

An Integrated Evaluation of Climate Change and Environmental Sustainability in G20 Countries Using Advanced MCDM Methods

Nazife ŞAHİN MACİT¹

Abstract

This study analytically assesses the climate change and environmental sustainability performance of G20 countries using data from the 2024 Climate Change Performance Index (CCPI) and Environmental Performance Index (EPI) reports. The analysis employs Sum-Weighted Information (SWI) and Ranking Alternatives with Weights of Criterion (RAWEC), which are Logarithmic Decomposition of Criteria Importance (LODECI)-based multi-criteria decision-making (MCDM) methods. The study created three separate decision matrices, taking into account the CCPI and EPI criteria individually, as well as their combination. The criterion weights were determined using the LODECI method; greenhouse gas emissions, climate policy, and air quality were the most significant criteria. The results show that China and Saudi Arabia demonstrate strong environmental performance in CCPI-based rankings, while Germany, the United Kingdom and France demonstrate strong performance in EPI-based evaluations. In the integrated analysis, Germany ranked first using both methods. The consistency of the rankings obtained using the SWI and RAWEC methods was high, which supports the reliability of the analyses. However, some differences in ranking were observed depending on the method used, the distribution of criteria and the country sample. Overall, the study emphasizes the pivotal role of methodological diversity and data-driven approaches in multidimensional environmental assessments for policy-making, while demonstrating the robustness of the findings through sensitivity and comparative analyses.

Keywords: *Climate Change, Environmental Sustainability, Multi-Criteria Decision Making.*



1. Asst. Prof., Gumushane University,
nazfe.sahin@gmail.com,
<https://orcid.org/0000-0002-7996-4704>

<https://doi.org/10.30798/makuiibf.1729026>

Article Type	Application Date	Admission Date
Research Article	June 30, 2025	December 13, 2025

1. INTRODUCTION

In terms of protecting natural resources and ensuring the continuity of ecosystem services, environmental sustainability has become a global priority. Achieving a balance between economic growth and the natural environment is critical to the long-term sustainability of social welfare and development. Natural systems, such as forests, freshwater sources, oceans, and the atmosphere, serve as inputs for economic activities and function as carbon sinks in the fight against climate change. They also provide ecosystem balancing services (Olafsson et al., 2014, p. 935).

Today, climate change is one of the greatest threats to environmental sustainability. Global warming, increased greenhouse gas emissions, water scarcity, extreme weather events, and biodiversity loss have multidimensional effects, causing environmental, economic, and social problems (Puška, Hodžić, Štilić, et al., 2024, p. 15; Zolfani et al., 2018, p. 357). International initiatives such as the Paris Agreement have highlighted the need for countries to work together to limit the effects of climate change. In this context, emission reduction, adaptation policies, and investments in green technology have emerged as key components of sustainable development policies (Lukić, 2025, p. 47; Puška, Hodžić, Štilić, et al., 2024, p. 15).

The G20 group, comprising developed countries, transition economies, and developing countries, accounts for a significant portion of the global economy and is responsible for a substantial proportion of worldwide CO₂ emissions (Appiah-Otoo et al., 2023, p. 1; Climate Transparency, 2018; Shah et al., 2023; Sikder et al., 2019, pp. 930–931;). For this reason, G20 countries must take on a more responsible and leading role in combating climate change. It is crucial to objectively compare the environmental sustainability performance of these countries, given their significant impact on energy consumption, production patterns, and environmental regulations, in order to assess the effectiveness of global climate policies (Codal et al., 2021, p. 2).

Assessing environmental impacts and measuring progress in tackling climate change requires complex, multidimensional analysis. In this regard, multi-criteria decision-making (MCDM) methods have emerged as an important tool for measuring environmental performance (Cook et al., 2017, p. 463; Lukić, 2025, pp. 47–48). The Environmental Performance Index (EPI) and the Climate Change Performance Index (CCPI) are widely used indices for monitoring countries' performance in terms of environmental sustainability and climate policies. The EPI is one of the most important tools for measuring environmental performance, while the CCPI provides an important reference point in the fight against climate change (Altıntaş, 2025; Doğan, 2022; Karahan et al., 2025; Keleş & Ersoy, 2023; Köse et al., 2024; Lukić, 2025;). The EPI assesses more than 180 countries to measure environmental health and sustainability, offering a broader environmental scope (Yale Center for Environmental Law and Policy, 2020). The CCPI, meanwhile, is an index that tracks countries' performance in combating climate change and CO₂ emissions (Germanwatch, 2021).

Significant gaps exist in the literature on environmental sustainability and climate change research. While most studies use indices such as the Environmental Performance Index (EPI) and the Climate Change Performance Index (CCPI), the application of newer methods such as the LODECI, the SWI, and the RAWEC is limited. Furthermore, analyses that focus on G20 countries or that jointly evaluate the EPI and the CCPI are rare. Current studies do not combine the LODECI, SWI and RAWEC methods, which restricts multidimensional assessments. This study aims to fill these gaps by using all three methods together to comparatively and comprehensively assess the environmental sustainability and climate change performance of G20 countries.

This study uses the LODECI, SWI and RAWEC methods to analyse the capacity of G20 countries to combat climate change and their levels of environmental sustainability. The RAWEC method was chosen to make computations faster, more understandable and more applicable by simplifying the steps in the decision-making process and avoiding complex calculations (Puška, Štilić, Pamucar et al., 2024). LODECI evaluates the importance of criteria through logarithmic separation, maximizing the distinction between alternatives and reducing the risk of overrating, thus ensuring a more balanced, consistent, and reliable decision-making process (Pala, 2024). The SWI approach was chosen due to its linear and compensatory structure, which balances differing priorities among criteria while providing a flexible and coherent assessment; its simple and transparent framework further enhances the reliability of the results (Dwivedi & Sharma, 2025). To this end, a comparative performance analysis has been conducted between countries, and scientific findings that could inform climate policy have been presented. A comprehensive roadmap has been presented to decision-makers, emphasising the need to support environmental policy design with multi-criteria evaluation models in order to achieve sustainable development goals.

The study is designed as a comprehensive framework spanning from theoretical foundations to empirical analyses. The first section presents the basic conceptual framework on environmental sustainability and climate change and explains the objectives of the study. The second section reviews current studies in the literature on environmental performance and climate change. The third section presents the methodological framework detailing the data set, evaluation criteria, and multi-criteria decision-making (MCDM) methods applied. The fourth chapter focuses on the empirical evaluation of G20 countries and presents a comprehensive analysis of the findings; it also includes sensitivity and comparison analyses examining the consistency of results under different scenarios of criterion weights and various MCDM methods. The final chapter summarizes the key findings, highlights policy implications, and offers forward-looking recommendations.

Within the scope of this study, the following research questions have been formulated to systematically guide the analyses in line with the identified research gaps and the objectives of the study:

1. How do G20 countries differ in terms of their capacity to combat climate change and achieve environmental sustainability when evaluated separately with CCPI and EPI indicators, and jointly with an integrated framework?
2. What advantages do advanced MCDM methods such as LODECI, SWI, and RAWEC offer compared to traditional approaches in the assessment of environmental performance?
3. How do the rankings of G20 countries change when CCPI and EPI indices are considered separately versus when they are integrated into a combined evaluation?
4. Which critical criteria (e.g., greenhouse gas emissions, climate policy, air quality) have the most significant impact on the environmental performance of G20 countries, and how do they influence country rankings?
5. To what extent are the results of SWI and RAWEC consistent and reliable, and how do they compare with other MCDM methods (CoCoSo, MARCOS, TOPSIS) in terms of robustness and stability?
6. What policy implications can be drawn from the findings for strengthening environmental strategies and supporting sustainable development goals in G20 countries?

The original contributions and innovations that this study brings to the existing body of literature can be summarised as follows:

The adoption of current and advanced methods, such as LODECI-based SWI and RAWEC, represents a significant methodological advance that goes beyond traditional multi-criteria decision-making approaches. Furthermore, analysing the EPI and CCPI indices separately and in an integrated manner enables a more comprehensive and holistic evaluation of environmental sustainability and climate change performance. Focusing on G20 countries allows for an objective and comparative analysis of actors with a significant impact on global environmental policies. In this context, the findings provide policymakers with actionable recommendations and contribute to filling methodological and thematic gaps in the relevant literature.

2. LITERATURE REVIEW

This section reviews the current literature on the main indices used to assess environmental sustainability and climate change performance, and their integration with multi-criteria decision-making (MCDM) methods. The Environmental Performance Index (EPI) and the Climate Change Performance Index (CCPI) are widely recognised as fundamental frameworks for analysing countries' environmental and climate sustainability levels. When evaluated alongside various MCDM methods, they provide a more comprehensive analysis (Altıntaş, 2021; Doğan, 2022; Lukić, 2025). In this context, a systematic review has been conducted on current academic studies in the literature on how these indices are applied with different MCDM techniques. Additionally, a literature review was conducted on the applications

of the LODECI, SWI and RAWEC methods used in this study across various sectors. The key findings are summarised in Table 1.

Zhou et al. (2007) employed a non-radial, non-linear DEA model to assess the environmental performance of OECD countries. They found a general improvement in environmental performance during the period 1995–1997. Abdullah (2017) developed an environmental performance index using the IVIF TOPSIS method. This method optimises decision-making by processing incomplete and uncertain data through a combination of linguistic terms, triple membership degrees and TOPSIS. The study identified Malaysia, Brunei and Singapore as the top-performing Southeast Asian nations. However, when compared using an entropy-based method, Singapore was found to have the highest performance.

Altıntaş (2021) analysed the environmental performance of the G20 countries in 2020 using EPI indicators and the Entropy, ROV, ARAS and COPRAS methods. The results revealed that water resources were the most important factor in determining environmental performance. Germany, Japan, the United Kingdom, France, and Italy are identified as the leading five countries in environmental performance according to the EPI and applied methods. Gök Kısa (2022) analysed the environmental performance of OECD countries using the entropy-based WASPAS method in line with the 2020 EPI indicators, finding that pollution emissions were the most important criterion, followed by biodiversity and habitat and waste management. The least important criterion was ecosystem services. Based on the environmental performance ranking using the WASPAS method, Denmark, Germany, France, Sweden and Japan demonstrated the best performance, while Hungary, Turkey and Mexico demonstrated the worst. Mohaghar et al. (2018) conducted a ranking of OECD countries' environmental performance based on the 2016 EPI reports, employing the Shannon entropy and TOPSIS techniques. They identified forests and fisheries as the most important factors, highlighting Norway, South Korea and Turkey as best practice examples.

Keleş (2024) used the ENTROPY, SD, CRITIC, MEREC, CILOS, and LOPCOW methods to determine the weights of environmental indicators based on 2022 EPI data from a sample of OECD countries. In the CRITIC, ENTROPY and SD methods, the criterion of fisheries had the highest weight. In the CILOS method, the criterion of acid rain had the highest weight. In the MEREC method, the criterion of water resources had the highest weight. Although the absence of fishing data in certain countries influenced this outcome in some methods, this was not the case for all methods. According to the average weights, the top three criteria were acid rain, fishing and water resources. Senir (2024) utilized the 2022 EPI data to evaluate sustainability performance across Eastern Europe, applying the ENTROPY, COPRAS, and WASPAS methods. Water resources, waste management and agriculture were identified as the most important criteria. Differences were observed in the country rankings obtained using the COPRAS and WASPAS methods, with the WASPAS method yielding more consistent results.

