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DYNAMIC ENVIRONMENTAL PERFORMANCE ASSESSMENT THROUGH THE LENS OF SDG 7 AND SDG 13: THE CASE OF EU COUNTRIES

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Abstract. Climate change mitigation directly benefits from the deployment of sustainable energy services. Integrating climate change strategies into national policies can also accelerate the adoption of sustainable energy solutions. This work employed a data envelopment analysis-based environmental performance index, constructed in accordance with the Hicks-Moorsteen productivity framework, to assess the dynamic performance of decision-making units in advancing toward sustainable energy targets (SDG7) and climate change mitigation objectives (SDG13). The present analysis is based on the environmental technology defined in terms of renewable energy consumption, net capital stock, labor force, Gross Domestic Product (DDP), carbon emission, and climate change performance index (CCPI). An application on assessing the environmental performance of European Union (EU) countries from 2014 to 2023 is included. Additional validation and analysis with respect to the mean environmental performance index and its rate of growth are implemented to monitor the dynamic performance trends of EU countries over time. The analysis results suggest that EU countries can be categorized into four clusters based on their mean EPI and its growth rate. Poland ranks among the top performers with the highest mean EPI and growth rate, while Estonia shows the lowest performance, should be prioritized in sustainability strategies. It is expected that this research provides the EU policymakers valuable information for investigating EU countries' progress towards the sustainable energy and climate change mitigation goals.

Keywords. Environmental efficiency, Sustainable energy, Climate change mitigation.

1. Introduction

Sustainable energy (SDG 7) is crucial for climate change mitigation (SDG 13) by reducing dependence on fossil fuels and promoting the adoption of renewable energy sources. SDG 7 aims to ensure universal access to reliable, affordable, sustainable, and modern energy services, whereas SDG 13 underscores the urgency of taking immediate action to combat climate change and mitigate its impacts. The two goals are closely interlinked, as sustainable energy solutions are essential for lowering greenhouse gas emissions and addressing the impacts of climate change.

The majority of studies on climate change agreed that the continuing greenhouse gas emissions from economic activities are widely acknowledged as a key factor contributing to climate change. Researchers have explored development efforts on sustainable energy, production efficiency, and climate change mitigation. Data Envelopment Analysis (DEA), which incorporates undesirable outputs such as carbon dioxide emissions into efficiency assessments, has been widely used in evaluating environmental efficiency. Moradi et al. [13] applied DEA to evaluate the energy performance of the agricultural sector, considering conservation agriculture as a strategy for achieving sustainable development. Wang [17] integrated DEA with the Malmquist index to evaluate energy and production efficiency, ultimately

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suggesting that China should increase the relative cost of energy consumption and improve the distribution of energy and related production inputs. Chen et al. [5] introduced a dynamic, multi-stage DEA framework to analyze the influence of CO_2 emissions on the environmental efficiency of China's industrial sector. Wysokiński et al. [18] utilized DEA with an input-oriented minimization perspective to examine the economic and energy efficiency of European Union (EU) agriculture. Tang et al. [16] employed a super-efficiency slacks-based measurement (SBM) DEA approach to evaluate energy efficiency across China's provinces and formulated policy recommendations to promote greater energy efficiency, mitigate CO_2 emissions, and contribute to achieving sustainable development goals (SDG). Shah et al. [15] evaluated energy efficiency and productivity dynamics across developed and developing members of the G20 using the super SBM DEA method.

Since 2005, the Climate Change Performance Index (CCPI) has provided analysis of countries' climate protection performance, helping to clarify both national and international climate policies. The CCPI employs a standardized framework to assess the climate performance of 63 countries and the European Union (EU), which collectively contribute to more than 90% of global greenhouse gas emissions. According to [3], the climate mitigation performance is evaluated across four categories: greenhouse gas emissions, renewable energy, energy use, and climate policy, playing a key role in guiding the implementation of the Paris Agreement. In recent years, climate variables have been increasingly integrated into DEA-based analyzes of production efficiency to enhance assessments of both energy and disaster efficiency. For instance, Hu et al. [8] employed DEA to evaluate the environmental performance of EU countries through the lens of ecological footprint and CCPI. Liu and Liu [9] utilized a network DEA model that incorporates climate change considerations to evaluate the economic efficiency of the twenty largest carbon dioxide-emitting countries. Lu et al. [10] employed a dynamic slacks-based DEA approach to investigate the impact of greenhouse gas emissions from production activities on climate change and their contribution to the occurrence of natural disasters. Shah et al. [15] utilized the DEA-Malmquist methodology to assess the effects of climate change on agricultural production efficiency in China, suggesting that climate-related factors may have artificially elevated average agricultural productivity during the study period. Bernard et al. [2] applied a nonparametric DEA-Malmquist productivity index to examine the influence of climate change on agricultural productivity growth in Africa.

