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EVALUATING DYNAMIC ENVIRONMENTAL PERFORMANCE USING ECOLOGICAL FOOTPRINT AND CLIMATE CHANGE PERFORMANCE INDICES

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Dedicated to Professor Hari Mohan Srivastava on the Occasion of His 85th Birthday

Abstract. Environmental performance has been an important indicator of economic sustainable development. Monitoring environmental performance and health outcomes can provide a better understanding of the relationship between the environment and human health, helping to shape a more sustainable and healthier future. This study aims to assess the environmental efficiency of European Union (EU) countries through the ecological footprint and climate change performance indices. A window slack-based measurement approach, using the net capital stock, labor, and energy consumption as inputs, climate change performance index and Gross Domestic Product (GDP) as the desirable output, and ecological footprint as undesirable output within the framework of data envelopment analysis, is employed to evaluate the dynamic environmental performance of EU countries from 2007 to 2019. To further explore the improvement of environmental performance in EU countries, the Global Malmquist-Luenberger index method is applied over the observation periods. Our results offer key insights into the environmental performance of EU countries and their advancements toward sustainable economic development.

Keywords. Environmental efficiency, DEA, Ecological footprint, Climate change Performance index.

1. Introduction

Environmental efficiency is essential for achieving sustainable economic growth. While nations work to enhance their economic performance, the environmental impact of their activities has to be taken into account. Assessing environmental efficiency can help pinpoint areas for improvement and evaluate the effectiveness of policies designed to mitigate harmful environmental externalizes. Numerous peer-reviewed studies connect the ecological and social consequences of human activities to premature mortality. For example, air pollution and exposure to toxic chemicals have been proven to raise the risk of respiratory and cardiovascular diseases, resulting in premature death [12]. In the same way, environmental degradation and the loss of biodiversity can contribute to the spread of infectious diseases and other health hazards [6]. Considering the substantial impact of environmental factors on human health, there is an increasing demand for empirical studies that track environmental performance. These studies offer essential insights into the effectiveness of environmental policies and help guide future decisions aimed at improving environmental quality and health outcomes.

The ecological footprint (EF) is a crucial tool for evaluating the impact of human activities on the environment [18]. Erb [5] explains that the EF of a region represents the amount of land and resources needed to support its population, encompassing the production of food, energy, and other goods. This

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demand has significant environmental consequences, such as the destruction of natural habitats, a decline in bio-diversity, and increased greenhouse gas emissions. As a result, these factors contribute to climate change, which threatens both human and non-human species. Since 2005, the Climate Change Performance Index (CCPI) has provided analysis of countries' climate protection performance contributing to a clearer understanding of 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. 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 [4].

This study aims to evaluate the environmental efficiency of EU countries using EF and CCPI indices. Data Envelopment Analysis (DEA), which serves as a powerful tool for assessing the relative efficiency of decision-making units (DMUs), has been used to evaluate the environmental efficiency of production systems with multiple inputs and outputs since its introduction by Charnes et al. [3]. In real-world production, desirable outputs, like the real gross domestic product (GDP), are always associated with various undesirable outputs, such as greenhouse gas emissions. To address undesirable outputs in the study of efficiency measurement, conventional DEA models have been adapted by introducing directorial distance functions/data transformation functions [19] or directly treating undesirable outputs as inputs [7]. The DEA models mentioned above are based on radial measures, which primarily focus on the proportional reduction or expansion of inputs/outputs, while neglecting the slacks in undesirable outputs. This may result in an overestimation in the efficiency measurement. To overcome this limitation, Tone [16] proposed the non-radial slacks-based measure (SBM) DEA, which provides more differentiation than radial DEA models by allowing non-proportional adjustments of undesirable outputs. Since then, the SBM-DEA approach has been widely used for measuring environmental efficiency [1, 20, 8]. However, the conventional SBM-DEA model is limited to static analysis and is unable to assess efficiency changes over time. Window analysis, combining cross-sectional and time-series data to evaluate dynamic effects, has been a widely used method for evaluating the dynamic efficiency of DMUs over time.

Different from previous works on the study of sustainability performance measurement, this work first considers the dynamic environmental efficiency measurement of EU countries through CCPI and the EF indices. We employ the window Slack-based Measurement (SBM) method, using the net capital stock, labor, and energy consumption as inputs, GDP and CCPI as the desirable output, and the EF indices as undesirable output within the framework of DEA, which allows for more accurate efficiency evaluations and tracks changes in environmental efficiency throughout the entire time period. Additionally, we combine the Global Malmquist-Luenberger Index (GMLI) with the window SBM-DEA method to assess the annual improvements in efficiency from 2007 to 2019. The remainder of this paper is structured as follows. In Section 2, the research methodologies including the SBM-DEA, window SBM-DEA and GMLI are presented. An empirical study on assessing the sustainability efficiency of EU countries through both of the EF and CCPI is investigated in Section 3. Section 4 presents a summary of the findings.