Karahan et al. (2025) analysed the environmental performance of Turkey and Eastern European countries using 2022 EPI data with the Entropy and PROMETHEE methods. They found that fishing had the greatest impact on performance, followed by water resources, while agriculture had the least impact. Gelmez et al. (2025) employed ARAS and WASPAS methods integrated with standard deviation (SD)-based weights to assess the environmental performance of OECD member countries, using 2022 EPI indicators as the data source. Their analysis revealed that water quality received the highest relative importance in the weighting results derived from the SD method, followed by air quality and the acid rain criterion. Moreover, the ARAS and WASPAS analyses highlighted Sweden, Denmark, and Finland as the three highest-ranking nations with regard to their environmental outcomes.

Gökgöz and Yalçın (2021) employed the CRITIC-TOPSIS and COPRAS multi-criteria decision-making methods to evaluate the climate change mitigation performance of European Union countries based on renewable energy sources. They identified Sweden and Denmark as the countries with the highest performance and found that industrialised EU countries performed relatively poorly. Köse et al. (2024) examined the climate change performance of G20 countries for the years 2020–21 using the MEREC and PROMETHEE methods. Significant differences in performance were observed before and during the pandemic, with the United Kingdom showing the highest performance in both periods. The study aims to raise awareness of climate change.

Puška, Hodžić, Štilić, et al. (2024) evaluated the climate change management of 27 European Union countries, taking into account 14 indicators included in the CCPI for the year 2023, using the fuzzy MABAC method. Altıntaş (2025) assessed the climate change performance of the G7 countries using MEREC-RAFSI methods based on CCPI 2023 data, identifying greenhouse gas emissions and climate policy as the most significant criteria. Lukić (2025) examined the climate change performance of the G7 countries using the AHP-CODAS method with CCPI 2024 data. According to the AHP method, the most important criterion was greenhouse gas emissions. It is stated that reducing these emissions could mitigate the negative effects of climate change in G7 countries. It was also found that Germany ranks first in terms of climate change performance, followed by the European Union, the United Kingdom, Italy, France, Japan, the United States and Canada.

Doğan (2022) examined the environmental performance of selected countries using EPI and CCPI data from 2021, employing the CRITIC-MABAC and equally weighted-MABAC methods. In the CRITIC analysis, energy use was the most important indicator within the CCPI criteria, whereas within the EPI, it was ecosystem services. When the fifteen criteria of both indices were evaluated together, ecosystem services were found to carry the highest weight. According to the ranking results, Denmark was the best country in the CCPI, and Canada was the worst; in the EPI, Finland and Sweden were the best countries, and Turkey was the worst; in the combined analysis, Sweden was the best country, and Turkey was the worst.

Table 1. Results of Literature Review on Applications of LODECI, SWI, and RAWEC Methods in Different Sectors

Authors/Year	Topic	Method
Pala (2024)	Assessment of social progress in the European Union	LODECI, CoCoSo-L
Yalçın et al. (2024)	Problem of selecting commercial insurance	SF-LODECI-ARTASI
Çilek and Şeyranlıoğlu (2025)	Financial Performance of Reinsurance Companies in Turkey	CRADIS, LODECI, AROMAN
Tufan and Ulutaş (2025)	Supplier Selection in the Food Industry	LODECI, CORASO
Pala et al. (2024)	Financial Performance Analysis of BIST Cement Sector	LODECI, CRADIS
Dwivedi and Sharma (2025)	Performance Measurement of Sustainable Development Goals: Case of Indian States	Shannon Entropy, SWI
Puška, Štilić, Pamucar et al. (2024)	Selection of Distribution Centers	LMAW, RAWEC
Nedeljković et al. (2024)	Selection of Agricultural Product Sales Channels	Fuzzy Set, RAWEC, MEREC
Mohamed et al. (2024)	Sustainable Material Selection for UAV Aerodynamic Wing	SVTNSs - LMAW, SVTNSs - RAWEC
Dündar and Karadağ (2025)	Facility Location Selection for a Cosmetic Company	F-LBWA, RAWEC
Shamsi et al. (2025)	Technology Selection	RWFAHP, ZE-RAWEC, and ZE-CRADIS
Do (2024)	Ranking of the Top Ten Universities in Vietnam	LOPCOW, RAM, PIV, RAWEC, SRP
Dündar (2024)	Performance Evaluation of IPARD-II Rural Development Programs	DIBR-RAWEC
Alrashdi et al. (2025)	Risk Assessment	SVN-Entropy, SVN-RAWEC
Durmus (2025)	Evaluation of Renewable Energy Performance in Turkey	MSD-CRITIC-RAWEC
Trung et al. (2025)	Material Selection for Production or Maintenance	RAWEC-AROMAN
Yürüyen and Ulutaş (2024)	Evaluation of Urban Competitiveness of European Cities	LOPCOW, RAWEC
Akbulut and Aydın (2024)	Sustainability Performance of Deposit Banks	MSD-MPSI-RAWEC
Karadağ (2025)	Financial Performance Evaluation of Turkish Football Clubs	Entropy, RAWEC, FUCA, SAW

Although environmental and climate indices such as the EPI and the CCPI are frequently referenced in the literature, traditional life cycle assessment (LCA) methods have generally been

favoured for analysing these indices. However, adapting methods such as LODECI, SWI and RAWEC to this field indicates a significant gap in the literature, given that these methods are current and have only been used in a limited number of studies. This study aims to address this by applying these methods for the first time in the context of environmental sustainability and climate change.

The limited number of comprehensive analyses conducted specifically for G20 countries and the scarcity of studies evaluating EPI and CCPI criteria together enhance the regional and thematic contribution of this study. Furthermore, the capacity of the methods to handle incomplete and uncertain data enables more reliable and inclusive decision-support processes for environmental performance analysis. In this respect, the study increases methodological diversity in environmental sustainability literature and offers a new evaluation perspective in the context of G20 countries.

3. MATERIALS AND METHODS

This study aims to analyse the climate change and environmental sustainability performance of the G20 countries using multi-criteria decision-making (MCDM) methods. The study draws on the 2024 EPI and CCPI reports, with the relevant indicators based on actual data from 2020 to 2022. The LODECI method was employed to determine the weights of the criteria, and the SWI and RAWEC methods were utilised to evaluate and rank the alternatives based on these criteria. Data for the study were collected from the CCPI and EPI indices between 16 and 24 April 2025.

The G20 countries were selected for this study because they account for a significant proportion of global economic activity and are the primary sources of environmental pressures. They account for 85% of global GDP, 75% of trade, 80% of global carbon emissions and a significant proportion of solid waste production (Terra dos Santos et al., 2023, p. 3), making the G20 a meaningful focus for research. This study focuses on 19 G20 countries.

A total of 14 criteria were considered, including four CCPI indicators and ten EPI indicators. The information relating to these criteria is detailed in Table 2. The environmental standing of G20 nations was evaluated in relation to both climate change and broader ecological performance dimensions. To this end, three separate decision matrices were created:

1. The first decision matrix is based solely on the criteria defined in the Climate Change Performance Index (CCPI).
2. The second matrix is structured based on the criteria defined in the Environmental Performance Index (EPI).
3. The third and final matrix combines the CCPI and EPI criteria comprehensively.

These decision matrices are presented in Tables 3, 4 and 5. Each matrix was analysed using the LODECI method and the environmental performance of each country was evaluated using the SWI and RAWEC methods, according to the objective criterion weights.

Table 2. List of Criteria

No	Criterion	Code	Criterion Direction	References
1	Greenhouse Gas Emissions	CCPI1	Min	Altıntaş (2025), Doğan (2022), Keleş and Ersoy (2023), Köse et al. (2024), Lukić (2025)
2	Renewable Energy	CCPI2	Max	Altıntaş (2025), Doğan (2022), Keleş and Ersoy (2023), Köse et al. (2024), Lukić (2025)
3	Energy Use	CCPI3	Min	Altıntaş (2025), Doğan (2022), , Keleş and Ersoy (2023), Köse et al. (2024), Lukić (2025)
4	Climate Policy	CCPI4	Max	Altıntaş (2025), Doğan (2022), Keleş and Ersoy (2023), Köse et al. (2024), Lukić (2025)
5	Climate Change	EPI1	Max	Altıntaş (2021), Doğan (2022), Gelmez et al. (2025), Karahan et al. (2025), Keleş (2024), Senir (2024)
6	Air Quality	EPI2	Max	Altıntaş (2021), Doğan (2022), Gelmez et al. (2025), Karahan et al. (2025), Keleş (2024), Senir (2024)
7	Sanitation & Drinking Water	EPI3	Max	Doğan (2022), Karahan et al. (2025), Keleş (2024), Senir (2024)
8	Heavy Metals	EPI4	Min	Altıntaş (2021), Doğan (2022), Gelmez et al. (2025), Karahan et al. (2025), Keleş (2024), Senir (2024)
9	Waste Management	EPI5	Max	Doğan (2022), Gelmez et al. (2025), Karahan et al. (2025), Senir (2024)
10	Biodiversity & Habitat	EPI6	Max	Altıntaş (2021), Doğan (2022), Gelmez et al. (2025), Karahan et al. (2025), Keleş (2024), Senir (2024)
11	Ecosystem Vitality	EPI7	Max	Altıntaş (2021), Doğan (2022), Gelmez et al. (2025), Karahan et al. (2025), Keleş (2024), Senir (2024)
12	Fisheries	EPI8	Max	Altıntaş (2021), Doğan (2022), Karahan et al. (2025), Keleş (2024)
13	Agriculture	EPI9	Min	Altıntaş (2021), Doğan (2022), Gelmez et al. (2025), Karahan et al. (2025), Keleş (2024), Senir (2024)
14	Water Resources	EPI10	Max	Altıntaş (2021), Doğan (2022), Gelmez et al. (2025), Karahan et al. (2025), Keleş (2024), Senir (2024)

Table 2 shows that the CCPI and EPI indicators used in our study are frequently used as criteria in other studies and provide a reliable and valid basis for assessing environmental performance.

Table 3. Decision Matrix for CCPI

Alternatives/Criteria	CCPI1	CCPI2	CCPI3	CCPI4
Country/Criteria Direction	min	max	min	max
United Kingdom	30.950	5.200	16.630	9.580
India	31.220	6.230	16.420	16.380
France	27.020	4.550	12.840	12.710
Brazil	20.390	10.270	14.770	16.300
Italy	23.200	7.380	13.520	6.490
Germany	28.470	7.380	14.540	15.390
Turkey	22.340	8.400	12.010	1.070
South Africa	20.770	3.060	15.960	9.740

(Table 3 cont.)

