbf{A}_p \mathbf{y}_{i,t-p} + \mathbf{B}\mathbf{x}_{i,t} + \mathbf{u}_{i,t},$$

where $\mathbf{y}_{i,t}$ is a $K \times 1$ vector of endogenous variables for country i at time t, $\mathbf{A}_p$ are $K \times K$ coefficient matrices for the lagged endogenous variables up to lag P, $\mathbf{x}_{i,t}$ is a $L \times 1$ vector of exogenous variables with a corresponding $K \times L$ coefficient matrix $\mathbf{B}$ and $\mathbf{u}_{i,t}$ is a $K \times 1$ vector of error terms, capturing the stochastic shocks in the system.

The error term $\mathbf{u}_{i,t}$ typically satisfies the following assumptions:

$$\mathbf{u}_{i,t} \sim \mathcal{N}(0, \mathbf{\Sigma}),$$

where $\mathbf{\Sigma}$ is the covariance matrix of the error terms, which may vary across entities but is assumed to be time-invariant.

The Generalized Impulse Response Function (GIRF) provides a method to analyse the dynamic response of the variables in a PVAR model to a shock in one of the error terms, without requiring orthogonalisation of shocks. This approach accounts for the contemporaneous correlations among the variables.

The GIRF for a shock to the j-th variable at time t is defined as:

$$\text{GIRF}_j(h, \delta) = \mathbb{E}[\mathbf{y}_{i,t+h} | \mathbf{u}_{i,t} = \delta] - \mathbb{E}[\mathbf{y}_{i,t+h}],$$

where h is the time horizon, δ is a $K \times 1$ vector of shocks, where δ_j represents the shock to the j-th variable, and other entries correspond to their observed historical values, and $\mathbb{E}[\cdot]$ denotes the expectation operator.

The response at horizon h can be computed using the moving average representation of the PVAR model:

$$\mathbf{y}_{i,t+h} = \sum_{s=0}^{h} \mathbf{\Psi}_s \mathbf{u}_{i,t+h-s},$$

where $\mathbf{\Psi}_s$ are the moving average coefficient matrices. The GIRF at horizon h is then:

$$\text{GIRF}_j(h, \delta) = \mathbf{\Psi}_h \mathbf{\Sigma} \mathbf{e}_j,$$

where $\mathbf{e}_j$ is a selection vector with a 1 in the j-th position and 0 elsewhere.

Unlike the Orthogonal Impulse Response Function (OIRF), the GIRF does not rely on orthogonalization techniques, such as Cholesky decomposition, and is invariant to the ordering of the variables.

5. Results

5.1. Principal Component Analysis

As described in 4.1, we tested a different number of principal components, i.e. the low-dimensional representation of the intrinsic relationship of the 32 input indicators.

We select the first three components of the Robust PCA to form the foundation of the DDEPI, accounting for an average of nearly 81.2% of the variability across years. Table 2 reports the cumulative average variance explained by the loadings across years, as well as the average R^2 on both the whole dataset and subsets with values trimmed for the $95th$ and $99th$ percentiles in order to check for the impact of outliers. In our context, in analogy with the classical R^2, we compute the RSS term as the squared residuals given after the reconstruction step using only the retained principal components and the TSS term as the total variance contained in the original variables.

Table 2: Results from Robust PCA. Mean is evaluated over years.

Number of Prin. Comp.	Mean Explained Variance	Mean R^2	Mean R^2 on 99th	Mean R^2 on 95th
1	$46.5 \pm 1.1\%$	$83.6 \pm 0.4\%$	$85.0 \pm 0.4\%$	$88.0 \pm 0.4\%$
2	$66.9 \pm 0.6\%$	$89.8 \pm 0.2\%$	$90.9 \pm 0.2\%$	$92.8 \pm 0.2\%$
3	$81.2 \pm 0.5\%$	$94.2 \pm 0.2\%$	$94.8 \pm 0.2\%$	$95.8 \pm 0.1\%$

Figure 1 shows the evolution of loadings across years for the three components. Loadings indicate the extent to which the original variables influence the component. The Blue (Red) colour of the bar denotes the positive (negative) contribution of the variable to the component. The height of the bar represents the magnitude of the contribution.

The first component shows relatively consistent behaviour over time, primarily driven by metrics related to developments in air quality. These include the Adjusted Emissions Growth Rate for Nitrous Oxides (NXA), the Adjusted Emissions Growth Rate for Carbon Dioxide (CDA), the Adjusted Emissions Growth Rate for Sulfur Dioxide (SDA), and the GHG Growth Rate adjusted by emissions intensity (GTI). Additionally, this component captures the influence of Lead Exposure (LED) and Unsafe Drinking Water (UWD).

The second component demonstrates dynamic behaviour, with loadings changing signs over the years. Specifically, from 2015 to 2020, the component is associated with variables such as Ozone Exposure in KBAs (OEB), the Species Protection Index (SPI), Terrestrial Biome Protection (TBN), Terrestrial KBAs Protection (TKP), the CO_2 Growth Rate (CDF), and the Share of Renewables (RSE). However, during 2021–2022, significant relationships are observed for CO Exposure (COE), Anthropogenic Particulate Matter Pollution (HPE), SO_2 Exposure (SOE), and Projected 2050 GHG Emissions (GHN).

The time-changing behaviour is also evident in the third component. Initially, it is driven by CO Exposure (COE), Anthropogenic Particulate Matter Pollution (HPE), Ozone Exposure (OZD), and SO_2 Exposure (SOE). However, in 2021 and 2022, it shows a stronger relationship with biodiversity-related metrics, such as the Species Protection Index (SPI), Terrestrial Biome Protection (TBN), and Terrestrial KBA Protection (TKP). For a comprehensive representation of the evolution of loadings, please refer to Table .7 in the Appendix.