2. Research Methodology

In this section, the research methodologies including the SBM-DEA, window SBM-DEA and GMLI employed in this study are presented [10].

2.1. **Slack-based measurement DEA model.** DEA is a commonly applied approach for assessing the relative efficiency of decision-making units (DMUs) with multiple inputs and outputs. It measures efficiency by computing the ratio of a DMU's total outputs to its total inputs. To aggregate multiple inputs and outputs, an endogenous weighting scheme is used in which the inputs/outputs weights are defined for each DMU to maximize its efficiency compared to its peers. The basic DEA framework known as the CCR model was developed by Charnes et al. [3]. Later, Banker extended CCR model and proposed the BCC model which assumes variable returns to scale and measures the technical efficiency of the DMUs. In the DEA literature, these two models are referred to as radial models. However, radial DEA models, which serve as the foundation of the DEA framework, have several limitations. First, they assume that all inputs and outputs can be proportionally adjusted to attain efficiency, which may not always be applicable in real-world situations [14]. Second, radial DEA models tend to neglect the slack in undesirable outputs. To overcome these limitations, Tone et al. [16, 17] introduced a non-radial SBM-DEA model that directly addresses slacks and relaxes the need for proportional changes in inputs and outputs.

Assume there are n DMUs, each with m inputs, s_1 desirable outputs and s_2 undesirable outputs. Denote X_{ij} as the ith inputs, $i = 1, 2, \cdots, m$, Y^g_{rj} as the rth desirable outputs, $r = 1, 2, \cdots, s_1$, and Y^b_{dj} as dth undesirable outputs, $d = 1, 2, \cdots, s_2$, of the jth DMU, $j = 1, 2, \cdots, n$. The production possibility set, assuming constant returns to scale, is defined in (2.1).

$$
\begin{aligned}
P = \{(x, y^g, y^b) \mid \quad & \sum_{j=1}^{n} \lambda_j X_{ij} \le x_i,\ i = 1, 2, \cdots, m, \\
& \sum_{j=1}^{n} \lambda_j Y^g_{rj} \ge y^g_r,\ r = 1, 2, \cdots, s_1, \\
& \sum_{j=1}^{n} \lambda_j Y^b_{dj} \le y^b_d, d = 1, 2, \cdots, s_2, \\
& \lambda_j \ge 0,\ j = 1, 2, \cdots, n\},
\end{aligned}
\tag{2.1}
$$

where $(\lambda_1, \lambda_2, \cdots, \lambda_n)$ represents the weighting vector. Let s^-_i, s^g_r and s^b_d denote the slack variables associated with the input, desirable output, and undesirable output constraints of (2.1), respectively. The SBM model with undesirable factors under the assumption of constant returns to scale and weak disposability can be described as follows [16]:

$$
\begin{aligned}
\rho^* = \min \quad & \frac{1 - \frac{1}{m} \sum_{i=1}^{m} \frac{s^-_i}{X_{i0}}}{1 + \frac{1}{s_1+s_2} (\sum_{r=1}^{s_1} \frac{s^g_r}{Y^g_{r0}} + \sum_{d=1}^{s_2} \frac{s^b_d}{Y^b_{d0}})} \\
\text{s.t.} \quad & \sum_{j=1}^{n} \lambda_j X_{ij} + s^-_i = X_{i0},\ i = 1, 2, \cdots, m, \\
& \sum_{j=1}^{n} \lambda_j Y^g_{rj} - s^g_r = Y^g_{r0},\ r = 1, 2, \cdots, s_1, \\
& \sum_{j=1}^{n} \lambda_j Y^b_{dj} + s^b_d = Y^b_{d0}, d = 1, 2, \cdots, s_2, \\
& s^-_i, s^g_r, s^b_d \ge 0,\ i = 1, 2, \cdots, m, r = 1, 2, \cdots, s_1, d = 1, 2, \cdots, s_2, \\
& \lambda_j \ge 0, j = 1, 2, \cdots, n.
\end{aligned}
\tag{2.2}
$$

The objective function of (2.2) is strictly decreasing with respect to $s^-_i, i = 1, 2, \cdots, m, s^g_r, r = 1, 2, \cdots, s_1$, and $s^b_d, d = 1, 2, \cdots, s_2$. The objective value satisfies $0 < \rho^* < 1$, and DMU_0 is efficient in the presence of undesirable outputs if and only if $\rho^* = 1$.