Alternatives/Criteria	CCPI1	CCPI2	CCPI3	CCPI4
Country/Criteria Direction	min	max	min	max
Russia	18.850	2.260	8.430	1.450
Mexico	27.830	2.380	16.550	9.040
Japan	21.420	5.000	13.150	2.500
Australia	23.200	5.570	8.040	8.900
Indonesia	19.720	10.830	14.760	11.900
Argentina	18.770	4.130	15.330	7.160
China	13.450	9.060	7.140	15.910
Canada	14.590	3.400	4.040	9.520
United States	16.880	3.030	6.690	16.200
Korea	13.960	3.460	5.610	6.950
Saudi Arabia	4.850	3.090	6.300	5.090

Table 4. EPI Decision Matrix

Alternatives/Criteria	EPI1	EPI2	EPI3	EPI4	EPI5	EPI6	EPI7	EPI8	EPI9	EPI10
Country/Criteria Direction	max	max	max	min	max	max	max	max	min	max
United Kingdom	67.800	69.800	100.000	99.800	65.400	71.500	72.800	38.100	76.900	78.300
India	35.000	6.800	25.400	31.600	31.800	11.200	30.400	37.000	65.100	30.800
France	61.300	65.200	88.200	98.900	59.600	61.500	67.800	43.200	72.800	82.500
Brazil	45.500	36.200	59.100	61.200	26.200	62.300	63.900	47.900	81.000	53.600
Italy	53.200	52.200	98.600	83.600	57.500	58.500	62.800	34.000	56.400	72.700
Germany	64.900	66.900	100.000	98.700	67.400	82.400	80.100	36.400	78.800	89.100
Turkey	37.000	34.800	63.000	55.800	29.700	20.000	34.700	49.600	59.200	67.900
South Africa	48.000	20.300	25.000	52.200	34.500	39.500	49.300	47.800	57.200	51.500
Russia	36.900	50.500	76.000	65.500	15.500	41.600	48.400	63.000	62.900	52.500
Mexico	46.400	29.700	58.200	52.800	26.300	31.700	46.600	38.400	56.800	69.500
Japan	59.700	59.900	78.100	100.000	73.600	47.400	59.200	48.500	63.300	76.500
Australia	46.600	80.900	99.500	90.300	45.700	55.200	62.500	48.100	65.300	87.200
Indonesia	32.100	22.700	33.200	33.400	26.700	30.700	38.900	39.900	72.200	36.700
Argentina	41.400	47.600	73.400	76.700	26.600	34.700	46.700	38.500	81.400	46.800
China	39.800	14.300	73.900	42.900	43.300	9.500	35.600	39.600	69.000	48.200
Canada	48.200	72.400	95.500	100.000	36.000	52.900	60.400	33.100	72.300	77.700
United States	50.100	65.800	96.200	82.500	41.700	40.700	53.500	46.500	83.000	63.900
Korea	47.000	44.500	90.100	89.400	64.700	32.800	48.800	34.900	61.800	84.300
Saudi Arabia	33.200	34.700	65.400	29.600	37.400	45.400	50.000	56.000	53.800	56.900

Table 5. CCPI and EPI Decision Matrix

Alternatives/ Criteria	CCPI1	CCPI2	CCPI3	CCPI4	EPI1	EPI2	EPI3	EPI4	EPI5	EPI6	EPI7	EPI8	EPI9	EPI10
Country/ Criteria Direction	min	max	min	max	max	max	max	min	max	max	max	max	min	max
UK	30.950	5.200	16.630	9.580	67.800	69.800	100.000	99.800	65.400	71.500	72.800	38.100	76.900	78.300
India	31.220	6.230	16.420	16.380	35.000	6.800	25.400	31.600	31.800	11.200	30.400	37.000	65.100	30.800
France	27.020	4.550	12.840	12.710	61.300	65.200	88.200	98.900	59.600	61.500	67.800	43.200	72.800	82.500
Brazil	20.390	10.270	14.770	16.300	45.500	36.200	59.100	61.200	26.200	62.300	63.900	47.900	81.000	53.600
Italy	23.200	7.380	13.520	6.490	53.200	52.200	98.600	83.600	57.500	58.500	62.800	34.000	56.400	72.700
Germany	28.470	7.380	14.540	15.390	64.900	66.900	100.000	98.700	67.400	82.400	80.100	36.400	78.800	89.100
Turkey	22.340	8.400	12.010	1.070	37.000	34.800	63.000	55.800	29.700	20.000	34.700	49.600	59.200	67.900
South Africa	20.770	3.060	15.960	9.740	48.000	20.300	25.000	52.200	34.500	39.500	49.300	47.800	57.200	51.500
Russia	18.850	2.260	8.430	1.450	36.900	50.500	76.000	65.500	15.500	41.600	48.400	63.000	62.900	52.500
Mexico	27.830	2.380	16.550	9.040	46.400	29.700	58.200	52.800	26.300	31.700	46.600	38.400	56.800	69.500
Japan	21.420	5.000	13.150	2.500	59.700	59.900	78.100	100.000	73.600	47.400	59.200	48.500	63.300	76.500
Australia	23.200	5.570	8.040	8.900	46.600	80.900	99.500	90.300	45.700	55.200	62.500	48.100	65.300	87.200
Indonesia	19.720	10.830	14.760	11.900	32.100	22.700	33.200	33.400	26.700	30.700	38.900	39.900	72.200	36.700
Argentina	18.770	4.130	15.330	7.160	41.400	47.600	73.400	76.700	26.600	34.700	46.700	38.500	81.400	46.800
China	13.450	9.060	7.140	15.910	39.800	14.300	73.900	42.900	43.300	9.500	35.600	39.600	69.000	48.200
Canada	14.590	3.400	4.040	9.520	48.200	72.400	95.500	100.000	36.000	52.900	60.400	33.100	72.300	77.700
United States	16.880	3.030	6.690	16.200	50.100	65.800	96.200	82.500	41.700	40.700	53.500	46.500	83.000	63.900
Korea	13.960	3.460	5.610	6.950	47.000	44.500	90.100	89.400	64.700	32.800	48.800	34.900	61.800	84.300
Saudi Arabia	4.850	3.090	6.300	5.090	33.200	34.700	65.400	29.600	37.400	45.400	50.000	56.000	53.800	56.900

3.1. LODECI Method

The LODECI method uses a maximisation-based normalisation procedure. The decision matrix $\theta = [\theta_{ij}]_{m \times n}$ consists of alternatives A_i ($i = 1, \dots, m$) and criteria C_j ($j = 1, \dots, n$). This decision matrix is normalised using Equation (1) for criteria that provide advantages (benefits) and criteria that create disadvantages (costs) (Pala, 2024, p. 4).

$$\vartheta_{ij} = \begin{cases} \theta_{ij} / \theta_j^{\max}, & \text{benefit - oriented criterion} \\ \theta_j^{\min} / \theta_{ij}, & \text{cost - oriented criterion} \end{cases} \quad (1)$$

The Separation value (AD) of each decision matrix element is calculated using the normalised decision matrix elements ϑ_{ij} as in Equation (2).

$$AD_{ij} = \max\{|\vartheta_{ij} - \vartheta_{rj}|\} \quad r \neq i, r = 1, 2, 3, \dots, m \quad (2)$$

Then, the Logarithmic Decomposition Value (LAD) of each criterion is obtained using Equation (3).

$$LAD_j = \ln \left(1 + \frac{\sum_{i=1}^m AD_{ij}}{m} \right) \quad (3)$$

Finally, the importance levels of the w_j criteria are obtained using Equation (4).

$$w_j = \frac{LAD_j}{\sum_{j=1}^n LAD_j} \quad (4)$$

Example Calculation (LODECI)

Step 1: Selection of Criterion and Data

In this section, the applied calculation process of the LODECI method was performed using the CCPI1-min criterion. Calculations were performed based on the decision matrix provided in Table 3. For example, the CCPI1-min criterion (C1-A1) for the United Kingdom has been considered. For this criterion, according to Table 3, the value for the United Kingdom is $\theta_{11} = 30.950$ and the minimum value among all countries is $\theta_1^{min} = 4.850$.

Step 2: Normalization

For a cost-focused criterion that is to be reduced, the normalized value is calculated using Equation (1).

$$\vartheta_{11} = \frac{\theta_1^{min}}{\theta_{11}} = \frac{4.850}{30.950} \cong 0.157$$

Similarly, the calculation of the ϑ_{ij} values for all countries under the CCPI1 criterion was done using Equation (1), with presentation of the results below:

$$\vartheta_{11} = 0.157, \vartheta_{21} = 0.155, \vartheta_{31} = 0.180, \vartheta_{41} = 0.238, \vartheta_{51} = 0.209, \dots, \vartheta_{19,1} = 1.000$$

Step 3: Calculation of Dissociation Values (AD)

The dissociation value (AD_{11}) for the United Kingdom is calculated using Equation (2) as follows:

$$AD_{11} = \max(|\vartheta_{11} - \vartheta_{21}|, |\vartheta_{11} - \vartheta_{31}|, |\vartheta_{11} - \vartheta_{41}|, \dots, |\vartheta_{11} - \vartheta_{m1}|)$$

$$AD_{11} = \max(|0.157 - 0.155|, |0.157 - 0.180|, |0.157 - 0.238|, \dots, |0.157 - 1.000|) = 0.843$$

Similarly, the calculation of the AD_{ij} decomposition values for all countries belonging to the CCPI1 criterion has been completed and is provided below:

$$AD_{11} = 0.843, AD_{21} = 0.845, AD_{31} = 0.821, AD_{41} = 0.762, \dots, AD_{19,1} = 0.845$$

Step 4: Calculation of Logarithmic Decomposition Value (LAD)

The logarithmic decomposition value (LAD_1) for the CCPI1 criterion is calculated using Equation (3). First, the sum and mean of all dissociation values are determined:

$$\sum AD_{i1} = 0.843 + 0.845 + 0.821 + \dots + 0.845 \cong 14.586$$

$$Mean = \frac{14.586}{19} \cong 0.768$$

Then, the logarithmic decomposition value is:

$$LAD_1 = \ln(1 + 0.768) = \ln(1.768) \cong 0.570$$

Similarly, the logarithmic separation values of all CCPI criteria are calculated as $LAD_1 \cong 0.570$, $LAD_2 \cong 0.487$, $LAD_3 \cong 0.494$, $LAD_4 \cong 0.540$.

Step 5: Calculation of Criterion Weight

Finally, the weight of the CCPI1 criterion is determined using Equation (4). The weight is obtained by dividing the logarithmic decomposition value of the CCPI1 criterion (LAD_1) by the sum of the logarithmic decomposition values of all CCPI criteria:

$$w_{CCPI1} = \frac{w_{CCPI1}}{(w_{CCPI1} + w_{CCPI2} + w_{CCPI3} + w_{CCPI4})} = \frac{0.570}{(0.570 + 0.487 + 0.494 + 0.540)} \cong 0.272$$

3.2. SWI Method

The SWI method is a non-multidimensional decision-making model based on the sum of the information obtained by multiplying the criteria weights with the logarithmic transformation of the normalized values. The SWI process includes the following steps (Dwivedi & Sharma, 2025, pp. 15-17):

Step 1: Creating the information matrix.