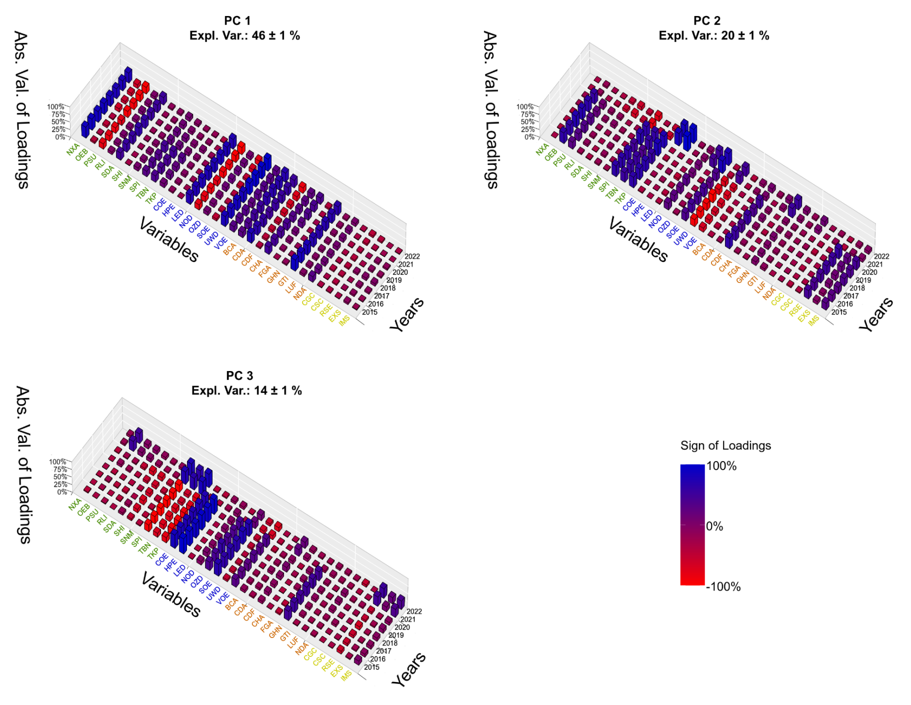


Figure 1: Evolution of Loadings across years for the first three Principal Components.

The loadings are then used to calculate the weights. Following the OECD methodology (OECD, 2008), the weights are determined by multiplying the highest loading of each variable by the proportion of explained variance for the corresponding factor. Finally, each country score is calculated through arithmetic aggregation.

Tables 3 and 4 present the rankings of the constructed index for 2022 for the top 10 and bottom 10 countries in environmental performance, alongside their corresponding positions in the EPI 2022 To ensure a fair comparison between the DDEPI and the EPI, we adjusted the EPI rankings by removing countries not included in the DDEPI. For a complete comparison of the rankings, please refer to Table .8 in the Appendix.

The comparison between the DDEPI and the EPI highlights significant alignment in identifying leading countries in terms of environmental performance. Both indices recognize Finland, Luxembourg, Sweden, Germany, the United Kingdom, Denmark, and Norway among the top-performing nations, albeit with slight variations in their rankings. The most significant discrepancies are observed for Ireland and the Netherlands, which rose by 10 and 6 positions, respectively, in the DDEPI compared to their EPI rankings. These improvements can be attributed to slightly stronger performance in indicators driving the DDEPI.

In the comparison of the bottom 10 countries in environmental performance, only four countries identified as the worst performers by the DDEPI also appear among the worst performers in the EPI. The largest discrepancies are observed for Burkina Faso and Central African Republic, which dropped by 54 and 38 positions, respectively. Such a result can be attributed to poor performance in areas like air quality, exposure to heavy metals, and drinking water quality, which are key drivers in the DDEPI.

Table 3: Comparison of ranking for 10 countries with the best environmental performance according to the DDEPI 2022 and their respective positions in the EPI 2022

Country Code	Country	DDEPI 2022	DDEPI 2022-Rank	EPI 2022	EPI 2022-Rank Adj.
FIN	Finland	4.95	1	73.8	4
LUX	Luxembourg	4.38	2	75.1	2
SWE	Sweden	4.12	3	70.3	6
DEU	Germany	3.96	4	74.5	3
GBR	United Kingdom	3.90	5	72.6	5
IRL	Ireland	3.72	6	65.8	16
DNK	Denmark	3.69	7	67.7	10
NLD	Netherlands	3.66	8	66.9	14
MLT	Malta	3.60	9	66.9	13
NOR	Norway	3.56	10	69.9.5	7

Source: EPI 2022 and authors' elaboration.

Table 4: Comparison of ranking for 10 countries with the worst environmental performance according to the DDEPI 2022 and their respective positions in the EPI 2022

Country Code	Country	DDEPI 2022	DDEPI 2022-Rank	EPI 2022	EPI 2022-Rank Adj.
TGO	Togo	-2.64	158	35.7	143
BFA	Burkina Faso	-2.68	159	42.2	105
IRQ	Iraq	-2.76	160	30.3	160
NPL	Nepal	-2.77	161	33.1	153
CAF	Central African Republic	-2.85	162	39	124
MDG	Madagascar	-2.86	163	30.1	161
GIN	Guinea	-3.01	164	36.5	139
PAK	Pakistan	-3.19	165	25.5	166
BGD	Bangladesh	-3.3	166	28.1	163
MLI	Mali	-3.48	167	34.5	148

Source: EPI 2022 and authors' elaboration.

Comparison of rankings in all countries provided additional context. Figure 2 illustrates the distribution of shared countries between the two indices for different portions of the index distribution: fixed 5% windows from 0-5% to 95%-100% on left-hand side and rolling 20% windows with a shift factor of 5% on right-hand side. These visualizations reveal a significant overlap, particularly in the upper and the lower quantiles. The found concordance is confirmed by the statistical tests revealing significant correlations, with Kendall's $\tau = 0.775$ and Spearman's $\rho = 0.932$, both with p-values close to 0, indicating that the indices largely agree on the relative environmental performance of countries. Furthermore, the Kruskal-Wallis test showed no statistically significant differences between the rank distributions of the two indices (p-value = 0.1209), underscoring their broad comparability.

While these findings reveal an overall agreement between the two indexes, especially for countries showing the worst and the best environmental performance, sensitive differences in the rankings of certain countries highlight the key role that specific variables play in determining a country's environmental performance. In some cases, these differences may be driven by particular factors that disproportionately affect the country rankings, further underscoring the importance of methodological decisions in shaping the index outcomes.

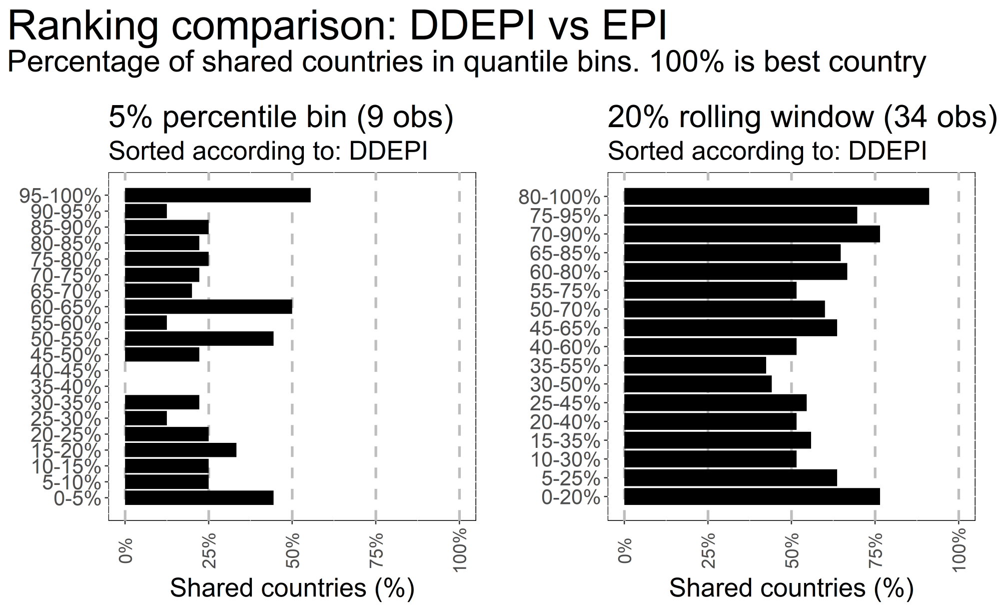


Figure 2: A comparative analysis of overall rankings: DDEPI 2022 vs. EPI 2022

5.2. Granger Causality and Impulse-Response Functions: Insights from DDEPI

This subsection discusses the results of the Granger Causality analysis, which identifies the causal relationships between the developed index and broad-scale country-specific dimensions measuring institutional quality and natural resources management. These findings are further examined using Generalized Impulse-Response Functions (GIRFs) based on the PVAR model to understand the dynamic effects of shocks on the above-mentioned dimensions.