The Malmquist productivity index is one of the most commonly applied methods for analyzing unit productivity; however, it does not preserve the properties of total factor productivity under variable returns to scale [12]. The Hicks-Moorsteen (HM) index that measures productivity growth by combining output and input quantity changes based on a specific base year technology is a generalization of the Malmquist index. Unlike the Malmquist index, the HM index is simultaneous input and output-oriented because it integrates both output and input quantity indices, eliminating the need to select a single orientation [7]. In recent years, the HM index has been used in various economic studies to assess total factor productivity growth. For instance, Rusielik [14] utilized the HM index to assess the productivity levels of agricultural activities across 25 EU countries and to examine the factors affecting these levels. Molinos-Senante et al. [12] examined changes in total factor productivity across a sample of 204 Spanish wastewater treatment plants using the HM productivity index. Mohammadian and Rezae [11] applied the HM productivity index to analyze firms listed on the Stock Exchange. Their approach was implemented on 26 pharmaceutical manufacturers from the Tehran Stock Exchange. The findings indicate that the HM productivity index offers stronger managerial insights compared to other indices, such as the Malmquist productivity index.

This work considers employing a DEA-based environmental performance index in the spirit of the HM indices for evaluating decision making units' progress towards the sustainable energy (SDG7) and climate change mitigation (SDG13) objects. These two interconnected goals highlight the crucial role of sustainable energy solutions in reducing greenhouse gas emissions and addressing climate change, forming the basis for the proposed environmental technology analysis through the lens of the renewable energy consumption, carbon emissions, net capital stock, labor force, GDP and CCPI. A real case study on assessing the environmental performance of EU countries for ten consecutive years (2014-2023) is included. Additional validation and sensitivity analysis with respect to the mean environmental performance index and its rate of growth are implemented to recognize the sources of inefficiency and propose appropriate policies to improve the efficiency. The remainder of this paper is structured as follows. In Section 2, an environmental performance index based on DEA, formulated in the spirit of the HM indices, is introduced. An empirical study on assessing the sustainability efficiency of EU countries in the light of SDG 7 and SDG 13 is investigated in Section 3. Novel findings and recommendations are also provided. Section 4 presents a summary of the findings.

2. Research Methodology

This section presents an environmental performance index constructed within the DEA framework and aligned with the theoretical structure of the HM productivity indices to measure the dynamic performance of DMUs in progressing toward policy objectives related to sustainable energy transitions and climate change mitigation [1].

2.1. Performance evaluation model with undesirable outputs.

Data Envelopment Analysis (DEA) is a widely used method for evaluating the relative efficiency of decision-making units (DMUs) that utilize multiple inputs to produce multiple outputs. It assesses efficiency by calculating the ratio of a DMU's total weighted outputs to its total weighted inputs. To handle multiple inputs and outputs, DEA employs an endogenous weighting scheme, where each DMU selects input and output weights that maximize its own efficiency relative to other DMUs. The original DEA model, known as the CCR model, was introduced by Charnes et al., assuming constant returns to scale [4]. Since its introduction, DEA has undergone significant theoretical advancements and has seen a wide range of practical applications.