Model (2.2) is a linear fractional program that can be converted into a linear program using the transformation method suggested by Charnes and Cooper [2] as described in (2.3).

$$
\begin{aligned}
\tau_0 = \min \quad & t - \tfrac{1}{m}\sum_{i=1}^{m}\frac{\hat{s}_i^-}{X_{i0}} \\
\text{s.t.} \quad & t + \tfrac{1}{s_1+s_2}\Big(\sum_{r=1}^{s_1}\frac{\hat{s}_r^g}{Y_{r0}^g} + \sum_{d=1}^{s_2}\frac{\hat{s}_d^b}{Y_{d0}^b}\Big) = 1, \\
& \sum_{j=1}^{n}\hat{\lambda}_j X_{ij} + \hat{s}_i^- = tX_{i0},\ i = 1,2,\cdots,m, \\
& \sum_{j=1}^{n}\hat{\lambda}_j Y_{rj}^g - \hat{s}_r^g = tY_{r0}^g,\ r = 1,2,\cdots,s_1, \\
& \sum_{j=1}^{n}\hat{\lambda}_j Y_{dj}^b + \hat{s}_d^b = tY_{d0}^b, d = 1,2,\cdots,s_2, \\
& s_i^-, s_r^g, s_d^b, \geq 0,\ i = 1,2,\cdots,m, r = 1,2,\cdots,s_1, d = 1,2,\cdots,s_2, \\
& t > 0, \hat{\lambda}_j \geq 0, j = 1,2,\cdots,n,
\end{aligned}
\tag{2.3}
$$

where $\hat{s}_i^- = ts_i^-, i = 1,2,\cdots,m, \hat{s}_r^g = ts_r^g, r = 1,2,\cdots,s_1, \hat{s}_d^b = ts_d^b, d = 1,2,\cdots,s_2$, and $\hat{\lambda}_j = t\lambda_j, j = 1,2,\cdots,n$.

The SBM-DEA model (2.3) provides a static analysis and do not take into account changes in efficiency over time. To address these limitations, window analysis has been a widely used technique for evaluating the dynamic performance of DMUs' efficiency over time. The window SBM-DEA analysis is presented in Section 2.2.

2.2. **Window SBM-DEA analysis.** Assume there are a total of T periods, where $t = 1,2,\cdots,T$, and the window begins at time t with a window width w (where $1 \leq w \leq T - t$) representing the number of periods included in a window. Therefore, $T - w + 1$ windows can be generated, with each window containing $n \times w$ DMUs. The input and output matrices for DMU_j^t in the window tw are represented in (2.4).

$$
X_{tw} = \begin{bmatrix} X_1^t & X_2^t & X_3^t & \cdots & X_n^t \\ X_1^{t+1} & X_2^{t+1} & X_3^{t+1} & \cdots & X_n^{t+1} \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ X_1^{t+w} & X_2^{t+w} & X_3^{t+w} & \cdots & X_n^{t+w} \end{bmatrix}, \ Y_{tw} = \begin{bmatrix} Y_1^t & Y_2^t & Y_3^t & \cdots & Y_n^t \\ Y_1^{t+1} & Y_2^{t+1} & Y_3^{t+1} & \cdots & Y_n^{t+1} \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ Y_1^{t+w} & Y_2^{t+w} & Y_3^{t+w} & \cdots & Y_n^{t+w} \end{bmatrix}
\tag{2.4}
$$

By using the input and output matrices in model (2.3), the results of the window SBM-DEA analysis are generated. The efficiency scores of DMUs in the first window $(t = 1)$ are evaluated relative to one another by inputting the inputs and outputs of DMU_j^t into model (2.3). The window is then shifted forward by one year, removing the previous year and incorporating the new one. This process is repeated until the final window, with each DMU attaining w efficiency levels within each window. The average of these values is taken as the efficiency score of a DMU within each window, allowing the DMU's performance to be monitored throughout the study period. Earlier studies confirm that using window widths of three or four yields reliable results and helps minimize the effects of model deficiencies [21]. In this paper, we choose a window with a width of $3 (w = 3)$. Consequently, we obtain 11 windows from 2007-2009 to 2017-2019, each comprises $81(n \times w = 27 \times 3)$ DMUs to be compared against each other.

2.3. **Global Malmquist-Luenberger index (GMLI).** While the window SBM-DEA approach offers greater flexibility in measuring efficiency variations over multiple periods, the ability to compare the performance of DMUs in consecutive periods can be highly beneficial. The Malmquist Index is commonly used in DEA models to assess efficiency improvements between two consecutive time points [11]. The limitation of the classical Malmquist index in addressing undesirable outputs led to the development of the Malmquist-Luenberger Index, which utilizes directional distance functions to handle both desirable and undesirable outputs simultaneously [10]. Let t and $t+1$ represent two-time points. According to [13], the Malmquist-Luenberger Index between these two periods, M_t^{t+1}, can be calculated as

$$MLI_t^{t+1} = \frac{(1+\theta_{t+1}^t)}{(1+\theta_t^t)} \left[\frac{(1+\theta_{t+1}^t)}{(1+\theta_{t+1}^{t+1})} \frac{(1+\theta_t^t)}{(1+\theta_t^{t+})} \right]^{\frac{1}{2}}, \tag{2.5}$$

where θ_t^{t+1} represents the optimal objective value derived from the SBM-DEA model (2.3) for a DMU in period t, using the inputs and outputs from period $t+1$.