Figure 3 reports a visual representation of the significant directional relationship between selected variables and the index (DDEPI). The nodes represent the analysed variables, and the colour of each node reflects its Total Degree of Centrality in the network. The Red (Green) arrow indicates a negative (positive) influence of one variable on the forecast of another.

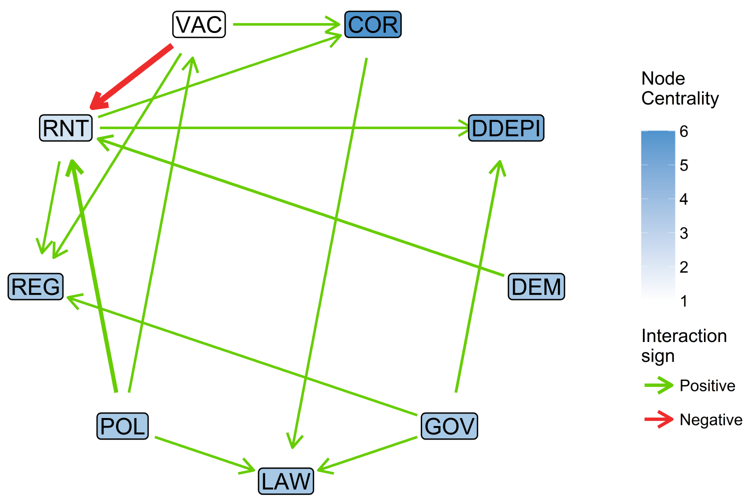


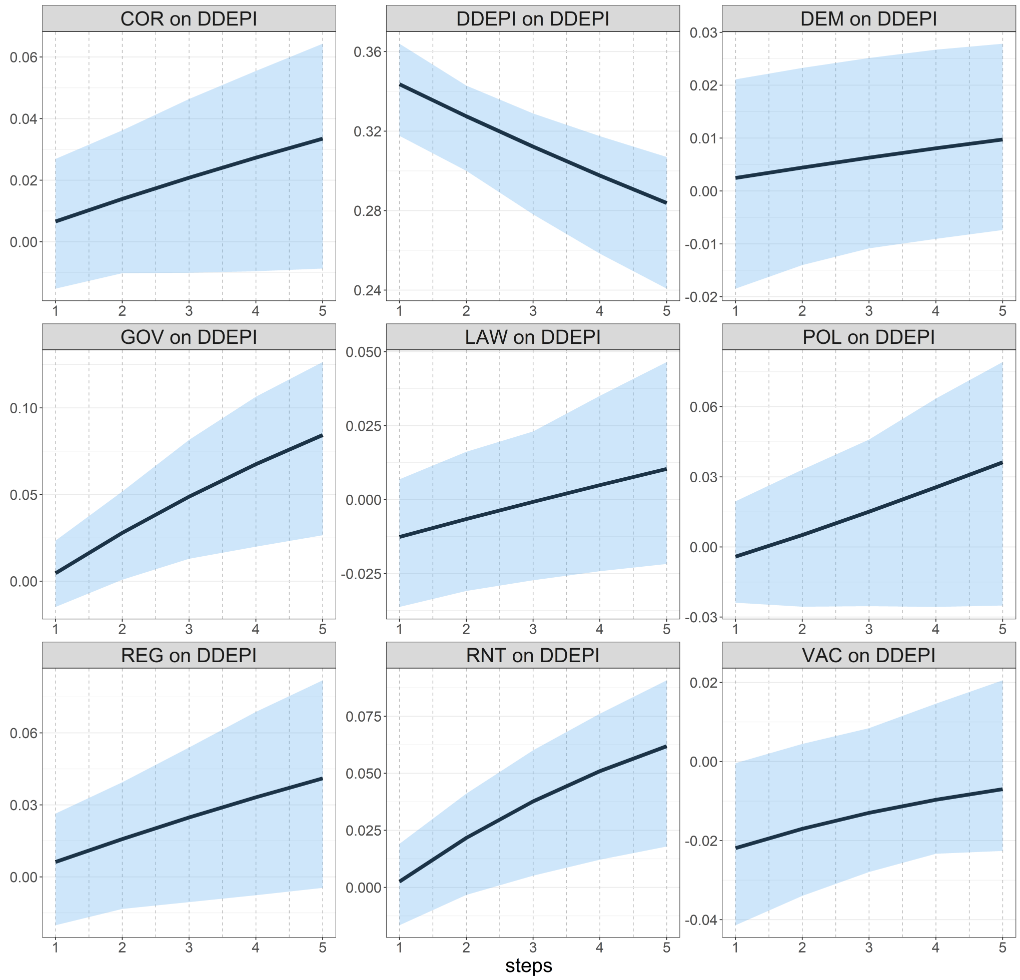
Figure 3: Network representing the Granger-causality relationship of the variables. The colour of the nodes represents the Total Degree of Centrality of the node in the network.

The DDEPI shows significant positive interactions with two analysed variables. In particular, the index is positively influenced by the natural resources rent (RNT) and government effectiveness (GOV), suggesting that changes in these variables may predict positive shifts in the DDEPI, while the reverse effect is not observed. None of the remaining variables presents a significant causal link with the proposed index.

To further investigate the relationship in the system, we examine the dynamic effects of the selected broad-scale country-specific dimensions on the DDEPI, using Generalized Impulse-Response Functions (GIRFs) based on the PVAR model.

Figure 4 shows the IRF of the DDEPI resulting from a one standard deviation shock applied to the other variables.

The IRF results reveal a moderate positive response of the DDEPI to the shock in the natural resource rent (RNT), which becomes statistically significant after



Notes: The shaded areas denote 95% confidence interval.