Let $x_{i,j}, i = 1, 2, \cdots, m$, represent the i-th input, $y_{r,j}, r = 1, 2, \cdots, s$, the r-th desirable output, and $u_{kj}, k = 1, 2, \cdots$, the k-th undesirable output of the j-th DMU, where $j = 1, 2, \cdots, n$. The envelopment form of CCR model for measuring the efficiency of DMU_0 can be described as follows [4]:

$$\max \theta_0 \tag{2.1a}$$

$$\text{s.t.} \sum_{j=1}^{n} \lambda_j x_{ij} \leq x_{i0}, i = 1, 2, \cdots, m, \tag{2.1b}$$

$$\sum_{j=1}^{n} \lambda_j y_{rj} \geq \theta_0 y_{r0}, r = 1, 2, \cdots, s, \tag{2.1c}$$

$$\lambda_j \geq 0, j = 1, 2, \cdots, n, \tag{2.1d}$$

where λ_j represents the contribution of each DMU_j in constructing the reference point for DMU_0. The optimal value of model (2.1), denoted by θ_0^*, represents the radial technical efficiency of DMU_0. Given the optimal solution, $\theta_0^* y_{r0}$, reflects the maximum achievable outputs for DMU_0 based on its input vector x_0. Constraint (2.1 b) ensures that the inputs used to form the benchmark do not exceed the observed inputs of DMU_0, i.e., x_{i0}, for $i = 1, c \cdots, m$. Constraint (2.1 c) requires that the outputs of the benchmark be at least as large as the potential outputs $\theta_0 y_{r0}$, for $r = 1, \cdots, s$. Both Éλ_j and θ_0 are decision variables in the model (2.1).

According to joint production theory, desirable outputs are inherently accompanied by undesirable outputs during the process of production. Eliminating the undesirable outputs is significant challenging without a total cessation of production processes. Therefore, they must be taken into account appropriately in the performance evaluation. Nevertheless, the conventional DEA models treated outputs mainly as desirable, while ignoring undesirable ones. The simultaneous modeling of desirable and undesirable outputs presents a complex and still unresolved challenge. In response, a range of environmental DEA models has been developed to assess environmental efficiency, addressing the limitations inherent in traditional measurement approaches [5, 6]. In this study, we employ the output-oriented measurement proposed by Färe et al. [6], which can be described in (2.2).

$$\max \theta_0 \tag{2.2a}$$

$$\text{s.t.} \sum_{j=1}^{n} \lambda_j x_{ij} \leq x_{i0}, i = 1, 2, \cdots, m, \tag{2.2b}$$

$$\sum_{j=1}^{n} \lambda_j y_{rj} \geq \theta_0 y_{r0}, r = 1, 2, \cdots, s, \tag{2.2c}$$

$$\sum_{j=1}^{n} \lambda_j u_{kj} = u_{k0}, k = 1, 2, \cdots, t, \tag{2.2d}$$

$$\lambda_j \geq 0, j = 1, 2, \cdots, n, \tag{2.2e}$$

where θ_0 denotes the technical efficiency score of DMU_0, and $\lambda = (\lambda_1^*, \lambda_2^*, \cdots, \lambda_n^*)$ represents the intensity vector. Denote (θ_0^*, λ^*) as the optimal solution to problem (2.2). The point $(\sum_{j=1}^n \lambda_j^* x_{ij}, \sum_{j=1}^n \lambda_j^* y_{rj})$ serves as a benchmarking reference for DMU_0. The constraint (2.2b) ensures that the input level of a benchmarked unit, $\sum_{j=1}^n \lambda_j^* x_{ij}$, does not exceed the observed input level of DMU_0. The constraint (2.2c) requires that any output level of the benchmark, $\sum_{j=1}^n \lambda_j^* y_{rj}$, should be greater than or equal to the potential output $\theta_0 y_{r0}, r = 1, \cdots, s$. Finally, the constraint (2.2d) guarantees that undesirable outputs are appropriately accounted for in the assessment of environmental efficiency.

2.2. **The environmental performance indices with the HM index framework.** This work considers employing a DEA-based environmental performance index in the spirit of the HM indices for evaluating decision making units' progress towards the SDG7 and SDG13 objects [1]. The Hicks-Moorsteen (HM) index that measures productivity growth by combining output and input quantity changes based on a specific base year technology is a generalization of the Malmquist index. It is often viewed as a superlative index number formula, providing a comprehensive measure of productivity that includes efficiency and technical changes.