While the Malmquist-Luenberger Index is widely used to measure dynamic environmental efficiency, the presence of mixed-period data may result in the absence of a feasible solution during the optimization process [9]. Oh [15] considered this infeasibility issue and introduced the Global Malmquist-Luenberger Index (GMLI) as a solution:

$$GMLI_t^{t+1} = \frac{1+\theta_{t+1}^T}{1+\theta_t^T}, \tag{2.6}$$

where θ_t^T is derived from the solution of model (2.3) when all input and output data sets for all periods (T) are considered, indicating the distance of a DMU in period t with respect to the global frontier. $GMLI_t^{t+1} > 1$ indicates an improvement in efficiency, whereas $GMLI_t^{t+1} < 1$ corresponds to a decline in a DMU's efficiency between periods t and $t+1$.

3. A Real Case Study

This work considers evaluating the dynamic environmental performance of EU countries from 2007 to 2019. We collected data from EU 27 countries during the 13 year observation period. The data includes energy consumption, net capital stock, labor force, GDP, CCPI and EF for each of these countries. The EF data is sourced from the Global Footprint Network (www.footprintnetwork.org). The data of CCPI can be found in the website of CCPI 2025 (https://ccpi.org/). The remaining variable information was gathered from the waste statistics of EU countries and the world bank data. The descriptive statistics and indices of the data set are shown in Tables 1-6, respectively.

Table 1. Total energy consumption (million tons of oil equivalent)

	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019
Mean	42.03929	42.325	39.95714	41.7	39.89643	39.94286	39.90714	38.18214	38.95714	39.67143	40.09643	40.25	40.01786
Max	213	221.7	208.3	223	211.7	215.8	221	210	212.8	216.9	218.6	215.2	214.7
Min	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.6	0.6	0.6	0.6	0.7	0.7
SD	55.49	56.51	53.25	55.85	53.05	54.02	54.73	51.75	52.6	53.37	53.54	53.21	52.89

TABLE 2. Labor (person)

	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019
Mean	8593593	8670135	8693070	8710654	8703512	8762019	8790602	8824922	8845973	8901602	8949251	8983859	9023371
Max	1861246	41917490	41978630	41949335	41729225	41853628	42212988	42458390	42660629	43567225	43819028	43935038	44433744
Min	167568	169526	171732	175583	180203	187135	196571	205532	212910	222635	233766	250448	265572
SD	11114680	11215354	11261077	11286291	11293426	11380387	11448290	11504606	11545033	11681668	11727040	11771075	11834362

TABLE 3. EF (global hectares)

	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019
Mean	6.29579	6.230794	5.502944	5.736339	5.640753	5.355204	5.300253	5.306268	5.266538	5.254748	5.444407	5.403307	5.305561
Max	14.11	14.94671	13.53007	15.49098	15.12413	13.84257	13.29181	12.45989	13.42772	12.78337	12.56056	13.41014	12.26467
Min	3.023024	3.391529	2.754523	2.842647	3.052674	2.670051	2.70689	2.791031	2.732348	2.899391	3.311992	3.466027	3.329297
SD	2.062027	2.077426	1.926496	2.278733	2.21169	2.0892	2.02212	1.894154	2.045798	1.882172	1.863554	1.940141	1.827637

TABLE 4. CCPI (score)

	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019
Mean	51.98347	52.99286	53.1	53.66429	56.94643	57.01071	60.96893	60.11714	60.14964	59.4925	58.7675	54.36036	55.23179
Max	63.8	65.6	66.7	67.4	69.9	68.1	72.61	75.23	77.76	71.19	66.17	74.32	76.28
Min	37.5	39.2	40.4	42.8	46.3	45.1	50.28	45.52	51.58	47.24	46.04	38.74	40.84
SD	4.8547	5.9310	6.5125	5.7476	5.7899	6.1282	5.6826	6.1916	5.7676	5.4524	4.3416	8.2402	8.6720

TABLE 5. GDP (current million euro)

	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019
Mean	464524.7	467291.6	440274.2	458714.4	472755.4	482438	486389.2	503672.1	530613	535025.6	551593.2	570011.1	591222.3
Max	2503000	2543133	2443805	2558935	2689838	2746773	2816098	2932023	3023553	3129374	3271307	3370332	3480297
Min	5790.4	6206.1	6259.6	6815.8	6924.6	7364.5	7944.4	8751.1	9996.6	10541	11936.4	13043.9	14294.2
SD	718703.2	704866.9	666725.5	695063.2	719288.1	741221.4	749120.8	783138.4	827511.9	825722.3	842226.7	864709.1	892749.3

To investigate the dynamic changes in environmental efficiency of EU countries, the window SBM-DEA analysis and the GMLI techniques are employed in this study. Table 7 summarizes the results of SBM-DEA analysis for evaluating the environmental performance of EU countries from 2007 to 2019, which can be used to further explore the improvement of environmental performance in EU countries by applying the GMLI technique over the observation periods. The environmental performance values obtained from the SBM-DEA analysis fall within the range of [0,1]. A lower performance value indicates relatively poorer efficiency. For instance, France had a value of 1, while Estonia had a value of 0.09 in 2007. It shows that France had better environmental performance than Estonia in 2007. France had an average annual environmental performance value of 1, indicating consistently excellent performance from 2007 to 2019. In contrast, Estonia had an average value of 0.298 over the periods, making it the poorest performer among EU countries, indicating generally unsatisfactory performance from 2007 to 2019.