Figure 4: Impulse-Response Function for the PVAR model

the first period, emphasising the crucial role of natural resources management in shaping environmental performance. Such a result is in line with the strand of research stating that the abundance of natural resources can help reduce CO_2 emissions in an economy by reducing the reliance on imported fossil energy sources and improving energy consumption efficiency Balsalobre-Lorente et al. (2018). A similar, though more pronounced effect, which significantly increases over time, is observed for government effectiveness (GOV), indicating that increases in governance efficiency can enhance environmental performance. This connection is further supported by evidence showing that government effectiveness is significantly correlated with reduced CO_2 emissions (Zhang et al., 2024) and plays a crucial role in lowering the ecological footprint (Wang et al., 2024). More generally, effective policy formulation and credible government commitments enable the creation of a stable framework for addressing environmental challenges, encouraging long-term investments in sustainable initiatives.

6. Conclusions

This paper contributes to the literature on sustainable development by introducing a new index for measuring environmental performance at the country level - the DDEPI. The proposed index is constructed using historical time-series data from YCELP, complemented by a set of mitigation indicators from the IMF, variables measuring changes in operating capacities, and data on renewable energy. While the YCELP variables are categorized into three policy dimensions—Environmental Vitality (EV), Environmental Health (EH), and Climate Change (CC)—based on the EPI methodology, the complementary variables are incorporated into a fourth dimension - Energy Transition (ET). The fourth dimension has been incorporated to emphasize the critical role of transitioning to sustainable and low-carbon energy systems in addressing global environmental challenges.

The proposed index addresses limitations commonly reported in the literature regarding the weighting methods used in most composite indices measuring environmental performance. While indices constructed using expert-based or equal weights may be prone to subjectivity biases or to the underestimation of key variables, the DDEPI is entirely data-driven and time-consistent, as it is developed using the Robust PCA model. This methodology effectively tackles the multidimensional nature of environmental performance by extracting the most significant information from the data. Starting from 32 variables representing four policy dimensions, the index is based on three principal components that explain an average of 81% of variance over the years. The DDEPI is calculated for 167 countries over the period 2015 through 2022.

The comparison between the DDEPI 2022 and the EPI 2022 rankings revealed both alignment and notable differences. Both indices consistently identify top-performing countries in environmental performance, with slight variations in their rankings. However, the DDEPI emphasizes different key drivers, such as air pollution, drinking water quality, and exposure to heavy metals, resulting in significant discrepancies for certain countries. Similarly, while there is some overlap in the identification of bottom-performing nations, the DDEPI highlights differences driven by its focus on specific indicators.

An analysis of the causal relationships between the developed index and country-specific dimensions highlighted the critical role of institutional quality and natural resource management in achieving sustainability goals, suggesting that changes in these variables may predict positive shifts in the DDEPI.

Furthermore, the application of the Impulse-Response Function based on a PVAR model allowed for the examination of the dynamic effects of shocks to selected broad-scale country-specific dimensions on the DDEPI. The results revealed a consistently positive impact of the natural resource rents on the DDEPI, emphasising the crucial role of resource management in shaping environmental performance. Similarly, a positive, though more pronounced effect, was observed for the government effectiveness (GOV), indicating that increases in governance efficiency can enhance environmental performance over time.

These findings underscore the complex and reciprocal relationship between institutional quality, natural resources management, and environmental performance, highlighting the importance of interactions between different actors. Policymakers should recognise that improvements in government effectiveness not only can foster better environmental outcomes but are also reinforced by environmental progress. Stronger institutions create a conducive environment for sustainability, while environmental improvements can, in turn, enhance institutional quality. In this context, governments must work in close collaboration with civil society and the private sector to safeguard the environment and promote sustainability, even in times of geopolitical instability. Transparent, accountable governance and a stable political environment have key roles in achieving long-term environmental goals, ensuring that progress is not derailed by external shocks.

While the findings provide valuable insights into countries' environmental performance and its drivers, it is important to acknowledge several limitations of the research. The presence of missing data led to a reduced number of variables used in the construction of the index. Additionally, due to data availability issues, the index was calculated over a relatively short period, which does not encompass a significant number of events with a notable impact on environmental performance and climate change goals, such as the Russo-Ukrainian war. A longer time frame would allow an analysis of the index's responsiveness to shocks induced by such events. Finally, the index is static, as it is calculated separately for each year. A model that captures intertemporal developments would provide a more accurate reflection of sustainability trends by accounting for the evolving nature of environmental performance over time.

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Table .5: Index's constituent variables

Variable (Lable)	**Description**	**Source**
Adjusted emissions growth rate for nitrous oxides (NXA)	Calculated as the average annual rate of increase or decrease in NO_x over the last ten years of data.	EPI
Ozone exposure in Key Biodiversity Areas (OEB)	Calculated as the average concentration of ground level ozone across a country's Key Biodiversity Areas.	EPI

Table .5: Index's constituent variables

Variable (Lable)	Description	Source
Phosphorus Surplus (PSU)	Serves as a proxy for potential pollution of water bodies due to excessive phosphorus fertilizer use.	EPI
Red List Index (RLI)	Tracks the overall extinction risk for species in a country, weighting species by the fraction of their range occurring within the country or region.	EPI
Adjusted emissions growth rate for sulfur dioxide (SDA)	Calculated as the average annual rate of increase or decrease in SO_2 over the last ten years of data.	EPI
Species Habitat Index (SHI)	Estimates potential population losses.	EPI
Sustainable Nitrogen Management Index (SNM)	Proxy for agricultural drivers of environmental damage.	EPI
Species Protection Index (SPI)	Evaluates the species-level ecological representativeness of each country's protected area network.	EPI
Terrestrial Biome Protection (TBN)	Percentage of the area of each of a country's biome types that are covered by protected areas.	EPI

Table .5: Index's constituent variables

Variable (Lable)	Description	Source
Terrestrial KBA Protection (TKP)	Percentage of the total area of terrestrial KBAs in a country that is covered by protected areas	EPI
CO Exposure (COE)	Population-weighted annual average concentration of the air pollutant at ground level.	EPI
Anthropogenic particulate matter pollution (HPE)	Measures the exposure to fine particulate matter pollution from anthropogenic sources.	EPI
Lead Exposure (LED)	Number of age-standardized disability-adjusted life-years lost per 100,000 persons (DALY rate) due to lead contamination in the environment.	EPI
NO_2 Exposure (NOD)	Number of age-standardized disability-adjusted life-years lost per 100,000 persons (DALY rate) due to exposure to ground-level NO_2 pollution.	EPI

Table .5: Index's constituent variables

Variable (Lable)	Description	Source
Ozone Exposure (OZD)	Number of age-standardized disability-adjusted life-years lost per 100,000 persons (DALY rate) due to exposure to ground-level ozone pollution.	EPI
SO_2 Exposure (SOE)	Population-weighted annual average concentration of the air pollutant at ground level.	EPI
Unsafe drinking water (UWD)	Number of age-standardized disability-adjusted life-years lost per 100,000 persons (DALY rate) due to exposure to unsafe drinking water.	EPI
Volatile Organic Compound Exposure (VOE)	Population-weighted annual average concentration of the air pollutant at ground level.	EPI
Adjusted emissions growth rate for black carbon (BCA)	Average annual rate of increase or decrease in black carbon over the years 2013–2022.	EPI
Adjusted emissions growth rate for carbon dioxide (CDA)	Average annual rate of increase or decrease in raw carbon dioxide emissions over the years 2013–2022	EPI