To develop the environmental performance indices with the HM index framework, the environmental technology set P is defined under the assumption of constant returns to scale, as defined in (2.3).

$$P = \{(x, y, u) \mid \begin{aligned} & \sum_{j=1}^{n} \lambda_j x_{ij} \leq x_i,\ i = 1, 2, \cdots, m, \\ & \sum_{j=1}^{n} \lambda_j y_{rj} \geq y_r,\ r = 1, 2, \cdots, s_1, \\ & \sum_{j=1}^{n} \lambda_j u_{dj} \leq u_d, d = 1, 2, \cdots, s_2, \\ & \lambda_j \geq 0,\ j = 1, 2, \cdots, n\}, \end{aligned} \tag{2.3}$$

where $(\lambda_1, \lambda_2, \cdots, \lambda_n)$ represents the weighting vector.

The desirable output distance function, which aims to maximize desirable outputs, and the undesirable output distance function, formulated as an input-oriented Shephard measure, are defined as

$$D_y(x, y, u) = min\{\theta \mid (x, \frac{y}{\theta}, u) \in P\}, \tag{2.4}$$

and

$$D_u(x, y, u) = max\{\phi \mid (x, y, \frac{u}{\phi}) \in P\}, \tag{2.5}$$

respectively.

Let $j' = 1, 2, \cdots, n$, denote the observation under evaluation. The distance functions specified in (2.4) and (2.5) can subsequently be estimated using DEA, as formulated in (2.6)

$$\begin{aligned}(D_y(x^0, y^{j'}, u^0))^{-1} = \quad & \max \theta \\ & \text{s.t.} \sum_{j=1}^{n} \lambda_j x_{ij} \leq x_{i0}, i = 1, 2, \cdots, m, \\ & \sum_{j=1}^{n} \lambda_j y_{rj} \geq \theta y_{rj'}, r = 1, 2, \cdots, s, \\ & \sum_{j=1}^{n} \lambda_j u_{kj} = u_{k0}, k = 1, 2, \cdots, t, \\ & \lambda_j \geq 0, j = 1, 2, \cdots, n,\end{aligned} \tag{2.6}$$

and (2.7)

$$\begin{aligned}(D_u(x^0, y^0, u^{j'}))^{-1} = \quad & \min \phi \\ & \text{s.t.} \sum_{j=1}^{n} \lambda_j x_{ij} \leq x_{i0}, i = 1, 2, \cdots, m, \\ & \sum_{j=1}^{n} \lambda_j y_{rj} \geq y_{r0}, r = 1, 2, \cdots, s, \\ & \sum_{j=1}^{n} \lambda_j u_{kj} = \phi u_{kj'}, k = 1, 2, \cdots, t, \\ & \lambda_j \geq 0, j = 1, 2, \cdots, n,\end{aligned} \tag{2.7}$$

respectively.

Given fixed levels of inputs and undesirable outputs, denoted by x^0 and u^0, respectively, the two desirable output vectors, y^m and y^n can be compared using the following quantity index:

$$Q_y(x^0, u^0, y^m, y^n) = \frac{D_y(x^0, y^m, u^0)}{D_y(x^0, y^n, u^0)},$$

where the denominator is obtained by setting $y_{rj'} = y_{r0}$ in (2.6), and $j' = 1, 2, \cdots, n$, denote an observation under consideration.

Similarly, a corresponding quantity index for the undesirable outputs u^m and u^n can be constructed by holding the inputs and desirable outputs constant at (x^0, y^0) :

$$Q_u(x^0, y^0, u^m, u^n) = \frac{D_u(x^0, y^0, u^m)}{D_u(x^0, y^0, u^n)},$$

where the denominator is obtained by setting $u_{kj'} = y_{k0}$ in (2.7).

The environmental performance index, formulated in accordance with the HM index framework, can thus be defined as follows.

$$E^{m,n}(x^0, y^0, u^0, y^m, y^n, u^m, u^n) = \frac{Q_y(x^0, u^0, y^m, u^n)}{Q_u(x^0, y^0, u^m, u^n)}. \tag{2.8}$$

The environmental performance index defined in equation (2.8) admits an intuitive interpretation by utilizing the homogeneity property of the distance functions. Specifically, in the simplest case involving a single desirable output and a single undesirable output, equation (2.8) reduces to $E^{m,n} = \dfrac{y^m/u^m}{y^n/u^n}$. This form of the index reflects a comparison between the desirable-to-undesirable output ratio of observation m and that of observation n. Fäare et al. demonstrated that the HM index specified in equation (2.8) satisfies several fundamental axiomatic properties, including homogeneity, time-reversal, transitivity, and dimensionality [6].