As the first step in the multi-criteria decision-making process, an information matrix (BM) is created, where the rows represent alternatives ($i = 1, 2, 3, \dots, m$) and the columns represent criteria ($j = 1, 2, 3, \dots, n$). Each cell in this matrix contains the performance value of the relevant alternative in relation to a specific criterion.

$$BM_{i,j} = [\theta_{i,j}]_{m \times n} = \begin{bmatrix} \theta_{1,1} & \theta_{1,2} & \dots & \theta_{1,n} \\ \theta_{2,1} & \theta_{2,2} & \dots & \theta_{2,n} \\ \vdots & \vdots & \ddots & \vdots \\ \theta_{m,1} & \theta_{m,2} & \dots & \theta_{m,n} \end{bmatrix} \quad (5)$$

Step 2: Normalise the information matrix.

The information matrix (BM) must be normalised to ensure that each criterion is evaluated on the same scale. In this process, for benefit-oriented criteria, the value in each cell of the matrix is normalised by dividing it by the sum of all values in the relevant column; for cost-oriented criteria, the inverse of each value ($1/x$) is taken, and the ratio of these inverse values to the column sum is used for normalisation.

$$\overline{BM}_{i,j} = \begin{cases} \frac{\theta_{i,j}}{\sum_{j=1}^n \theta_{i,j}}, & \text{benefit-oriented criterion} \\ \frac{1/\theta_{i,j}}{\sum_{j=1}^n 1/\theta_{i,j}}, & \text{cost-oriented criterion} \end{cases} \quad (6)$$

Step 3: Calculation of SWI.

The SWI (Sum of Weighted Information) value for each alternative is calculated by taking the base-2 logarithm of the normalised benefit and cost criterion values, multiplying these by the relevant criterion weights and then summing the resulting information scores for each alternative across all criteria.

$$SWI = BM'_i = \sum_{j=1}^n w_j \left(\log_2 \frac{1}{BM_{i,j}} \right) \quad (7)$$

Here, w_j is the criterion weight, and the sum of the w_j weights is 1.

Step 4: Ranking the alternatives:

Alternatives are finally ranked according to their SWI scores. The alternative with the lowest SWI score is considered the preferred solution.

Example Calculation (SWI)

In this section, the applied calculation process of the SWI method is demonstrated using the CCPI1-min criterion (C1–A1) for the United Kingdom, based on the decision matrix provided in Table 3.

Step 1: Identify the criterion value.

According to Table 3, the value of the United Kingdom for the CCPI1-min criterion is:

$$\theta_{11} = 30.950$$

Step 2: Cost-oriented normalisation.

Since this criterion is cost-oriented, the reciprocal of the value is first taken. Then, the reciprocals of all countries are calculated, summed, and the United Kingdom's reciprocal is divided by this total to obtain the normalised value, as follows (see Equation (6)):

$$\frac{1}{\theta_{11}} = \frac{1}{30.950} \cong 0.032$$

$$\sum_{i=1}^{19} \frac{1}{\theta_{i1}} \cong 1.084$$

$$\overline{BM}_{1,1} = \frac{\frac{1}{\theta_{11}}}{\sum_{i=1}^{19} \frac{1}{\theta_{i1}}} = \frac{0.032}{1.084} \cong 0.030$$

Step 3: Calculate the SWI value.

Finally, the SWI score is obtained using Equation (7). The inverse of the normalised value is taken, its base-2 logarithm is calculated, and the result is multiplied by the criterion weight ($w_{CCPI1} = 0.272$):

$$SWI_{11} = w_{CCPI1} * \log_2 \left(\frac{1}{\overline{BM}_{1,1}} \right) = 0.272 * \log_2 \left(\frac{1}{0.030} \right) \cong 1.381$$

3.3. RAWEC Method

The RAWEC method is a unique multi-criteria decision-making method that combines the construction of a weighted normalized decision matrix and the calculation of deviation from ideal and anti-ideal values in a single step. This approach includes the following stages (Puška, Štilić, Pamucar et al., 2024, pp. 5-6):

Step 1: Creating the decision matrix.

The decision matrix is defined as follows, given alternatives $A = \{A_1, A_2, \dots, A_m\}$ and criteria $C = \{C_1, C_2, \dots, C_n\}$.

$$\beta = [\beta_{ij}]_{m \times n} \quad (8)$$

In this context, β_{ij} represents the performance value of alternative A_i in relation to criterion C_j .

Step 2: Double normalisation.

For each criterion in the decision matrix, two types of normalisation value are calculated.

$$\sigma_{ij} = \begin{cases} \frac{\beta_{ij}}{\max_i \beta_{ij}}, \text{benefit-oriented criterion} \\ \frac{\min_i \beta_{ij}}{\beta_{ij}}, \text{cost-oriented criterion} \end{cases}, \sigma'_{ij} = \begin{cases} \frac{\beta_{ij}}{\max_i \beta_{ij}}, \text{cost-oriented criterion} \\ \frac{\min_i \beta_{ij}}{\beta_{ij}}, \text{benefit-oriented criterion} \end{cases} \quad (9)$$

This ensures that each criterion is normalised in terms of both 'maximum benefit' and 'minimum cost'.

Step 3: Calculating criterion-weighted deviation values.

Two types of total deviation value are calculated for each alternative.

$$\text{Deviation Value} \leftrightarrow \begin{cases} \tau_i = \sum_{j=1}^n w_j (1 - \sigma_{ij}), \text{deviation from the positive ideal} \\ \tau'_i = \sum_{j=1}^n w_j (1 - \sigma'_{ij}), \text{deviation from the negative ideal} \end{cases} \quad (10)$$

In this context, w_j represents the weight of criterion C_j , and $\sum w_j = 1$ represents the total weight.

Step 4: Calculating the RAWEC score.

The final RAWEC score for each alternative is obtained as follows:

$$\nabla_i = \frac{\tau'_i - \tau_i}{\tau'_i + \tau_i}, \quad -1 \leq \nabla_i \leq 1 \quad (11)$$

The higher the score ∇_i , the more preferable alternative A_i is considered. The best alternative is the one with the highest ∇_i .

Example Calculation (RAWEC)

In this section, the application of the RAWEC method is illustrated using the CCPI1-min criterion (C1–A1) for the United Kingdom, based on the decision matrix provided in Table 3.

Step 1: Identify the criterion value and reference points.

According to Table 3, the value of the United Kingdom for the CCPI1-min criterion is:

$$\beta_{11} = 30.950$$

The minimum and maximum values among all countries for the CCPI1 criterion are determined as:

$$\beta_{i1}^{min} = 4.850, \beta_{i1}^{max} = 31.220$$

Step 2: Double normalisation (Equation 9).

For a cost-oriented criterion, the double normalisation values are computed as:

$$\sigma_{11} = \frac{\beta_{i1}^{min}}{\beta_{11}} = \frac{4.850}{30.950} \cong 0.157; \sigma'_{11} = \frac{\beta_{11}}{\beta_{i1}^{max}} = \frac{30.950}{31.220} \cong 0.991$$

Step 3: Criterion-weighted deviation values (Equation 10).

Using the criterion weight $w_1=0.272$, the deviations from the positive and negative ideals are calculated as:

$$\tau_{11} = w_1 * (1 - \sigma_{11}) = 0.272 * (1 - 0.157) \cong 0.229$$

$$\tau'_{11} = w_1 * (1 - \sigma'_{11}) = 0.272 * (1 - 0.991) \cong 0.002$$

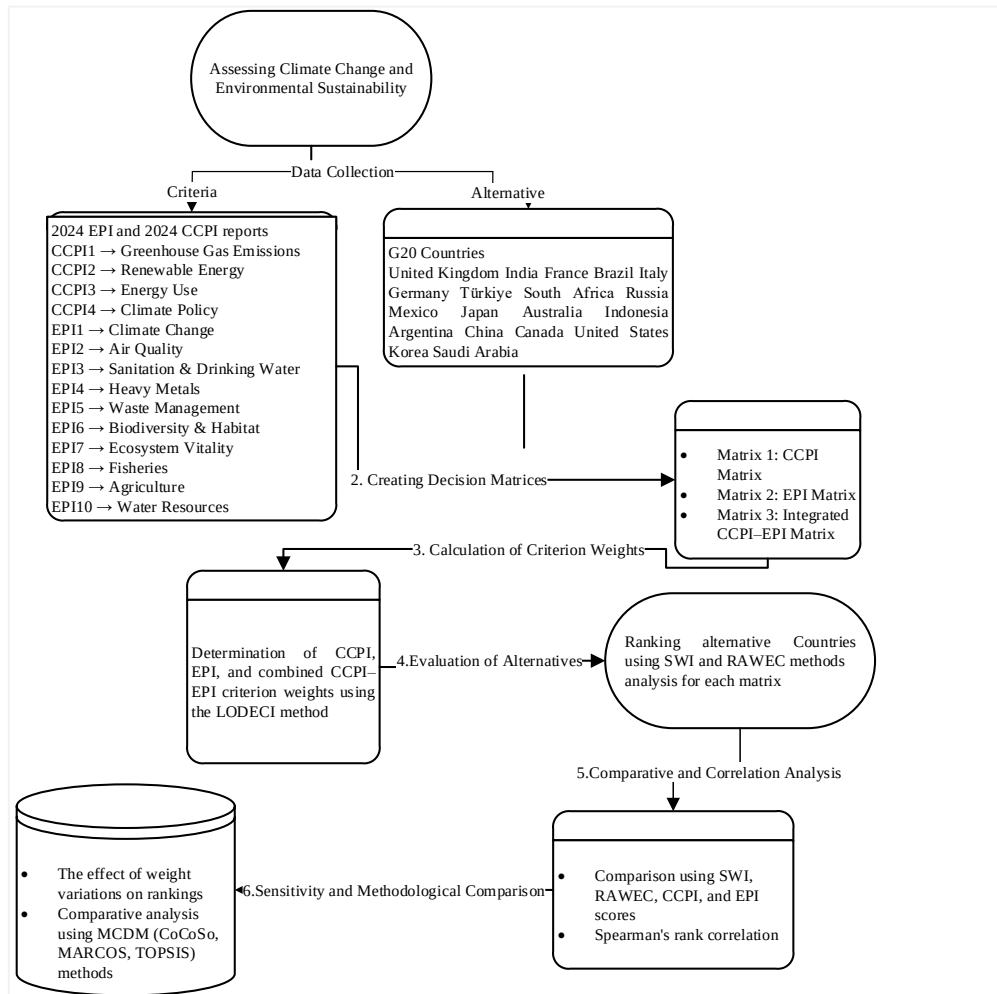
Step 4: Calculate the RAWEC score (Equation 11).

Finally, the RAWEC score for the United Kingdom is obtained as follows:

$$\nabla_{11} = \frac{\tau'_{11} - \tau_{11}}{\tau'_{11} + \tau_{11}} = \frac{(0.002 - 0.229)}{(0.002 + 0.229)} \cong -0.983$$

The methodological process of the research, the data sets used and the analysis stages are shown in the flow diagram in Figure 1.