Table .5: Index's constituent variables

Variable (Lable)	Description	Source
CO_2 growth rate (country-specific targets) (CDF)	Average annual rate of increase or decrease in raw carbon dioxide emissions over the years 2013–2022 relative to country-specific targets	EPI
Adjusted emissions growth rate for methane (CHA)	Average annual rate of increase or decrease in raw methane emissions over the years 2013–2022.	EPI
Adjusted emissions growth rate for F-gases (FGA)	Average annual rate of increase or decrease in raw fluorinated gas emissions over the years 2013–2022.	EPI
Projected 2050 GHG Emissions (GHN)	Extrapolation of each country's emissions trajectory over the most recent 10 years of data to 2050.	EPI
GHG growth rate adjusted by emissions intensity (GTI)	Recognizes that countries with high emissions intensity of GDP most urgently need to rapidly decarbonize	EPI
Net carbon fluxes due to land cover change (LUF)	Net carbon fluxes from land use, land cover change, and forestry (LULCF) over the last decade, normalized by countries' forested area in 2000.	EPI

Table .5: Index's constituent variables

Variable (Lable)	Description	Source
Adjusted emissions growth rate for nitrous oxides (NDA)	Calculated as the average annual rate of increase or decrease in raw nitrous oxide emissions over the years 2013–2022	EPI
Change in solar capacity (CSC)	Change in operating solar power capacity	GEM
Change in gas and oil capacity (CGC)	Change in operating gas and oil power capacity	GEM
Share of renewables (RSE)	Share of electricity generated by renewables (hydropower, solar, wind, biomass and waste, geothermal, wave, and tidal sources)	Ember
Explicit fossil fuel subsidies (EXS)	Reflects underpricing due to supply costs being greater than prices paid by users.	IMF
Implicit fossil fuel subsidies (IMS)	Reflects the difference between supply costs and socially efficient prices	IMF

Table .6: Correlates of Environmental Performance

Variable	Description	Source
Control of Corruption	Perceptions of the extent to which public power is exercised for private gain, including both petty and grand forms of corruption, as well as "capture" of the state by elites and private interests.	WGI by World Bank
Rule of Law	Perceptions of the extent to which agents have confidence in and abide by the rules of society, and in particular the quality of contract enforcement, property rights, the police, and the courts, as well as the likelihood of crime and violence.	WGI by World Bank
Regulatory Quality	Perceptions of the ability of the government to formulate and implement sound policies and regulations that permit and promote private sector development.	WGI by World Bank
Political Stability and Absence of Violence/Terrorism	Perceptions of the likelihood of political instability and/or politically motivated violence, including terrorism.	WGI by World Bank

Table .6: Correlates of Environmental Performance

Variable	**Description**	**Source**
Government Effectiveness	Perceptions of the quality of public services, the quality of the civil service and the degree of its independence from political pressures, the quality of policy formulation and implementation, and the credibility of the government's commitment to such policies.	WGI by World Bank
Voice and Accountability	Perceptions of the extent to which a country's citizens are able to participate in selecting their government, as well as freedom of expression, freedom of association, and a free media.	WGI by World Bank
Democracy Index (EUI-DI)	Snapshot of the state of democracy.	World Bank
Total natural resources rents (% of GDP)	Sum of oil rents, natural gas rents, coal rents (hard and soft), mineral rents, and forest rents.	World Bank

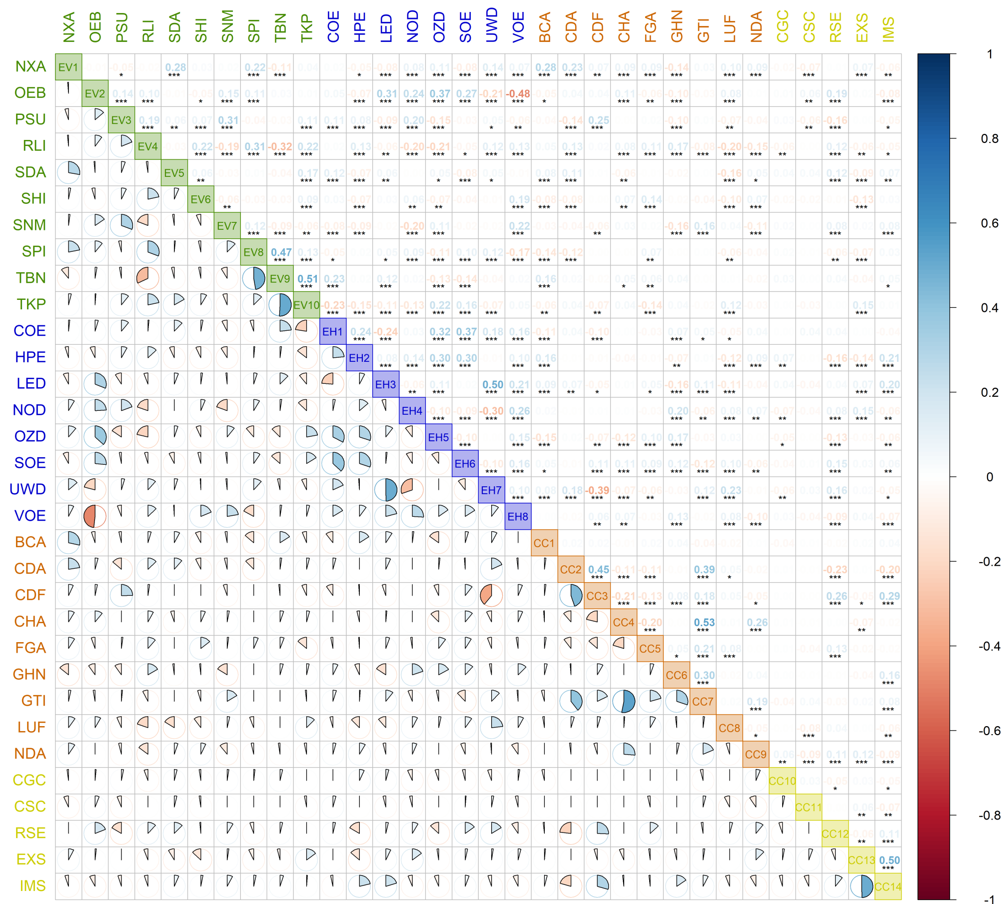

Figure .5: Partial correlation for the final 32 variables. The *, ** and *** symbols denote the p-values at 10th, 5th and 1st significance level, respectively.