3. A Real Case Study

This work considers evaluating the dynamic environmental performance of EU countries from 2014 to 2023 through the lens of SDG 7 and SEG 13. We collected data from EU 27 countries during the 10 year observation period. The data includes renewable energy consumption, capital, labor force, Gross Domestic Product (GDP), CCPI and carbon emission for each of these countries. Labor force and capital stock have been used as inputs in several efficiency analysis relative to the environmental performance assessment. To promote renewable energy sources, reducing greenhouse gas emissions, and mitigating the effects of climate change objectives, renewable energy consumptions are also included as input. Outputs consist of the CCPI and GDP as desirable outputs and carbon emissions as undesirable output. The data of CCPI can be found in the website of CCPI [3]. The remaining variable information was gathered from the EU statistics and the world bank data. The descriptive statistics and indices of the data set are shown in Tables 1-7, respectively.

Table 1. Labor (hours/week)

	2014	2015	2016	2017	2018	2019	2020	2021	2022	2023
Mean	38.06296	38.04444	38	38	38.02222	38.01481	37.92593	37.89259	37.86667	37.76667
Max	41.9	42.2	42.2	42	42	41.7	41.8	41.3	41	40.9
Min	30.2	30.1	30.3	30.3	30.4	30.4	30.3	31.2	31.3	31.3
SD	2.51429	2.505123	2.478678	2.436107	2.410766	2.425617	2.421314	2.243954	2.247221	2.301003

Table 2. Capital (million units of national currency)

	2014	2015	2016	2017	2018	2019	2020	2021	2022	2023
Mean	46583	64441	1808	13619	36693	34465	40931	56357	50491	30757
Max	1194902	1584387	51656	314665	965091	869756	981737	1332704	1148503	682710
Min	-15456	-19566	-27025	-25855	-52019	-35310	-11877	-3480	-20742	-26771
SD	229695	304524	11969	61192	186050	167349	188664	255923	220581	131814

Table 3. Non-renewable energy consumption (Mtoe)

	2014	2015	2016	2017	2018	2019	2020	2021	2022	2023
Mean	28.14661	28.64788	29.18439	29.38383	29.23292	28.79314	25.77826	27.46255	26.29778	25.02049
Max	175.0052	176.24	179.848	180.0446	174.514	173.1623	159.7163	163.0947	155.9172	146.6791
Min	0.571536	0.569286	0.562752	0.556686	0.644602	0.64239	0.535716	0.524214	0.602217	0.594461
SD	41.5602	42.07863	42.72179	42.67892	41.9062	41.40999	37.2125	39.27778	37.69507	35.71966

Table 4. Renewable energy consumption (Mtoe)

	2014	2015	2016	2017	2018	2019	2020	2021	2022	2023
Mean	5.90154	6.174343	6.352643	6.582835	6.85227	7.099455	7.240263	7.644858	7.828142	8.083213
Max	29.39476	30.85997	31.45201	32.95536	34.88604	36.14774	37.68366	39.0053	40.98277	40.32094
Min	0.028464	0.030714	0.037248	0.043314	0.055398	0.05761	0.064284	0.075786	0.097783	0.105539
SD	7.41344	7.772922	7.97543	8.257794	8.545101	8.798883	8.988984	9.4397	9.822602	9.920717

Table 5. Climate change performance index (CCPI)

	2014	2015	2016	2017	2018	2019	2020	2021	2022	2023
Mean	60.3463	60.33593	59.5837	58.79778	54.70222	55.47259	52.77222	51.24481	55.58519	55.12296
Max	75.23	77.76	71.19	66.17	74.32	76.28	75.77	74.42	76.67	79.61
Min	45.52	51.58	47.24	46.04	38.74	40.84	39.98	37.02	40.41	37.94
SD	6.305349	5.841302	5.636909	4.482547	8.350183	8.900265	9.74519	9.715199	9.288444	9.42894

Table 6. GDP (trillion PPS)

	2014	2015	2016	2017	2018	2019	2020	2021	2022	2023
Mean	439.5536	455.8095	468.1187	487.6817	504.7131	523.0329	502.9296	547.715	597.6486	637.0619
Max	2782.597	2851.302	2949.992	3072.101	3163.352	3202.754	3117.399	3318.195	3550.129	3738.834
Min	10.9384	12.2552	12.9446	14.6829	15.8079	16.8413	16.4639	18.775	20.1405	22.6257
SD	665.7837	681.9	703.4446	739.0382	749.3526	769.4413	735.7533	790.0276	849.5086	903.9127