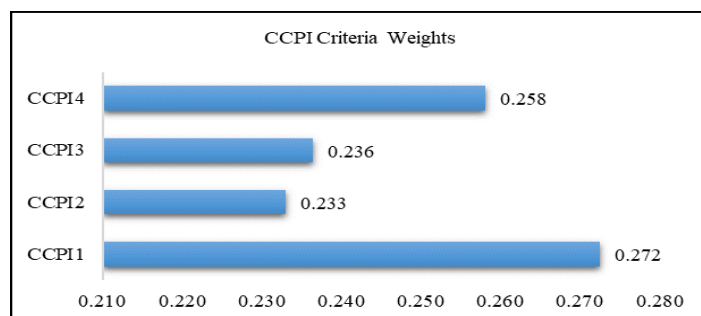
Figure 1. Flowchart Showing the Methodological Process of the Study



4. FINDINGS

During the analysis, the weights of the Climate Change Performance Index criteria were determined using the LODECI method based on the decision matrix presented in Table 3. First, the decision matrix was normalised using Equation (1), and then the decomposition values of the criteria for each alternative in the normalised matrix were calculated using Equation (2). The logarithmic decomposition values and weight values for each criterion were then calculated using Equations (3) and (4). The calculated weights of the criteria are presented visually in Figure 2.

Figure 2. Weightings of CCPI Criteria



The relative weights of the criteria influencing climate change performance were determined using the LODECI method. The findings indicate that the CCPI1 (greenhouse gas emissions) criterion holds the highest weight at 0.272, representing the most decisive factor in the decision-making process. This is followed by CCPI4 (climate policy) at 0.258, CCPI3 (energy use) at 0.236, and CCPI2 (renewable energy) at 0.233. This distribution reflects the relative importance of the criteria and suggests a relatively balanced weighting across them. Notably, the higher weight of CCPI1 compared to the other criteria underscores its critical role in evaluating climate change performance.

Having determined the weights of the CCPI criteria, the steps specific to the SWI and RAWEC methods were incorporated into the decision matrix shown in Table 3. In line with this integration, the climate change performance of the G20 countries was systematically evaluated. Thanks to the application of the SWI and RAWEC methods, an objective ranking was obtained by correlating the performance of each country with the criterion weights. The final findings of this analysis process are presented in detail in Table 6.

Table 6. Comparative Assessment of G20 Countries' Climate Change Performance Based on SWI, RAWEC and CCPI Scores

Countries	SWI Score	Ranking	RAWEC Score	Ranking	CCPI Score	Ranking
United Kingdom	4.672	14	-0.134	15	62.36	3
India	4.411	10	-0.017	10	70.25	1
France	4.470	11	-0.046	11	57.12	6
Brazil	4.041	4	0.148	4	61.74	4
Italy	4.516	12	-0.078	13	50.60	8
Germany	4.300	8	0.015	8	65.77	2
Turkey	5.088	18	-0.376	19	43.82	13
South Africa	4.674	15	-0.087	14	49.53	9
Russia	5.229	19	-0.345	18	31.00	17
Mexico	4.913	16	-0.215	17	55.81	7
Japan	4.961	17	-0.191	16	42.08	15
Australia	4.315	9	-0.012	9	45.72	10
Indonesia	4.127	6	0.074	6	57.20	5
Argentina	4.634	13	-0.069	12	45.39	12
China	3.681	1	0.308	1	45.56	11
Canada	4.039	3	0.155	3	31.55	16
United States	4.109	5	0.130	5	42.79	14
Korea	4.245	7	0.051	7	29.98	18
Saudi Arabia	4.023	2	0.216	2	19.33	19

The findings indicate that China exhibited the highest performance according to the SWI and RAWEC methods, while Saudi Arabia, Canada, and Brazil ranked among the top performers, and Turkey, Russia, and Japan were positioned at the lower end. In contrast, the CCPI results present a different ranking order, with India and Germany occupying the top positions, and Saudi Arabia, Korea, and Canada situated at the bottom. When the SWI, RAWEC, and CCPI rankings are considered

collectively, only Brazil consistently occupies the fourth position across all three measures, highlighting that country rankings may vary depending on the criteria and methods employed. To evaluate the consistency of the rankings across the methods in a greater depth, a Spearman rank correlation analysis was performed on the SWI, RAWEC and CCPI rankings. The results are presented in Table 7.

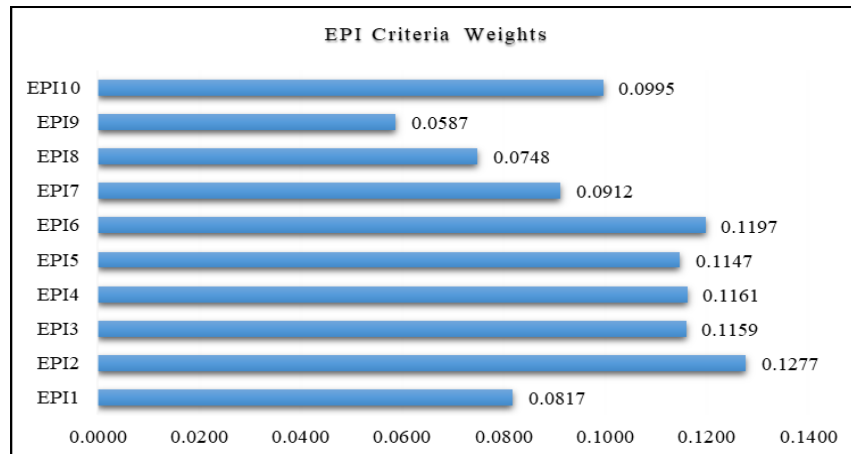
Table 7. Spearman Rank Correlation Coefficients Between SWI, RAWEC and CCPI Rankings

	SWI	RAWEC	CCPI
SWI	1		
RAWEC	0.993	1	
CCPI	-0.046	-0.084	1

According to the results of the Spearman correlation analysis presented in Table 7, a very high correlation of 0.993 was found between the SWI and RAWEC methods. The correlation between SWI and CCPI was -0.046, and the correlation between RAWEC and CCPI was -0.084. These values suggest that the SWI and RAWEC rankings are highly correlated, whereas the CCPI rankings demonstrate a weak negative correlation with these two methods.

The second analysis, conducted within the EPI framework, used the LODECI method to calculate criterion weights with the decision matrix in Table 4. The results are shown in Figure 3.

Figure 3. Weighting Values of EPI Criteria



Based on the obtained results, the air quality (EPI2) criterion holds the highest weight at 0.1277, indicating that addressing air pollution and ensuring breathable air are the most critical elements for environmental sustainability. This is followed by biodiversity and habitat (EPI6) at 0.1197, heavy metals (EPI4) at 0.1161, sanitation and drinking water (EPI3) at 0.1159, and waste management (EPI5) at 0.1147. In contrast, climate change (EPI1) at 0.0817, ecosystem vitality (EPI7) at 0.0912, and water resources (EPI10) at 0.0995 exert a moderate influence. The fisheries (EPI8) criterion is relatively minor at 0.0748, while agriculture (EPI9) is the least significant at 0.0587. These findings suggest that agricultural activities have a more limited impact on environmental performance compared to the other criteria.

The SWI and RAWEC methods were applied to the decision matrix in Table 4, which is based on EPI criterion weights, in order to analyse the environmental performance of countries. The results of this analysis, presented in Table 8, are compared with the countries' rankings in the EPI report using the SWI and RAWEC methods.

Table 8. Comparative assessment of G20 countries' environmental performance based on SWI, RAWEC and EPI scores

Countries	SWI Score	Ranking	RAWEC Score	Ranking	EPI Score	Ranking
United Kingdom	3.963	2	0.486	2	72.6	2
India	5.184	19	-0.516	19	27.6	19
France	4.032	3	0.401	4	67.0	3
Brazil	4.363	11	0.109	11	53.0	9
Italy	4.090	6	0.341	6	60.3	7
Germany	3.920	1	0.547	1	74.5	1
Turkey	4.560	15	-0.003	14	37.2	16
South Africa	4.624	16	-0.045	16	42.7	14
Russia	4.441	12	0.051	12	46.7	12
Mexico	4.489	13	0.049	13	44.2	13
Japan	4.087	5	0.356	5	61.4	5
Australia	4.033	4	0.406	3	63.1	4
Indonesia	4.734	17	-0.154	18	33.6	18
Argentina	4.509	14	-0.022	15	47.0	11
China	4.794	18	-0.144	17	35.4	17
Canada	4.191	7	0.238	7	61.1	6
United States	4.210	8	0.225	8	57.2	8
Korea	4.257	10	0.209	10	50.6	10
Saudi Arabia	4.237	9	0.234	9	42.5	15

The findings indicate that Germany consistently demonstrated the highest performance across SWI, RAWEC, and EPI scores, while the United Kingdom generally occupied the upper ranks. India, China, and Indonesia were positioned at the lower end, whereas Brazil, Russia, Mexico, Turkey, and South Africa fell within the middle ranks, with their performance varying across methods. While the SWI and RAWEC rankings exhibit overall consistency, EPI scores highlight differing priorities and outcomes for certain countries. This finding is supported by the Spearman rank correlation analysis presented in Table 9.

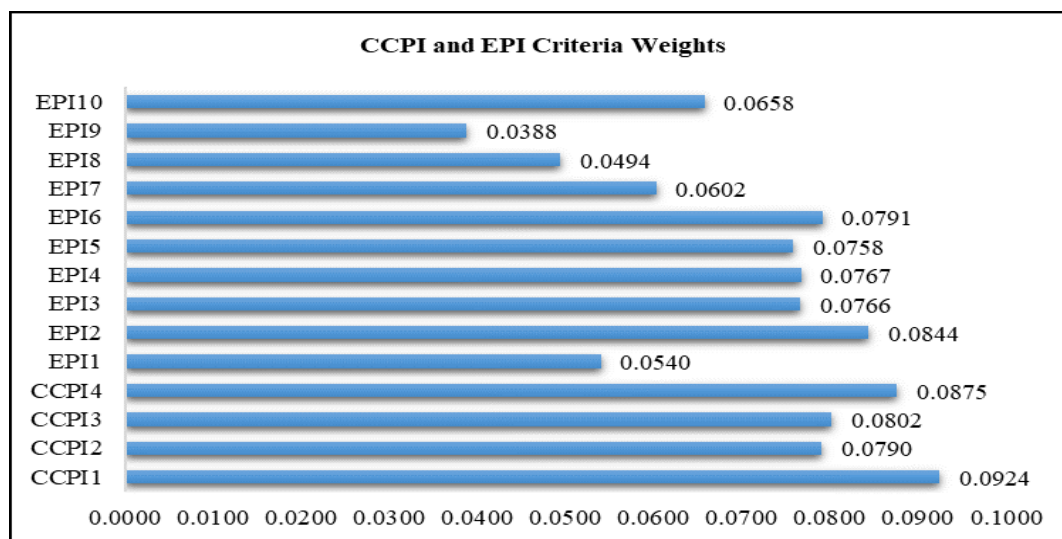
Table 9. Spearman rank correlation coefficients between SWI, RAWEC and EPI rankings for G20 countries

	SWI	RAWEC	EPI
SWI	1		
RAWEC	0.995	1	
EPI	0.949	0.940	1

There is a very high positive correlation between the SWI and RAWEC methods ($\rho = 0.995$). This indicates that both methods largely rank countries similarly in terms of environmental performance. Similarly, the correlation between EPI and SWI is also quite high ($\rho = 0.949$), as is the relationship between EPI and RAWEC ($\rho = 0.940$).