Table .7: Robust PCA factor loadings across years

Policy Level	**Var.**	**2015**	**2016**	**2017**	**2018**	**2019**	**2020**	**2021**	**2022**
				First component					
EV	NXA	0.358	0.361	0.356	0.354	0.337	0.327	0.328	0.324
	OEB	-0.051	-0.026	-0.063	-0.030	-0.107	-0.087	-0.097	-0.116
	PSU	-0.173	-0.176	-0.178	-0.155	-0.202	-0.199	-0.211	-0.218
	RLI	0.081	0.092	0.094	0.091	0.092	0.106	0.092	0.086
	SDA	0.237	0.258	0.260	0.278	0.271	0.256	0.250	0.244
	SHI	-0.011	0.008	0.020	0.024	0.023	0.028	0.029	0.044
	SNM	0.105	0.091	0.086	0.077	0.053	0.045	0.044	0.053
	SPI	0.181	0.204	0.195	0.229	0.156	0.149	0.126	0.112
	TBN	0.210	0.213	0.216	0.232	0.143	0.133	0.089	0.069
	TKP	0.129	0.155	0.158	0.188	0.109	0.097	0.054	0.036
EH	COE	0.043	0.059	0.070	0.060	0.076	0.094	0.050	0.032
	HPE	0.004	0.007	0.027	-0.006	0.027	0.037	0.000	-0.027
	LED	0.310	0.315	0.326	0.324	0.321	0.327	0.322	0.320
	NOD	-0.170	-0.174	-0.180	-0.163	-0.199	-0.179	-0.217	-0.234
	OZD	0.114	0.113	0.108	0.132	0.145	0.144	0.134	0.112
	SOE	-0.069	-0.049	-0.036	-0.038	-0.075	-0.066	-0.125	-0.155
	UWD	0.337	0.341	0.347	0.344	0.381	0.384	0.390	0.397
	VOE	0.183	0.192	0.192	0.164	0.185	0.187	0.185	0.176
CC	BCA	0.177	0.210	0.242	0.249	0.287	0.297	0.296	0.304
	CDA	0.325	0.293	0.266	0.236	0.255	0.256	0.262	0.247
	CDF	-0.042	-0.061	-0.080	-0.077	-0.116	-0.129	-0.149	-0.180
	CHA	0.239	0.231	0.219	0.217	0.191	0.174	0.171	0.164

(continued)

Policy Level	**Variable**	**2015**	**2016**	**2017**	**2018**	**2019**	**2020**	**2021**	**2022**
	FGA	0.007	0.051	0.083	0.119	0.171	0.204	0.214	0.208
	GHN	0.04	0.021	0.021	0.005	-0.006	0.008	-0.020	-0.049
	GTI	0.371	0.344	0.328	0.305	0.293	0.303	0.301	0.290
	LUF	0.076	0.072	0.068	0.068	0.062	0.068	0.057	0.045
	NDA	0.183	0.154	0.126	0.12	0.115	0.121	0.115	0.100
	CGC	-0.019	-0.016	-0.041	-0.024	-0.022	-0.02	-0.018	-0.022
	CSC	-0.029	-0.037	-0.037	-0.043	-0.046	-0.036	-0.053	-0.057
ET	EXS	0.056	0.052	0.064	0.084	0.054	0.055	0.012	0.001
	IMS	0.021	0.026	0.051	0.084	0.045	0.048	0.002	-0.018
	RSE	-0.014	0.016	0.007	0.058	-0.011	0.009	-0.027	-0.045
					Second component				
	NXA	-0.001	-0.017	-0.023	-0.026	0.027	0.029	-0.013	-0.004
	OEB	0.350	0.342	0.381	0.371	0.356	0.33	0.055	0.052
	PSU	0.224	0.237	0.246	0.237	0.188	0.155	0.008	0.013
	RLI	0.034	0.065	0.053	0.032	0.070	0.072	-0.035	-0.015
	SDA	-0.020	-0.015	0.006	0.023	0.094	0.068	-0.086	-0.063
EV	SHI	0.044	0.058	0.056	0.040	0.037	0.007	-0.128	-0.112
	SNM	0.019	0.018	0.013	-0.005	0.015	0.018	-0.071	-0.055
	SPI	0.355	0.351	0.341	0.293	0.364	0.346	-0.184	-0.162
	TBN	0.313	0.324	0.318	0.257	0.328	0.338	-0.041	-0.017
	TKP	0.350	0.359	0.359	0.327	0.401	0.391	-0.111	-0.080
	COE	-0.029	-0.007	0.021	0.006	-0.034	-0.007	0.411	0.419
	HPE	0.000	0.008	0.027	0.034	-0.015	0.016	0.484	0.465
	LED	-0.023	-0.042	-0.024	-0.067	-0.002	0.004	0.024	0.042
EH									

(continued)

Policy Level	Variable	2015	2016	2017	2018	2019	2020	2021	2022
	NOD	0.217	0.214	0.209	0.231	0.160	0.162	0.105	0.097
	OZD	0.034	0.036	0.034	-0.009	-0.019	0.000	0.285	0.298
	SOE	0.258	0.289	0.275	0.286	0.220	0.254	0.412	0.399
	UWD	-0.232	-0.233	-0.227	-0.264	-0.174	-0.166	-0.051	-0.031
	VOE	-0.133	-0.139	-0.125	-0.139	-0.144	-0.124	0.274	0.290
	BCA	-0.019	-0.045	-0.051	-0.051	-0.001	-0.014	-0.024	-0.041
	CDA	0.028	0.003	-0.002	-0.023	-0.004	-0.010	0.071	0.091
	CDF	0.347	0.317	0.270	0.315	0.262	0.29	0.134	0.141
	CHA	0.035	0.054	0.065	0.081	0.114	0.080	0.007	0.056
CC	FGA	0.016	0.003	-0.006	-0.031	-0.016	0.000	0.096	0.125
	GHN	0.121	0.123	0.119	0.132	0.065	0.092	0.309	0.316
	GTI	0.076	0.047	0.056	0.046	0.071	0.056	0.095	0.122
	LUF	0.007	0.016	0.028	0.017	0.024	0.031	0.046	0.050
	NDA	0.012	0.017	0.015	0.026	0.033	0.016	0.131	0.161
	CGC	-0.038	-0.016	-0.035	-0.005	-0.047	-0.025	0.005	0.016
	CSC	-0.028	-0.020	-0.005	-0.013	-0.022	-0.016	0.049	0.040
ET	EXS	0.104	0.086	0.142	0.165	0.192	0.207	0.066	0.068
	IMS	0.231	0.225	0.225	0.254	0.261	0.284	0.100	0.097
	RSE	0.281	0.271	0.287	0.303	0.306	0.327	-0.041	-0.023
					Third component				
	NXA	-0.027	-0.006	-0.017	0.007	-0.006	-0.028	0.051	0.069
	OEB	0.007	0.022	0.035	-0.020	0.077	0.029	0.326	0.317
	PSU	0.018	-0.004	-0.028	-0.015	0.046	0.032	0.136	0.123
	RLI	0.000	-0.029	-0.047	-0.014	-0.020	-0.063	0.112	0.112