Table 7. Green house gas emission (million tones of CO_2 equivalent)

	2014	2015	2016	2017	2018	2019	2020	2021	2022	2023
Mean	118.5561	119.8779	130.7063	121.4123	119.22211	113.5378	102.0799	108.0133	107.1067	99.06669
Max	754.8759	758.7097	748.3283	738.9187	714.1201	647.1257	572.623	614.8099	617.3317	551.3271
Min	2.829444	2.105983	1.789091	1.932095	2.055392	2.695736	2.442336	2.948957	3.518785	3.561721
SD	165.5407	166.6965	172.7112	165.3394	160.6798	149.0152	133.7964	143.7478	143.2168	130.2636

In this study, a DEA-based environmental performance index in the spirit of the HM indices is employed for evaluating the environmental performance of EU countries from 2014 to 2023. Tables 8 summarizes the dynamics of the EPI across 2014-2023. The last two columns of Table 8 list the mean value of the EPI and the rate of growth, respectively.

To explore the relationship between the mean EPI and two types of outputs, the dynamic of the EPI and two types of outputs are presented in Figure 1. In this study, the desirable output index is related to GDP and CCPI, and the undesirable output index is related to carbon emissions. As illustrated in Figure 1, the value of the CCPI increased significantly after 2017. This increase can be attributed to a change in the evaluation methodology implemented that year. Specifically, the weighting criteria were adjusted from 30% emissions level, 30% development of emissions, 10% renewable energies, 10% efficiency, and 20% climate policy to 40% GHG emissions, 20% renewable energy, 20% energy use, and 20% climate policy. Consequently, the value of mean EPI also exhibited more notable changes. The variations observed in CCPI, GDP, and greenhouse gas emissions around 2020 are likely attributable to the impacts of the COVID-19 pandemic. The Pearson correlation coefficient between the EPI and CCPI is 0.8469; Meanwhile, the Pearson correlation coefficients between the EPI and the GDP is 0.4421, and between the EPI and carbon emissions is -0.7642. This suggests that the EPI is closer to the climate change efficiency in comparison to the GDP and carbon emissions.

Based on the result in Table 8, the EU countries are classified into four clusters based on the mean EPI and its growth rate, as illustrated in Figure 2. Group 1 comprises the following EU countries, characterized by high growth rates in the EPI and a broad range of mean EPI values: Ireland, Croatia, Cyprus, Latvia, Lithuania, Luxembourg, Hungary, Malta, Slovenia, and Slovakia. Within the group, Malta stands