In the third stage, the CCPI and EPI criteria were integrated for use in climate change and environmental sustainability performance assessments. In this context, criterion weights were calculated using the LODECI method, as shown in Table 5. The results are presented in Figure 4.

Figure 4. Integrated CCPI and EPI Criteria Weights



The most important criterion is Greenhouse Gas Emissions (CCPI1) with a weight of 0.0924, followed by Climate Policy (CCPI4) at 0.0875 and Air Quality (EPI2) at 0.0844. Energy Use (CCPI3), Biodiversity and Habitat (EPI6), and Renewable Energy (CCPI2) are also of high importance, with weights of 0.0802, 0.0791, and 0.0790, respectively. Criteria of medium importance include Waste Management (EPI5, 0.0758), Heavy Metals (EPI4, 0.0767), Sanitation & Drinking Water (EPI3, 0.0766), and Water Resources (EPI10, 0.0658). Relatively less important criteria are Ecosystem Vitality (EPI7, 0.0602), Climate Change (EPI1, 0.0540), and Fisheries (EPI8, 0.0494), while Agriculture (EPI9, 0.0388) is the least significant. These results indicate that criteria related to greenhouse gas emissions and energy exert the most significant influence on climate change and environmental sustainability performance.

Finally, the climate change and environmental sustainability performance of the countries was analyzed using the SWI and RAWEC methods, based on the decision matrix and the integrated CCPI and EPI criteria weights presented in Table 5. The findings are presented in a comparative manner in Table 10.

Table 10. Comparative assessment of the climate change and environmental sustainability performance of G20 countries according to the SWI and RAWEC methods

Countries	SWI Score	Ranking	RAWEC Score	Ranking
United Kingdom	4.203	7	0.1795	7
India	4.922	19	-0.3702	19
France	4.180	6	0.1901	5
Brazil	4.254	10	0.1274	10
Italy	4.234	8	0.1589	8
Germany	4.049	1	0.3175	1
Turkey	4.739	18	-0.1284	17
South Africa	4.641	16	-0.1219	15
Russia	4.708	17	-0.1345	18
Mexico	4.633	15	-0.1223	16
Japan	4.384	11	0.0959	11
Australia	4.129	2	0.2339	2
Indonesia	4.528	13	-0.0626	13
Argentina	4.551	14	-0.0873	14
China	4.416	12	0.0519	12
Canada	4.139	3	0.2094	4
United States	4.176	5	0.1796	6
Korea	4.253	9	0.1430	9
Saudi Arabia	4.165	4	0.2209	3

Upon examining the table, significant similarities and some differences are observed in the rankings of the SWI and RAWEC methods. Germany, Australia, the United Kingdom, Italy, South Korea, Brazil, Japan, China, Indonesia, Argentina, and India are ranked similarly in both methods, while minor differences are observed in some countries, such as France, Saudi Arabia, and Canada. These differences stem from the different calculation structures of the two methods, and the literature also indicates that different MCDM methods can produce different rankings for the same data set (Ecer & Pamucar, 2022; Goswami et al., 2021; Keleş & Ersoy, 2023; Mathew & Sahu, 2018; Pamučar & Ćirović, 2015). Overall, a high degree of consistency is observed in the rankings between the two methods. This is also supported by Spearman's rank correlation analysis, as shown in Table 11.

Table 11. Spearman Rank Correlation Coefficient Between the SWI and RAWEC Methods

	SWI	RAWEC
SWI	1	
RAWEC	0.993	1

The Spearman correlation coefficient of 0.993 obtained between the SWI and RAWEC methods indicates that the ranking results are highly similar, demonstrating the ability of both methods to produce consistent and reliable climate change and environmental sustainability performance assessment results.

4.1. Sensitivity and Comparison Analysis

A sensitivity and comparative analysis was undertaken to evaluate the robustness and stability of the proposed framework integrating CCPI and EPI. The analysis proceeded in two phases: the first phase involved a sensitivity analysis to assess how variations in criteria weights affect the ranking of alternatives across different scenarios, while the second phase examined the effects of different multi-criteria decision-making (MCDM) methods on the resulting rankings.

4.1.1. Sensitivity Analysis of Criteria Weights

In this section, changes in the rankings of alternatives resulting from variations in criterion weights were evaluated using sensitivity analysis. To this end, an initial scenario was established in which all criteria were assigned equal weights ($w_j = 1/n$). In subsequent scenarios, a single criterion was prioritized over the others, with its weight set at 0.400, while the weights of the remaining $n - 1$ criteria were calculated using Equation (12) (Ersoy et al., 2026; Hasanzadeh et al., 2023). As presented in Table 12, the sensitivity scenario matrix was constructed accordingly.

$$w_j = \frac{1 - w_k}{n - 1} \quad (12)$$

w_k : Weight of the primary criterion (e.g., 0.400)

n : Total number of criteria

w_j : Weight values of the remaining criteria

Table 12. Sensitivity Scenarios

Scenario/Criteria	CCPI1	CCPI2	CCPI3	CCPI4	EPI1	EPI2	EPI3	EPI4	EPI5	EPI6	EPI7	EPI8	EPI9	EPI10
scenario 1 (S1)	0.0714	0.0714	0.0714	0.0714	0.0714	0.0714	0.0714	0.0714	0.0714	0.0714	0.0714	0.0714	0.0714	0.0714
scenario 2 (S2)	0.4000	0.0462	0.0462	0.0462	0.0462	0.0462	0.0462	0.0462	0.0462	0.0462	0.0462	0.0462	0.0462	0.0462
scenario 3 (S3)	0.0462	0.4000	0.0462	0.0462	0.0462	0.0462	0.0462	0.0462	0.0462	0.0462	0.0462	0.0462	0.0462	0.0462
scenario 4 (S4)	0.0462	0.0462	0.4000	0.0462	0.0462	0.0462	0.0462	0.0462	0.0462	0.0462	0.0462	0.0462	0.0462	0.0462
scenario 5 (S5)	0.0462	0.0462	0.0462	0.4000	0.0462	0.0462	0.0462	0.0462	0.0462	0.0462	0.0462	0.0462	0.0462	0.0462
scenario 6 (S6)	0.0462	0.0462	0.0462	0.0462	0.4000	0.0462	0.0462	0.0462	0.0462	0.0462	0.0462	0.0462	0.0462	0.0462
scenario 7 (S7)	0.0462	0.0462	0.0462	0.0462	0.0462	0.4000	0.0462	0.0462	0.0462	0.0462	0.0462	0.0462	0.0462	0.0462
scenario 8 (S8)	0.0462	0.0462	0.0462	0.0462	0.0462	0.0462	0.4000	0.0462	0.0462	0.0462	0.0462	0.0462	0.0462	0.0462
scenario 9 (S9)	0.0462	0.0462	0.0462	0.0462	0.0462	0.0462	0.0462	0.4000	0.0462	0.0462	0.0462	0.0462	0.0462	0.0462
scenario 10 (S10)	0.0462	0.0462	0.0462	0.0462	0.0462	0.0462	0.0462	0.0462	0.4000	0.0462	0.0462	0.0462	0.0462	0.0462
scenario 11 (S11)	0.0462	0.0462	0.0462	0.0462	0.0462	0.0462	0.0462	0.0462	0.0462	0.4000	0.0462	0.0462	0.0462	0.0462
scenario 12 (S12)	0.0462	0.0462	0.0462	0.0462	0.0462	0.0462	0.0462	0.0462	0.0462	0.0462	0.4000	0.0462	0.0462	0.0462
scenario 13 (S13)	0.0462	0.0462	0.0462	0.0462	0.0462	0.0462	0.0462	0.0462	0.0462	0.0462	0.0462	0.4000	0.0462	0.0462
scenario 14 (S14)	0.0462	0.0462	0.0462	0.0462	0.0462	0.0462	0.0462	0.0462	0.0462	0.0462	0.0462	0.0462	0.4000	0.0462
scenario 15 (S15)	0.0462	0.0462	0.0462	0.0462	0.0462	0.0462	0.0462	0.0462	0.0462	0.0462	0.0462	0.0462	0.0462	0.4000

The impact of the SWI and RAWEC methods on the rankings was examined by considering 15 different weight scenarios for the criteria in the sensitivity scenario matrix presented in Table 12, and the results are illustrated in Figures 5 and 6.

Figure 5. Country Rankings Across Different Scenarios (SWI)