Tables 8 and 9 summarizes the results of the window SBM-DEA analysis and the GMLI techniques, respectively. As mentioned in section 2.2, a window with a width of $3(w = 3)$ is chosen in this study. Consequently, we obtain 11 windows from 2007-2009 to 2017-2019, each comprises $81(n \times w = 27 \times 3)$

Table 6. Capital (million units of national currency)

	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019
Mean	−61323.9	−55951.8	19705.5	31676.8	44119.9	62458.7	107545	84837.8	119572.3	90132.5	70164.1	63558.6	51215.9
Max	266417	260313	257194.1	578320.8	841372	1190506	2191786	1591404	2408181	1633968	1105470	1066190	518806.7
Min	−1686558	−1615705	−37927	−104180	−72089	−26301	−10736	−21728	−9113	−15703	−24397	−34932	−106083
SD	333269.4	324804.7	70330.6	127476.9	173701.5	232840.6	420329.6	306880.9	461658.2	315362.2	217019.1	210652.8	125865.7

Table 7. The results of SBM-DEA analysis

	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019
Austria	1	0.507657	0.468291	0.55	0.53	0.546	0.555	0.539	0.582808	0.470443	0.484332	1	0.444164
Belgium	0.356315	1	1	1	1	1	1	1	0.704029	1	0.518047	0.723947	0.565068
Bulgaria	1	1	1	1	1	1	0.2	0.201	0.188589	0.166931	0.167116	0.1684	0.2085
Croatia	1	1	1	1	1	0.408	0.63	0.316	0.3023	0.2714	1	1	1
Cyprus	1	1	1	1	1	1	1	1	1	1	1	1	1
Czechia	0.2018	0.5899	1	0.81	0.788	0.749	0.495	0.467	0.3651	0.187965	0.196889	0.1916	0.2335
Denmark	1	1	1	1	1	1	1	1	1	1	1	1	1
Estonia	0.0903	0.5150	0.2316	0.235	0.386	0.247	0.299	0.304	0.3656	0.2111	0.2004	0.2284	0.5567
Finland	0.4761	0.4398	0.3876	0.455	0.769	0.757	1	0.731	1	0.6536	0.6463	0.8480	1
France	1	1	1	1	1	1	1	1	1	1	1	1	1
Germany	1	1	1	1	1	1	1	1	1	1	1	1	1
Greece	1	0.7773	1	1	1	0.9	0.421	0.581	0.3541	0.6032	0.7403	0.6271	0.6540
Hungary	1	1	1	1	1	1	1	0.477	0.2209	0.1952	0.2460	0.1877	0.2708
Ireland	1	1	1	1	1	1	1	1	1	1	1	1	1
Italy	1	1	1	1	1	1	1	1	1	1	1	1	1
Latvia	0.4088	1	1	1	0.552	0.538	0.587	0.247	0.2987	0.1917	0.1863	0.3081	1
Lithuania	1	1	1	0.578	0.572	1	0.285	0.239	0.3016	0.1962	0.1944	1	1
Luxembourg	1	1	1	1	1	1	1	1	1	1	1	0.4858	1
Malta	1	1	1	1	1	1	1	1	1	1	1	1	1
Netherlands	1	1	1	1	0.61	0.552	0.558	0.579	0.5158	0.8039	0.5416	0.5253	0.6366
Poland	0.1179	0.5146	1	0.571	1	1	1	1	0.3682	0.4955	0.5009	0.5614	0.7334
Portugal	0.7576	1	1	1	1	1	0.768	1	1	0.3823	0.3783	4534	0.6569
Romania	1	1	1	1	1	1	0.778	1	1	1	1	1	0.9999
Slovakia	0.3937	0.7354	0.825	0.85	0.691	1	0.304	0.279	0.3172	0.5050	0.5587	0.5483	0.559
Slovenia	0.2145	0.6166	0.5839	0.618	0.618	0.369	0.37	0.335	0.407	0.2625	0.2557	0.5209	0.4626
Spain	1	0.75	1	1	1	0.582	0.525	0.708	0.4932	0.4574	0.5369	0.7386	0.6412
Sweden	1	1	1	1	1	1	1	1	1	0.5712	1	1	1

DMUs to be compared against each other. Table 8 shows that the average efficiency score for EU countries is 0.78, suggesting a potential for improvement of up to 22%. Additionally, efficiency scores vary significantly, ranging from 0.5871 to 0.9604, reflecting a broad spectrum of environmental performance across the EU countries. The France ranks highest in efficiency with a score of 0.9604, while Hungary records the lowest at 0.5871. Following the France, the next top-performing countries are Ireland (0.9534), and Cyprus (0.9185). Over half of the countries (17 out of 27) have efficiency scores ranging between 0.7 and 0.9, reflecting a moderate level of environmental performance. In contrast, the remaining six countries, Bulgaria, Czechia, Denmark, Estonia, Luxembourg, and Poland, exhibit lower efficiency, with average scores below 0.7. Figure 1 shows the average efficiencies of EU countries obtained from the results of window SBM-DEA.