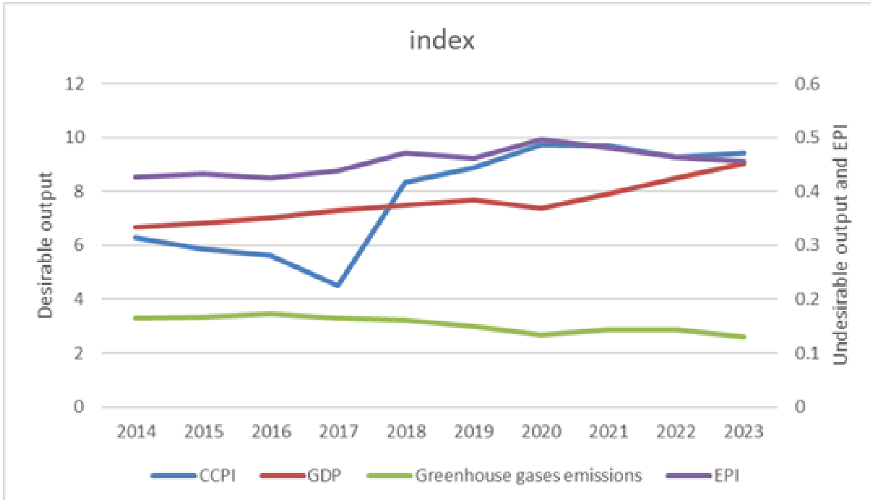

Fig. 1. Dynamics of the EPI

out with the lowest mean EPI, recorded at 0.0259, whereas Ireland exhibits the highest mean EPI, at 0.6985. For the remaining countries in Group 1, mean EPI values range between 0.0839 and 0.6599. Group 2, by contrast, shows less variability in EPI growth rates but continues to display a relatively wide dispersion in mean EPI values. The group encompasses the following EU countries: Bulgaria, Belgium, Czechia, Germany, Greece, Denmark, Italy, Spain, France, Austria, Portugal, Netherlands, Romania, Finland, and Sweden. Among them, Greece and Finland featured a negative rate of growth in the EPI. This trend calls for further research into its underlying causes and the identification of potential policy measures to enhance performance across the countries concerned. Czechia, Germany, and the Netherlands demonstrated mean EPI values exceeding one, indicating superior performance relative to other EU countries. For the remaining countries in the group, mean EPI values ranged from 0.3726 to 0.9697. Group 3 features the best-performing group, exhibiting the highest mean EPI and the highest growth rate of mean EPI. Poland falls into this group with mean EPI and its rate of growth amounted to 1.9962 and 2%, respectively. The mean EPI exhibited an upward trend during the period 2015-2020, followed by a subsequent decline over the remainder of the study period. Group 4 comprises the country featuring the lowest environmental performance, viz. Estonia. Estonia exhibited a declining trend in its mean EPI over the study period, with a mean EPI of 0.1912 and an average growth rate of -8%. This relatively low performance, both in terms of level and growth, compared to other EU countries, may be attributed to the slow pace of renewable energy adoption, weak climate policies, and environmental degradation. To improve its environmental standing, the Estonian government should invest in renewable energy sources like wind and solar, improve energy efficiency, and strengthen climate policies. In addition, protecting forests and wetlands and making better use of EU green funding will help Estonia reduce emissions, support biodiversity, and transition toward a cleaner, more sustainable future.

4. Conclusion

This work employed a DEA-based environmental performance index, constructed in accordance with the Hicks-Moorsteen productivity framework, to assess the dynamic performance of EU countries in advancing toward SDG7 and SDG13. The proposed environmental technology analysis is defined in terms of the renewable energy, carbon emissions, and climate change performance index. A real case study on assessing the environmental performance of EU countries from 2014 to 2023 is included. Additional validation and analysis with respect to the mean EPI and its rate of growth are implemented to