EV

(continued)

Policy Level	Variable	2015	2016	2017	2018	2019	2020	2021	2022
	SDA	0.068	0.068	0.003	-0.018	-0.071	-0.128	0.069	0.083
	SHI	-0.060	-0.112	-0.131	-0.109	-0.095	-0.118	0.036	0.044
	SNM	-0.025	-0.029	-0.033	-0.051	-0.050	-0.058	0.044	0.073
	SPI	-0.222	-0.241	-0.245	-0.240	-0.225	-0.230	0.409	0.413
	TBN	-0.132	-0.143	-0.153	-0.147	-0.092	-0.089	0.381	0.371
	TKP	-0.173	-0.206	-0.200	-0.197	-0.148	-0.155	0.439	0.438
EH	COE	0.440	0.425	0.409	0.405	0.413	0.402	-0.025	-0.033
	HPE	0.499	0.482	0.464	0.487	0.471	0.483	-0.018	-0.033
	LED	-0.012	-0.015	-0.006	0.002	0.000	0.018	0.047	0.073
	NOD	0.116	0.140	0.115	0.091	0.125	0.111	0.110	0.077
	OZD	0.276	0.296	0.350	0.289	0.278	0.286	-0.004	-0.018
	SOE	0.389	0.359	0.378	0.372	0.411	0.399	0.201	0.177
	UWD	-0.058	-0.060	-0.049	-0.023	-0.056	-0.064	-0.098	-0.077
	VOE	0.250	0.237	0.229	0.265	0.248	0.272	-0.124	-0.132
CC	BCA	0.081	0.06	0.046	0.018	-0.001	-0.042	-0.033	0.010
	CDA	0.040	0.068	0.048	0.081	0.059	0.044	0.001	0.016
	CDF	0.083	0.114	0.095	0.109	0.154	0.100	0.222	0.200
	CHA	0.007	-0.004	-0.012	-0.007	0.027	-0.015	0.097	0.075
	FGA	-0.044	-0.037	0.004	0.06	0.083	0.093	0.03	0.042
	GHN	0.309	0.321	0.304	0.317	0.316	0.302	0.062	0.029
	GTI	0.024	0.066	0.071	0.093	0.076	0.061	0.070	0.061
	LUF	0.022	0.027	0.027	0.034	0.030	0.020	0.046	0.053
	NDA	0.038	0.037	0.053	0.09	0.104	0.113	0.038	0.034
ET	CGC	0.003	0.013	0.070	0.020	0.027	0.039	-0.016	-0.072

(continued)

Policy Level	**Variable**	**2015**	**2016**	**2017**	**2018**	**2019**	**2020**	**2021**	**2022**
	CSC	0.013	0.02	0.023	0.011	0.029	0.041	0.016	0.005
	EXS	0.027	0.041	0.028	0.026	0.035	0.025	0.158	0.205
	IMS	0.139	0.101	0.101	0.106	0.123	0.096	0.268	0.281
	RSE	-0.092	-0.079	-0.085	-0.111	-0.061	-0.067	0.310	0.321

Table .8: Complete comparison of rankings

Country Code	Country	DDEPI 2022	DDEPI 2022-Rank	EPI 2022	EPI 2022-Rank Adj.
FIN	Finland	4.95	1	73.8	4
LUX	Luxembourg	4.38	2	75.1	2
SWE	Sweden	4.12	3	70.3	6
DEU	Germany	3.96	4	74.5	3
GBR	United Kingdom	3.90	5	72.6	5
IRL	Ireland	3.72	6	65.8	16
DNK	Denmark	3.69	7	67.7	10
NLD	Netherlands	3.66	8	66.9	14
MLT	Malta	3.60	9	66.9	13
NOR	Norway	3.56	10	69.9	7
FRA	France	3.50	11	67.0	12
EST	Estonia	3.45	12	75.7	1
AUT	Austria	3.38	13	68.9	8
CHE	Switzerland	3.37	14	67.8	9
SVN	Slovenia	3.35	15	62.4	24
JPN	Japan	3.33	16	61.4	27
ISL	Iceland	3.27	17	64.3	19
PRT	Portugal	3.26	18	61.9	26
BEL	Belgium	3.25	19	66.8	15
GRC	Greece	3.00	20	67.3	11

(continued)

Country Code	Country	DDEPI 2022	DDEPI 2022-Rank	EPI 2022	EPI 2022-Rank Adj.
ESP	Spain	2.97	21	64.0	22
CAN	Canada	2.91	22	61.1	28
USA	United States of America	2.63	23	57.2	35
ITA	Italy	2.51	24	60.3	29
HRV	Croatia	2.51	25	62.3	25
SVK	Slovakia	2.37	26	65.1	18
AUS	Australia	2.34	27	63.1	23
BRB	Barbados	2.26	28	53.1	46
LVA	Latvia	2.22	29	60.2	30
CZE	Czech Republic	2.20	30	65.5	17
POL	Poland	2.10	31	64.2	20
NZL	New Zealand	2.09	32	57.3	33
ALB	Albania	2.09	33	52.2	52
LTU	Lithuania	2.09	34	64.1	21
CYP	Cyprus	1.96	35	53.9	43
TWN	Taiwan	1.87	36	50.1	60
KOR	South Korea	1.74	37	50.6	58
CUB	Cuba	1.65	38	52.5	50
HUN	Hungary	1.61	39	59.8	31
CRI	Costa Rica	1.60	40	55.5	40

(continued)

Country Code	Country	DDEPI 2022	DDEPI 2022-Rank	EPI 2022	EPI 2022-Rank Adj.
BGR	Bulgaria	1.60	41	56.2	37
ROU	Romania	1.57	42	57.3	34
UKR	Ukraine	1.52	43	54.6	41
BHS	Bahamas	1.43	44	55.9	38
SGP	Singapore	1.40	45	53.0	48
VCT	Saint Vincent and the Grenadines	1.37	46	54.2	42
ATG	Antigua and Barbuda	1.29	47	55.6	39
MNE	Montenegro	1.23	48	47.7	74
BLR	Belarus	1.21	49	58.2	32
MUS	Mauritius	1.14	50	47.3	79
GAB	Gabon	1.14	51	53.3	44
LCA	Saint Lucia	1.08	52	51.1	57
ISR	Israel	1.06	53	48.0	70
BRA	Brazil	1.04	54	53.0	47
FJI	Fiji	1.03	55	46.0	87
PAN	Panama	1.02	56	52.9	49
URY	Uruguay	1.01	57	44.1	96
JAM	Jamaica	0.92	58	48.5	68
ECU	Ecuador	0.91	59	51.3	55
CHL	Chile	0.83	60	49.6	64

(continued)