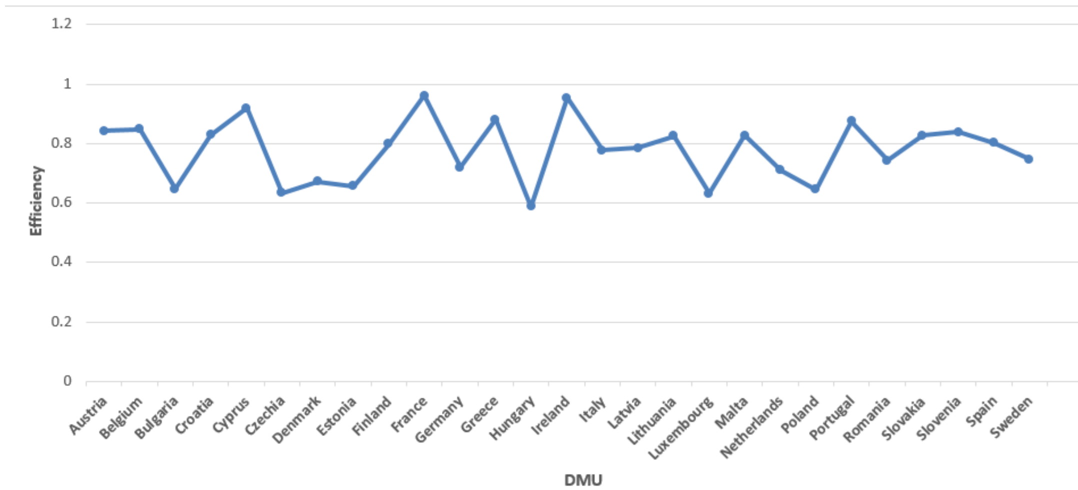

Fig. 1. The average efficiencies of EU countries obtained from the results of window SBM-DEA

Table 8 also presents the results based on three-year time windows, showing that Hungary experienced a significant decline in efficiency - dropping by 53% from 0.84 in the first window to 0.39 in the eleventh window. Czechia followed a similar trend, with its efficiency score falling sharply from 0.86 to 0.41 between 2007 and 2019, dropping by 51.7%. In contrast to these two countries, which showed the greatest efficiency deterioration, Luxembourg's average efficiency rose rapidly, increasing from 0.44 in window 1 to 0.64 in window 11, a substantial increase of 46.9%. In addition to countries with significant improvements or deteriorations in environmental performance, Bulgaria also experienced a change in efficiency trend greater than 20% over the observed time period. The efficiency of the remaining countries remained relatively stable over time.

While window analysis helps track efficiency variations over the observation period, the GMLI technique offers a more detailed assessment of country performance, highlighting efficiency improvements or declines between consecutive years. To compare the environmental performance of EU countries in adjacent years from 2007-2008 to 2018-2019, the results obtained from SBM-DEA analysis and equation (2.6) are employed to compute the GMLI. Table 9 presents a summary of the GMLI results. The findings indicate that most countries experienced changes in environmental efficiency across each consecutive two-year period, and exhibited both periods of progress and decline between 2007 and 2019. A value less than 1 means that the country's environmental performance declined during that period, suggesting it was undergoing a phase of deterioration. For example, Spain's value for 2007-2008 was 0.875, while Austria's value for the same period was 0.754. This indicates that Austria's environmental performance deteriorated more than Spain's between 2007 and 2008. Conversely, a value greater than 1 indicates that a country's environmental performance improved in the period. For instance, Slovakia had a value of 1.246 for 2007-2008, while Belgium's value for the same period was 1.475. Compared to Slovakia's 1.246, this means that Belgium's improvement in environmental performance from 2007 to 2008 was greater than Slovakia's. Notably, some countries have GMLI values equal to 1, such as Cyprus, Denmark, France, Germany, Ireland, Italy, Malta, and Sweden. This indicates that the environmental performance of these countries did not change during these periods and remained relatively stable. As shown in the window analysis, Czechia's efficiency scores steadily decreased from 0.8578 to 0.4143 over the analyzed period. This is consistent with the GMLI results, where Czechia recorded the number of periods with a GMLI value below one - 8 out of 12 periods. On a broader scale, the average GMLI across all countries were less than one in 6 out of the 12 evaluated periods. Consequently, the overall average GMLI value of 0.99 suggests that the environmental efficiency of EU countries slightly declined from 2007 to 2019.