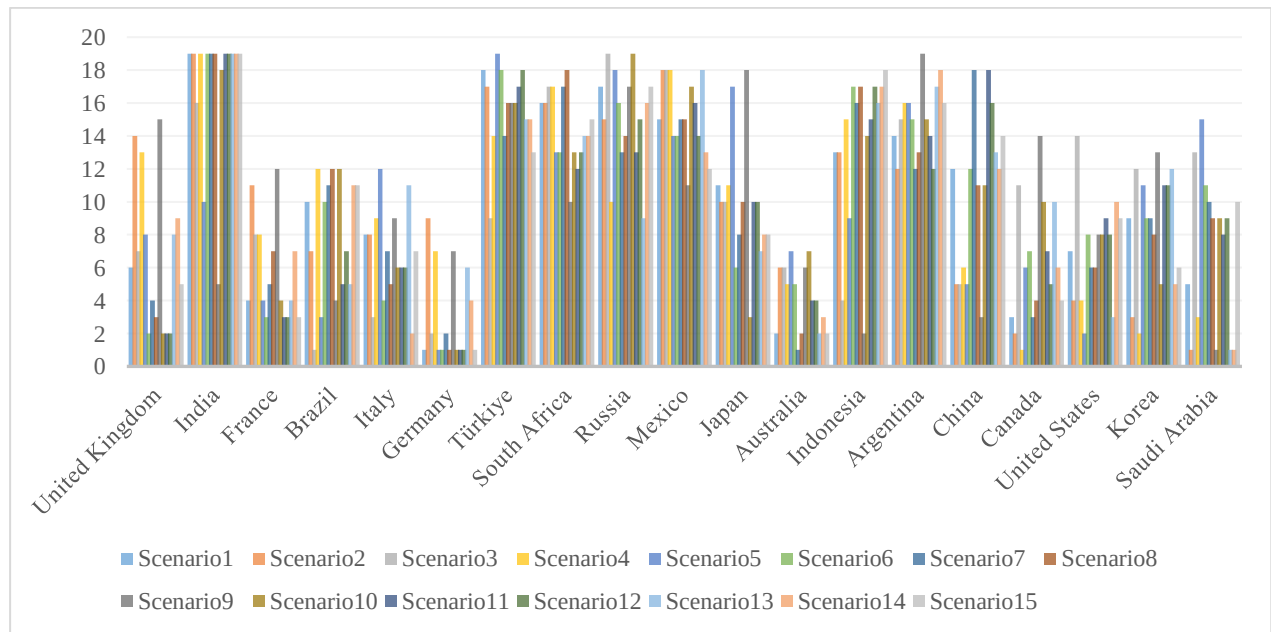
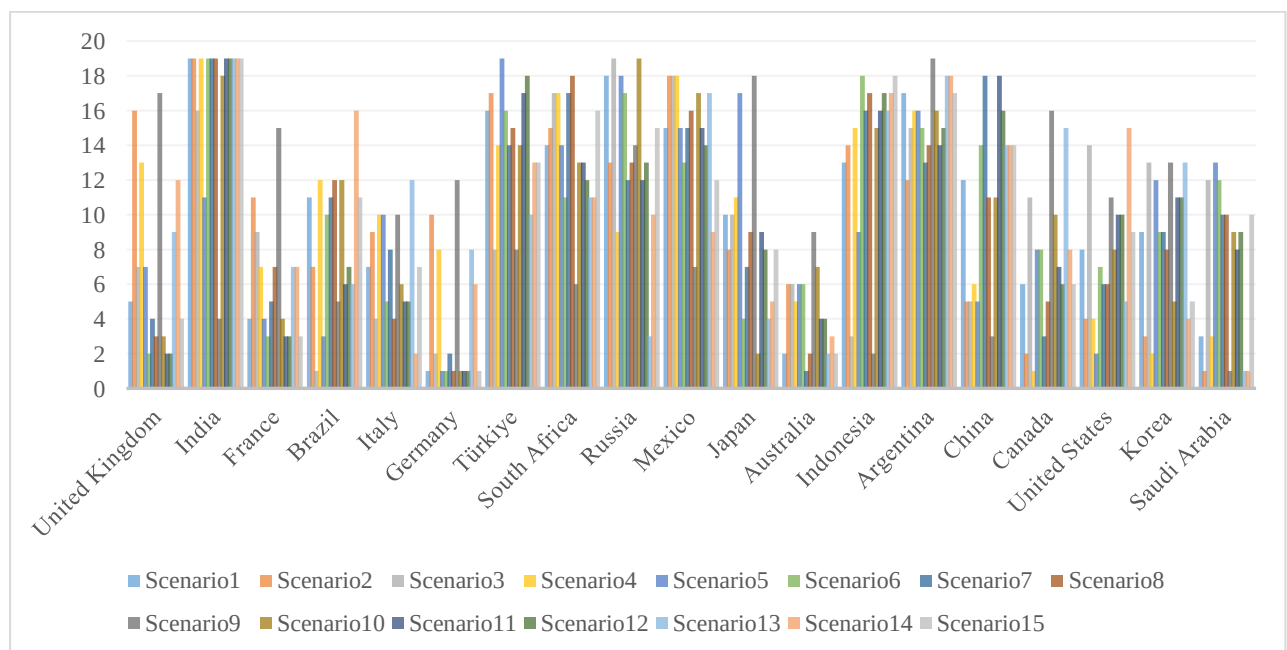


Figure 6. Country Rankings Across Different Scenarios (RAWEC)



The data reveal that Germany generally ranks high, while India ranks low. On the other hand, countries such as Turkey, Brazil, China, and Japan show significant fluctuations between scenarios. These findings indicate that criterion weights have a significant impact on ranking results and that each country does not maintain a fixed position across all scenarios.

Correlation analysis was used to examine the consistency of scenario-based ranking results. Table 13 shows the comparative correlation values of the ranking results obtained with the SWI and RAWEC methods under 15 different sensitivity scenarios (S1–S15) compared with the LODECI-SWI and LODECI-RAWEC methods.

Table 13. Correlation Across Scenarios

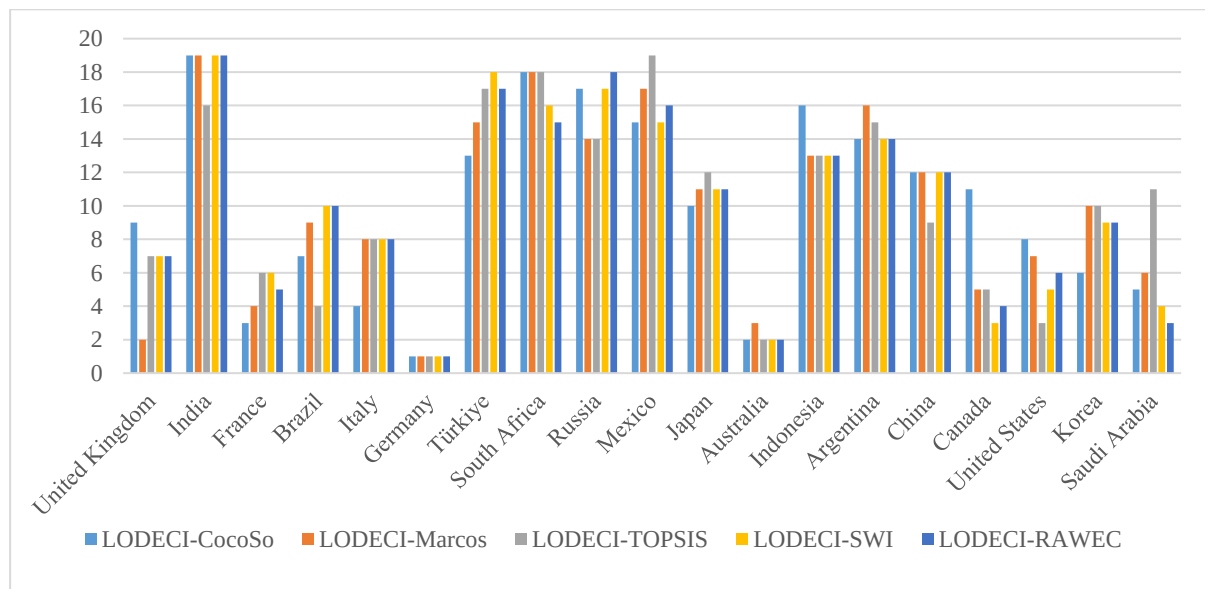
	S1	S2	S3	S4	S5	S6	S7	S8	S9	S10	S11	S12	S13	S14	S15
LODECI-SWI	0.9912	0.7561	0.4754	0.7684	0.6175	0.8368	0.8754	0.9175	0.2351	0.7807	0.8298	0.8737	0.7754	0.8509	0.8649
LODECI-RAWEC	0.9754	0.6807	0.4825	0.7281	0.6614	0.7737	0.8474	0.8684	-0.1825	0.7825	0.8228	0.8316	0.4737	0.5877	0.8404

Table 13 indicates that Scenario 1 exhibits the highest correlation values for both LODECI-SWI (0.9912) and LODECI-RAWEC (0.9754), demonstrating strong consistency in the rankings. Scenario 8 also presents consistent results with high correlation values, whereas Scenarios 2 and 3 display comparatively lower correlations. Notably, Scenario 9 shows a negative correlation with LODECI-RAWEC (-0.1825), distinguishing it from the other scenarios. Overall, high correlation values support the validity of the rankings, while low or negative values provide critical insight into the influence of criterion weights on the ranking outcomes.

4.1.2. Comparative Assessment of the Proposed Methods versus Other MCDM Models

In this section, the validity and reliability of the preferred methods have been comprehensively compared using various MCDM methods with different normalization approaches. Although previous studies have demonstrated the effect of different normalization techniques on alternative rankings (Ersoy et al., 2026; Malefaki et al., 2025), this study comparatively evaluated the validity and reliability of the proposed system using the CoCoSo, MARCOS, and TOPSIS methods, and the obtained ranking results are presented in Figure 7.

Figure 7. Comparing Alternative Ranking Methods



The data in Figure 7 show that MCDM methods based on different normalization approaches (LODECI-CoCoSo, LODECI-MARCOS, LODECI-TOPSIS, LODECI-SWI, LODECI-RAWEC) produce significant differences in country rankings. Germany and Australia consistently rank high

across all methods, while India, Mexico, South Africa, and Turkey remain in the lower ranks in most methods. In some countries, such as Canada, the United States, and Saudi Arabia, fluctuations in rankings between methods have been observed. Overall, the findings emphasize that different normalization techniques affect rankings and highlight the importance of evaluating the validity and reliability of the system by comparing different methods.

Table 14. Correlation Analysis Among MCDM Methods

	SWI	RAWEC	CoCoSo	MARCOS	TOPSIS
SWI	1.0000	0.9930	0.8596	0.9351	0.8737
RAWEC	0.9930	1.0000	0.8807	0.9351	0.8544
CoCoSo	0.8596	0.8807	1.0000	0.8632	0.8035
MARCOS	0.9351	0.9351	0.8632	1.0000	0.8912
TOPSIS	0.8737	0.8544	0.8035	0.8912	1.0000

Table 14's correlation analysis reveals a very high correlation (0.9930) between the SWI and RAWEC methods, with MARCOS also showing a high correlation with them. CoCoSo and TOPSIS, on the other hand, have lower correlations compared to other methods, indicating that they may produce different results in the rankings. The SWI and RAWEC methods provide consistent and reliable results in the rankings by placing countries with strong performance at the top and those with weak performance at the bottom. High correlation and stable performance support the validity and reliability of these methods.

5. CONCLUSION

In this study, the climate change and environmental sustainability performance of G20 countries was evaluated using data from the 2024 Environmental Performance Index (EPI) and Climate Change Performance Index (CCPI) reports, through the application of multi-criteria decision-making (MCDM) methods. Three separate decision matrices were created within the scope of the research; the first was based on only CCPI data, the second was based on only EPI data, and the third was based on the combined criteria of both indices. Criteria weights were calculated using the LODECI method, and the rankings of the countries were carried out using the SWI and RAWEC methods. Thus, both a systematic and multidimensional analysis approach was adopted in the environmental performance assessment.

In the first phase of the study, the four CCPI criteria (greenhouse gas emissions, renewable energy, energy use, and climate policy) were analyzed. According to the LODECI results, greenhouse gas emissions emerged as the most significant criterion, followed by climate policy, energy use, and renewable energy. This underscores the critical importance of emission reduction in addressing climate change. Similar findings have been reported by Altıntaş (2025) and Lukić (2025), who also highlight the decisive role of the CCPI1 (emissions) criterion. However, the literature presents divergent results: Köse et al. (2024) emphasize climate policy, while Keleş and Ersoy (2023) identify energy use as more

prominent in certain years. These discrepancies are likely attributable to methodological choices, contextual conditions, and national policy priorities.

In the second phase of the study, EPI data reflecting environmental sustainability were analyzed. According to the LODECI results, air quality emerged as the most significant criterion, followed by biodiversity and habitat, heavy metals, sanitation and drinking water, and waste management. This indicates that criteria directly impacting human health are prioritized. Some discrepancies are observed when compared to the literature: while Karahan et al. (2025) and Keleş (2024) emphasize fisheries, this criterion received relatively low weight in the present study; similarly, the agriculture criterion had the lowest weight, consistent with findings by Altıntaş (2021) and Gelmez et al. (2025). The observed variation in EPI results may stem from differences in countries' environmental priorities, data coverage, and the MCDM methods employed, highlighting the necessity of conducting environmental assessments in accordance with country-specific conditions and data availability.