Country Code	Country	DDEPI 2022	DDEPI 2022-Rank	EPI 2022	EPI 2022-Rank Adj.
DMA	Dominica	0.82	61	49.3	65
TTO	Trinidad and Tobago	0.72	62	52.5	51
MKD	North Macedonia	0.67	63	50.3	59
PER	Peru	0.66	64	46.5	84
COL	Colombia	0.65	65	49.7	63
SRB	Serbia	0.63	66	49.8	62
BRN	Brunei Darussalam	0.59	67	48.3	69
VUT	Vanuatu	0.57	68	45.0	92
ARG	Argentina	0.55	69	47.0	80
MEX	Mexico	0.43	70	44.2	95
GRD	Grenada	0.41	71	45.8	88
RUS	Russia	0.37	72	46.7	82
BIH	Bosnia and Herzegovina	0.36	73	46.0	86
SUR	Suriname	0.36	74	56.9	36
KAZ	Kazakhstan	0.26	75	47.8	72
SLB	Solomon Islands	0.25	76	42.2	106
GEO	Georgia	0.21	77	47.3	77
VEN	Venezuela	0.17	78	53.3	45
NIC	Nicaragua	0.13	79	47.4	76
ZWE	Zimbabwe	0.09	80	51.6	54

(continued)

Country Code	Country	DDEPI 2022	DDEPI 2022-Rank	EPI 2022	EPI 2022-Rank Adj.
BLZ	Belize	0.09	81	47.4	75
JOR	Jordan	0.07	82	47.3	78
MDA	Moldova	-0.04	83	46.1	85
ARM	Armenia	-0.06	84	44.9	93
BOL	Bolivia	-0.27	85	45.3	90
ARE	United Arab Emirates	-0.27	86	51.6	53
HND	Honduras	-0.40	87	40.2	115
CHN	China	-0.41	88	35.4	144
QAT	Qatar	-0.52	89	46.8	81
TLS	Timor-Leste	-0.53	90	49.9	61
MYS	Malaysia	-0.55	91	41.0	113
THA	Thailand	-0.56	92	45.7	89
SLV	El Salvador	-0.57	93	41.6	111
CPV	Cabo Verde	-0.59	94	38.0	130
PRY	Paraguay	-0.60	95	39.5	122
DOM	Dominican Republic	-0.62	96	47.7	73
BWA	Botswana	-0.65	97	49.2	66
ZAF	South Africa	-0.68	98	42.7	102
GUY	Guyana	-0.72	99	49.0	67
LBN	Lebanon	-0.78	100	39.9	118

(continued)

Country Code	Country	DDEPI 2022	DDEPI 2022-Rank	EPI 2022	EPI 2022-Rank Adj.
KWT	Kuwait	-0.82	101	44.4	94
SYC	Seychelles	-0.88	102	47.9	71
HTI	Haiti	-0.93	103	36.4	140
LKA	Sri Lanka	-0.93	104	38.8	126
NAM	Namibia	-0.95	105	44.0	97
SLE	Sierra Leone	-1.02	106	39.9	119
TUN	Tunisia	-1.04	107	45.3	91
GNQ	Equatorial Guinea	-1.04	108	41.7	110
AGO	Angola	-1.08	109	40.1	116
AZE	Azerbaijan	-1.09	110	40.5	114
UZB	Uzbekistan	-1.14	111	42.6	103
ZMB	Zambia	-1.15	112	46.7	83
DJI	Djibouti	-1.16	113	32.3	155
OMN	Oman	-1.18	114	51.3	56
SWZ	Eswatini	-1.18	115	38.7	127
PNG	Papua New Guinea	-1.18	116	36.9	138
IRN	Iran	-1.24	117	41.8	108
MNG	Mongolia	-1.25	118	37.2	134
CIV	Cote d’Ivoire	-1.26	119	42.9	101
SAU	Saudi Arabia	-1.44	120	42.5	104
GNB	Guinea-Bissau	-1.44	121	42.0	107

(continued)

Country Code	Country	DDEPI 2022	DDEPI 2022-Rank	EPI 2022	EPI 2022-Rank Adj.
MAR	Morocco	-1.45	122	39.5	121
COG	Republic of Congo	-1.49	123	41.6	112
BHR	Bahrain	-1.51	124	35.3	145
TZA	Tanzania	-1.51	125	43.6	100
MOZ	Mozambique	-1.56	126	39.0	125
DZA	Algeria	-1.58	127	41.7	109
EGY	Egypt	-1.58	128	43.7	99
NGA	Nigeria	-1.71	129	37.9	131
COM	Comoros	-1.73	130	38.2	129
UGA	Uganda	-1.79	131	35.8	142
ERI	Eritrea	-1.84	132	29.0	162
SEN	Senegal	-1.86	133	43.8	98
PHL	Philippines	-1.86	134	32.1	157
CMR	Cameroon	-1.95	135	38.6	128
GHA	Ghana	-1.96	136	36.9	135
LSO	Lesotho	-1.98	137	36.9	137
KEN	Kenya	-2.04	138	36.9	136
COD	Dem. Rep. Congo	-2.05	139	39.5	120
GMB	Gambia	-2.07	140	37.6	133
MRT	Mauritania	-2.09	141	34.6	147
SDN	Sudan	-2.13	142	39.1	123

(continued)

Country Code	Country	DDEPI 2022	DDEPI 2022-Rank	EPI 2022	EPI 2022-Rank Adj.
MMR	Myanmar	-2.17	143	27.1	165
GTM	Guatemala	-2.23	144	32.5	154
VNM	Viet Nam	-2.27	145	24.6	167
BDI	Burundi	-2.37	146	33.5	152
LBR	Liberia	-2.41	147	34.3	149
MWI	Malawi	-2.43	148	35.1	146
TJK	Tajikistan	-2.44	149	32.3	156
AFG	Afghanistan	-2.46	150	31.0	159
RWA	Rwanda	-2.47	151	33.9	150
KHM	Cambodia	-2.49	152	31.2	158
NER	Niger	-2.54	153	40.0	117
ETH	Ethiopia	-2.55	154	36.3	141
IDN	Indonesia	-2.57	155	33.6	151
BEN	Benin	-2.58	156	37.8	132
IND	India	-2.60	157	27.6	164
TGO	Togo	-2.64	158	35.7	143
BFA	Burkina Faso	-2.68	159	42.2	105
IRQ	Iraq	-2.76	160	30.3	160
NPL	Nepal	-2.77	161	33.1	153
CAF	Central African Republic	-2.85	162	39.0	124

(continued)

Country Code	**Country**	**DDEPI 2022**	**DDEPI 2022-Rank**	**EPI 2022**	**EPI 2022-Rank Adj.**
MDG	Madagascar	-2.86	163	30.1	161
GIN	Guinea	-3.01	164	36.5	139
PAK	Pakistan	-3.19	165	25.5	166
BGD	Bangladesh	-3.30	166	28.1	163
MLI	Mali	-3.48	167	34.5	148

Notes: To ensure a fair comparison between the DDEPI and the EPI, we adjusted the EPI rankings by removing countries not included in the DDEPI.