Table 8. The results of the window SBM-DEA approach

Window	W1	W2	W3	W4	W5	W6	W7	W8	W9	W10	W11	Average
DMU	07-09	08-10	09-11	10-12	11-13	12-14	13-15	14-16	15-17	16-18	17-19	
Austria	0.8880	0.5620	0.5808	0.8173	0.914	0.899	0.96	0.9278	0.8895	0.9068	0.9128	0.8417
Belgium	0.9189	0.7228	0.7617	0.831	0.842	0.927	0.8106	0.8593	0.9260	0.8002	0.9190	0.8472
Bulgaria	0.8155	0.8545	0.7299	0.7076	0.595	0.4883	0.7863	0.4566	0.6047	0.4641	0.6107	0.6467
Croatia	0.8367	0.9012	0.8633	0.7073	0.875	0.8656	0.9243	0.7280	0.8465	0.6774	0.8832	0.8281
Cyprus	0.8623	0.9640	0.9398	0.9183	0.9633	0.997	0.9903	0.9584	0.9361	0.8003	0.7732	0.9185
Czechia	0.8578	0.8310	0.8324	0.719	0.7656	0.7223	0.6203	0.3412	0.4768	0.3950	0.4143	0.6342
Denmark	0.7251	0.6027	0.6181	0.6836	0.7636	0.831	0.7223	0.4515	0.7493	0.6538	0.5876	0.6717
Estonia	0.6148	0.6544	0.6583	0.6476	0.6533	0.7946	0.7146	0.7921	0.3770	0.6607	0.6596	0.6570
Finland	0.7854	0.4693	0.5804	0.7926	0.8803	0.8716	0.9066	0.8252	0.8699	0.8972	0.9088	0.7989
France	0.9740	0.9229	0.8835	0.9813	0.9886	0.964	0.9743	0.9640	0.9722	0.9739	0.9658	0.9604
Germany	0.7896	0.9128	0.5791	0.5623	0.883	0.3926	0.637	0.6897	0.9027	0.7234	0.8399	0.7193
Greece	0.9935	0.8866	0.9748	0.956	0.9036	0.6993	0.902	0.8943	0.8016	0.8115	0.8569	0.8801
Hungary	0.8382	0.7275	0.5959	0.639	0.7723	0.6803	0.582	0.4703	0.3638	0.3948	0.3937	0.5871
Ireland	0.9209	0.9853	0.9889	0.973	0.975	0.9876	0.9173	0.8647	0.8821	0.9971	0.9949	0.9534
Italy	0.7617	0.9165	0.9026	0.9056	0.8993	0.6503	0.7166	0.8118	0.7563	0.5850	0.6464	0.7775
Latvia	0.8049	0.9173	0.7035	0.8473	0.8443	0.922	0.9526	0.8156	0.4588	0.7010	0.6755	0.7857
Lithuania	0.8264	0.7649	0.7666	0.794	0.916	0.8153	1	0.7869	0.6672	0.8353	0.9019	0.8250
Luxembourg	0.4373	0.4383	0.5196	0.7083	0.712	0.762	0.7366	0.5292	0.8393	0.6211	0.6422	0.6315
Malta	0.8782	0.960	0.9654	0.885	0.8816	0.8403	0.8623	0.6935	0.3342	0.8729	0.9146	0.8262
Netherlands	0.6830	0.5698	0.6373	0.635	0.7556	0.7806	0.8643	0.7978	0.6502	0.7149	0.7335	0.7111
Poland	0.6760	0.5627	0.6883	0.7256	0.7196	0.7196	0.655	0.5930	0.6361	0.5694	0.5595	0.6459
Spain	0.8976	0.9686	0.9747	0.8606	0.8256	0.8676	0.8506	0.8687	0.8124	0.8572	0.8478	0.8756
Romania	0.8935	0.8541	0.9208	0.7693	0.715	0.7523	0.59	0.6906	0.4748	0.7426	0.7742	0.7434
Slovakia	0.7791	0.8314	0.9316	0.8436	0.8966	0.9363	1	0.6553	0.7761	0.7317	0.7153	0.8270
Slovenia	0.7544	0.8022	0.8790	0.8043	0.903	0.8876	0.916	0.8657	0.8742	0.7648	0.7690	0.8382
Portugal	0.9327	0.9118	0.9363	0.7646	0.7986	0.624	0.7886	0.6861	0.7224	0.7634	0.9017	0.8028
Sweden	0.6452	0.5813	0.6536	0.749	0.947	0.9696	0.768	0.6976	0.6840	0.7798	0.7304	0.7460