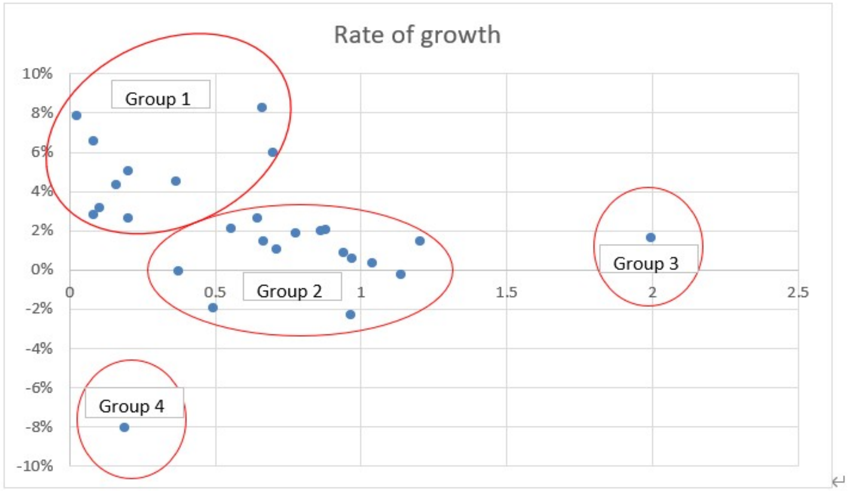

Fig. 2. Mean EPI and its rates of growth

Table 8. Dynamics of the EPI across 2014-2023

	2014	2015	2016	2017	2018	2019	2020	2021	2022	2023	Mean EPI	Rate of growth
Austria	0.613	0.597	0.61	0.582	0.587	0.693	0.766	0.641	0.661	0.719	0.6448	3%
Belgium	0.786	0.81	0.725	0.731	0.906	0.943	1.035	0.908	0.898	0.898	0.864	2%
Bulgaria	0.651	0.663	0.609	0.563	0.602	0.609	0.816	0.726	0.771	0.665	0.6653	1%
Croatia	0.233	0.208	0.19	0.168	0.156	0.17	0.229	0.193	0.216	0.256	0.2011	3%
Cyprus	0.075	0.059	0.062	0.057	0.071	0.089	0.119	0.107	0.092	0.111	0.0839	7%
Czechia	1.257	1.106	1.093	0.932	1.208	1.142	1.376	1.315	1.352	1.286	1.2025	1%
Denmark	0.68	0.652	0.721	0.727	0.755	0.767	0.75	0.711	0.659	0.713	0.7112	1%
Estonia	0.293	0.207	0.235	0.226	0.189	0.179	0.158	0.153	0.159	0.123	0.1912	−8%
Finland	0.631	0.563	0.552	0.479	0.411	0.456	0.494	0.415	0.463	0.486	0.4929	−2%
France	0.695	0.707	0.718	0.77	0.779	0.783	0.845	0.83	0.834	0.819	0.778	2%
Germany	1.006	1.028	1.014	1.031	1.043	1.02	1.061	1.061	1.078	1.034	1.0376	0%
Greece	1.192	1.004	0.946	0.842	1.012	0.98	1.06	0.936	0.844	0.889	0.9664	−2%
Hungary	0.498	0.512	0.5	0.507	0.634	0.638	0.866	0.766	0.78	0.915	0.6599	8%
Ireland	0.551	0.546	0.582	0.57	0.877	0.888	0.844	0.639	0.729	0.777	0.6985	6%
Italy	0.783	0.807	0.794	0.827	0.86	0.893	1.001	0.95	0.94	0.932	0.8787	2%
Latvia	0.112	0.113	0.098	0.088	0.089	0.091	0.112	0.095	0.112	0.132	0.1038	3%
Lithuania	0.198	0.198	0.189	0.17	0.151	0.166	0.244	0.232	0.214	0.264	0.2019	5%
Luxembourg	0.082	0.092	0.078	0.069	0.078	0.086	0.097	0.009	0.084	0.095	0.0848	3%
Malta	0.028	0.021	0.017	0.016	0.017	0.023	0.029	0.028	0.036	0.045	0.0259	8%
Netherlands	1.085	1.134	1.153	1.151	1.163	1.215	1.254	1.141	1.043	1.052	1.1391	0%
Poland	1.801	1.78	1.873	2.008	2.043	2.001	2.179	2.163	2.052	2.062	1.9962	2%
Portugal	0.539	0.559	0.579	0.532	0.527	0.534	0.662	0.517	0.553	0.588	0.5571	2%
Romania	1.036	1.015	0.933	0.866	0.94	0.929	1.065	0.971	0.953	1.024	0.9697	1%
Slovakia	0.335	0.331	0.346	0.315	0.323	0.331	0.415	0.414	0.395	0.462	0.3655	5%
Slovenia	0.137	0.129	0.137	0.123	0.133	0.17	0.223	0.207	0.179	0.178	0.1612	4%
Spain	0.872	0.902	0.865	0.9	0.956	0.945	1.05	1.016	0.98	0.932	0.9418	1%
Sweden	0.437	0.395	0.397	0.366	0.32	0.334	0.381	0.339	0.369	0.403	0.3726	0%

monitor the dynamic performance trends of EU countries over the observation time. Results of the analysis imply that EU countries can be grouped into four clusters with respect to the mean EPI and its rate of growth. Poland falls into the best-performing group, featuring the highest mean EPI and the highest growth rate. Estonia is the one featuring the lowest environmental performance, should be given an especial importance when developing strategies for increase in sustainability. This study features several limitations, which suggest potential directions for future research. First, the time span of the analysis could be expanded by incorporating alternative or extended data sources. Second, the DEA model could be enhanced by including additional environmental performance indicators. Third, the use of non-radial DEA models, such as slack-based measures or range-adjusted measures, may provide more nuanced estimates of environmental efficiency. Fourth, given that many real-world indicators are imprecise or estimated, the application of fuzzy DEA models to assess the dynamic environmental performance of EU countries represents a promising avenue for further investigation.

Statements and Declarations

The authors declare no conflict of interest.

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