Table 9. The results of the GMLI technique

	07-08	08-09	09-10	10-11	11-12	12-13	13-14	14-15	15-16	16-17	17-18	18-19
Austria	0.754	0.9735	1.0558	0.9871	1.0105	1.0058	0.9897	1.0286	0.9286	1.0095	1.3478	0.722
Belgium	1.4749	1	1	1	1	1	1	0.852	1.1737	0.759	1.1357	0.9078
Bulgaria	1	1	1	1	1	0.6	1.0008	0.99	0.9815	1	1.0008	1.0351
Croatia	1	1	1	1	0.704	1.1577	0.8074	0.9894	0.9762	1.5736	1	1
Cyprus	1	1	1	1	1	1	1	1	1	1	1	1
Czechia	1.3145	1.2658	0.905	0.9878	0.9782	0.8548	0.9813	0.9305	0.8703	1.9976	0.9958	1.0352
Denmark	1	1	1	1	1	1	1	1	1	1	1	1
Estonia	1.3899	0.8132	1.0024	1.12227	0.8997	1.0417	1.0038	1.0475	0.8865	0.9909	1.0233	1.2679
Finland	0.9756	0.9639	1.0483	1.2158	0.9932	1.1383	0.8655	1.1554	0.827	0.9952	1.1227	1.0823
France	1	1	1	1	1	1	1	1	1	1	1	1
Germany	1	1	1	1	1	1	1	1	1	1	1	1
Greece	0.8885	1.1255	1	1	0.95	0.7479	1.1126	0.8564	1.1839	1.0854	0.9351	1.0166
Hungary	1	1	1	1	1	1	0.7385	0.88267	0.9787	1.0427	0.9535	1.0699
Ireland	1	1	1	1	1	1	1	1	1	1	1	1
Italy	1	1	1	1	1	1	1	1	1	1	1	1
Latvia	1.4194	1	1	0.776	0.9910	1.0319	0.7857	1.0417	0.9176	0.9950	1.1029	1.5291
Lithuania	1	1	0.789	0.9962	1.2723	0.6425	0.9642	1.0508	0.9186	0.9983	1.675	1
Luxembourg	1	1	1	1	1	1	1	1	1	1	0.743	1.3459
Malta	1	1	1	1	1	1	1	1	1	1	1	1
Netherlands	1	1	1	0.805	0.9640	1.0039	1.0135	0.9601	1.1900	0.8548	0.9989	1.0734
Poland	1.35510	1.3201	0.7855	1.2731	1	1	1	0.684	1.0928	1.0033	1.0407	1.1102
Portugal	1.1377	1	1	1	1	0.884	1.1312	1	0.691	0.9971	1.0544	1.1404
Romania	1	1	1	1	1	0.889	1.1249	1	1	1	1	1
Slovakia	1.2455	1.0519	1.0137	0.9141	1.1873	0.652	0.9808	1.0297	1.1427	1.0358	0.9929	1.0078
Slovenia	1.33196	0.9796	1.0215	1	0.8461	1.0007	0.9745	1.0539	0.8977	0.9945	1.211	0.9619
Spain	0.875	1.1429	1	1	0.791	0.964	1.12	0.8741	09759	1.0549	1.1314	0.9436
Sweden	1	1	1	1	1	1	1	1	1	1	1	1
Average	1.0801	1.0236	0.9860	1.0028	0.9845	0.9487	0.985	0.9767	0.9785	1.0248	1.0539	1.0463

4. Conclusion

This study is the first to examine environmental performance dynamically using both of the EF and CCPI as a comprehensive evaluation factors within the DEA framework. The window SBM-DEA model generated average efficiency scores for EU countries across the 13-year period from 2007 to 2019. Our results show that France was the most environmentally efficient country, achieving a score of 0.9604, while Hungary recorded the lowest efficiency score at 0.5871. Three countries achieved a relative efficiency score above 0.9, while over half of the countries had scores ranging between 0.7 and

0.9. Only six countries showed lower performance, with scores below 0.7. The average efficiency score across all 27 EU countries was 0.78, indicating an improvement potential of at least 0.22.

Besides providing accurate efficiency scores, the window SBM-DEA model also enables the tracking and monitoring of performance trends over time. The highest progress in environmental performance belongs to Luxembourg with the efficiency score increasing from 0.44 in 2007-2008 to 0.64 in 2016-2017. The worst fall in environmental efficiency belongs to Hungary, where the efficiency score decreased from 0.84 in 2007-2008 to 0.39 in 2016-2017, followed by Czechia, where the efficiency score decreased from 0.86 in 2007-2008 to 0.41 in 2016-2017. The efficiency of the remaining countries remained relatively stable over time.

In addition to the window analysis, the GMLI technique was employed to examine performance variations more deeply and to identify efficiency improvements or declines between consecutive years from 2007 to 2019. The GMLI results indicate that most EU countries have experienced both phases of improvement and decline from 2007 to 2019. The overall average GMLI value of 0.99 suggests that the environmental efficiency of EU countries slightly declined from 2007 to 2019.

Our findings offer valuable insights for policymakers, enabling them to make informed decisions that contribute to more effective and proactive environmental policies in achieving sustainable economic development. Moreover, due to many indicators are imprecise or estimated in the empirical applications, a fuzzy window SBM-DEA analysis for evaluating dynamic environmental performance of EU countries is worth investigating for future research.

Statements and Declarations

The authors declare no conflict of interest.

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