In the third phase of the study, climate change and environmental sustainability performance were comprehensively evaluated by integrating the CCPI and EPI criteria. The combined analysis using the LODECI method highlighted greenhouse gas emissions, climate policy, and air quality as the most influential factors. These findings indicate that carbon emissions, the effectiveness of climate policies, and the mitigation of air pollution are the primary determinants of environmental performance. In contrast, criteria such as ecosystem vitality, fisheries, and agriculture had a relatively limited impact, suggesting that some indicators play a dominant role in the assessment while others contribute less. Although these results are partially consistent with studies that jointly evaluate the CCPI and EPI, such as Doğan (2022), differences arise due to variations in methodology, data year, and country samples.

The performances of the countries were ranked using the SWI and RAWEC methods. In the analysis based on CCPI data, China, Saudi Arabia, Canada and Brazil were ranked high in both methods, while Turkey, Russia and Japan were ranked low. However, these rankings showed inconsistencies when compared to the original CCPI index. For example, China and Saudi Arabia received high scores in the SWI and RAWEC analyses, but were ranked low in the CCPI ranking. This difference can be explained by the fact that while the CCPI offers a limited perspective focused only on climate, multi-criteria methods have a broader assessment capacity. In the analysis based on EPI criteria, countries such as Germany, the United Kingdom, France and Australia were ranked high in both EPI scores and SWI and RAWEC results, while countries such as India, Indonesia and China were ranked low. This harmony shows that SWI and RAWEC overlap with the EPI to a great extent. In the analysis conducted with combined criteria weights, Germany ranked first in both methods, reinforcing its environmental leadership. Countries such as Australia, the United Kingdom, Italy, Korea, Brazil and Japan were ranked similarly by both methods, while small differences were observed in countries such as Canada, France and Saudi Arabia. This situation reveals the impact of the sensitivity of the methods and the differences in criterion-based performance on the rankings.

The Spearman rank correlation coefficient between the SWI and RAWEC methods was found to be ($\rho \approx 0.993\text{--}0.995$), which showed an almost perfect positive relationship between the two methods. This finding reveals that the methods can be used safely as alternatives to each other. On the other hand, low or negative correlations were observed between the CCPI index and SWI and RAWEC, indicating that methodological differences cause significant effects on the rankings. In comparisons made with EPI, SWI and RAWEC exhibited high positive correlations, confirming that these methods are powerful tools in environmental sustainability analyses. These methods provide more detailed, multidimensional and flexible analysis compared to traditional indexing approaches, allowing decision makers to develop more robust policy recommendations.

In the study, the robustness and stability of the proposed approach within the integrated use of CCPI and EPI criteria were tested through sensitivity and comparative analyses. Sensitivity analyses showed that criterion weights could significantly affect alternative rankings in different scenarios; Germany generally ranked high, India ranked low, while fluctuations were observed between scenarios in some countries, such as Turkey, Brazil, China, and Japan. Comparative analyses tested the reliability of the proposed system against MCDM methods (CoCoSo, MARCOS, TOPSIS) with different normalization approaches; Germany and Australia consistently ranked high, while India, Mexico, South Africa, and Turkey remained low. The SWI and RAWEC methods ensured consistency in the rankings with high correlation values, while more variable results were observed in other methods. Overall, sensitivity and comparative analyses reveal that the SWI and RAWEC methods produce both valid and reliable rankings and maintain consistent performance rankings even when MCDM methods are compared under different scenarios. These findings suggest that the proposed approach can be reliably applied for assessing climate change and environmental sustainability performance.

Beyond these findings, this study offers both theoretical and practical contributions. Theoretically, the CCPI and EPI indicators have been evaluated within a comprehensive framework using different Multi-Criteria Decision Making (MCDM) methods, contributing to the literature; this demonstrates that climate-related and broader environmental indicators can be systematically combined. Practically, the results offer actionable insights for policymakers: low-performing countries such as India, Turkey, and Russia should prioritize renewable energy, emissions reduction, and air quality; high-performing countries such as Germany and the United Kingdom can serve as examples for integrated policy design and effective climate governance. Nevertheless, the study has certain limitations: the reliance solely on data from the 2024 reports, the focus of the analysis on G20 countries, and the assumptions inherent in the LODECI weighting method may restrict the generalizability of the findings. Future studies should expand the temporal and geographical scope, compare alternative weighting and ranking techniques, and integrate new sustainability metrics such as circular economy or SDG-based indicators. Such studies will enhance the robustness and applicability of MCDM methods in assessing

climate change and environmental sustainability performance, thereby strengthening their significance in both academic research and policy-making across different contexts.

This study does not require Ethics Committee approval.

The author declares that the study was conducted in accordance with research and publication ethics.

The author confirms that no part of the study was generated, either wholly or in part, using Artificial Intelligence (AI) tools.

The author declares that there are no financial conflicts of interest involving any institution, organization, or individual associated with this article.

The author affirms that the entire research process was performed by the sole declared author of the study.

REFERENCES

- Abdullah, L. (2017). A fuzzy decision making method in developing environmental performance index. *WSEAS Transactions on Environment and Development*, 13, 350-359.
- Akbulut, O. Y., & Aydın, Y. (2024). Türk bankaları için MSD-MPSI-RAWEC modelini kullanan hibrit çok boyutlu performans ölçüm modeli. *Mehmet Akif Ersoy Üniversitesi İktisadi ve İdari Bilimler Fakültesi Dergisi*, 11(3), 1157-1183. <https://doi.org/10.30798/makuiibf.1464469>
- Alrashdi, I., Ali, A. M., Sallam, K. M., & Abdel-Basset, M. (2025). Assessment and analysis of development risks under uncertainty: The impact of disruptive technologies on renewable energy development. *Energy Nexus*, 100371.
- Altıntaş, F. F. (2021). Çevre performanslarının ENTROPİ tabanlı ROV, ARAS ve COPRAS yöntemleri ile ölçülmesi: G20 Grubu Ülkeleri Örneği. *Social Sciences Research Journal*, 10 (1), 55-78.
- Altıntaş, F. F. (2025). Analysis of climate change performances of G7 group countries: An application using the MEREC-based RAFSI method. *Journal of Mehmet Akif Ersoy University Economics and Administrative Sciences Faculty*, 12(1), 214-245. <https://doi.org/10.30798/makuiibf.1489592>
- Appiah-Otoo, I., Chen, X., & Ampah, J. D. (2023). Does financial structure affect renewable energy consumption? Evidence from G20 countries. *Energy*, 272, 127130. <https://doi.org/10.1016/j.energy.2023.127130>
- Climate Transparency. (2018). *Brown to Green: The G20 transition to a low-carbon economy*. Climate Transparency, c/o Humboldt-Viadrina Governance Platform. <https://www.climate-transparency.org/wp-content/uploads/2019/01/2018-BROWN-TO-GREEN-REPORT-FINAL.pdf>
- Codal, K. S., Ari, I., & Codal, A. (2021). Multidimensional perspective for performance assessment on climate change actions of G20 countries. *Environmental Development*, 39, 100639. <https://doi.org/10.1016/j.envdev.2021.100639>
- Cook, D., Saviolidis, N. M., Davíðsdóttir, B., Jóhannsdóttir, L., & Ólafsson, S. (2017). Measuring countries' environmental sustainability performance: The development of a nation-specific indicator set. *Ecological Indicators*, 74, 463-478. <https://doi.org/10.1016/j.ecolind.2016.12.009>
- Çilek, A., & Şeyranlıoğlu, O. (2025). Türkiye'deki Reasürans şirketlerinin finansal performansının LODECI, CRADIS ve AROMAN MCDM yöntemleriyle ölçülmesi. *Uluslararası İşletme ve Ekonomi Çalışmaları Dergisi*, 7(1), 1-18. <https://doi.org/10.54821/uiecd.1587675>
- Do, D. T. (2024). Assessing the Impact of Criterion Weights on the ranking of the top ten universities in Vietnam. *Engineering, Technology & Applied Science Research*, 14(4).
- Doğan, H. (2022). Seçilmiş ülkelerin çevresel performanslarının bütünsel CRITIC-MABAC yöntemleriyle ölçülmesi. *Journal of Emerging Economies & Policy*, 7(2), 433-448.

- Durmus, Z. (2025). Assessment of renewable energy performance in Turkey using a novel integrated MSD-CRITIC-RAWEC model. *Journal of Operational and Strategic Analytics (JOSA)*, 3(1), 49-64. <https://doi.org/10.56578/josa030105>
- Dündar, S. (2024). Performance evaluation of IPARD-II rural development programs with integrated DIBR-RAWEC methods. *Pamukkale University Journal of Engineering Sciences*, 31(3), 0-0.
- Dündar, S., & Karadağ, İ. (2025). Selection of a facility location for a cosmetics company by integrated F-LBWA and I-RAWEC methods. *International Journal of Fuzzy Systems*, 1-20. <https://doi.org/10.1007/s40815-024-01960-4>
- Dwivedi, P. P., & Sharma, D. K. (2025). Performance measures of sustainable development goals using SWI MCDM methods: a case of the Indian states. *International Transactions in Operational Research*, 1-33. <https://doi.org/10.1111/itor.13609>
- Ecer, F., & Pamucar, D. (2022). A novel LOPCOW-DOBI multi-criteria sustainability performance assessment methodology: An application in developing country banking sector. *Omega*, 112(2022), 1-17. <https://doi.org/10.1016/j.omega.2022.102690>
- Ersoy, N., Özçalıcı, M., & Trung, D. D. (2026). A hybrid MCDM approach for SDGs assessment of EU countries. *Spectrum of Decision Making and Applications*, 3(1), 164-186. <https://doi.org/10.31181/sdmap31202637>
- Gelmez, E., Eren, H., & Özceylan, E. (2025). Evaluation of environmental performance of OECD countries using SD-based ARAS and WASPAS methods. *Gazi University Journal of Science*, 38(2), 808-831. <https://doi.org/10.35378/gujs.1458807>
- Germanwatch. (2021). *Climate change performance index (CCPI) 2021*. <https://www.germanwatch.org/en/ccpi>
- Goswami, S. S., Behera, D. K., Afzal, A., Kaladgi, A. R., Khan, S. A., Rajendran, P., Subbiah, R., & Asif, M. (2021). Analysis of a robot selection problem using two newly developed hybrid MCDM models of TOPSIS-ARAS and COPRAS-ARAS. *Symmetry*, 13(8), 1331. <https://doi.org/10.3390/sym13081331>
- Gök Kısa, A. C. (2022). A multi-criteria decision making approach for evaluating environmental performances of OECD countries. In N. İyit, B. Hastaoğlu Özbek, & A. Toptaş (Eds.), *Current research in social, human and administrative sciences* (pp. 223-238). Gece Kitaplığı.
- Gökgöz, F., & Yalçın, E. (2021). Can renewable energy sources be a viable instrument for climate change mitigation? Evidence from EU countries via MCDM methods. *Climate Change Science*, 19-39. <https://doi.org/10.1016/B978-0-12-823767-0.00002-1>
- Hasanzadeh, R., Mojaver, P., Khalilarya, S., & Azdast, T. (2023). Air co-gasification process of LDPE/HDPE waste based on thermodynamic modeling: Hybrid multi-criteria decision-making techniques with sensitivity analysis. *International Journal of Hydrogen Energy*, 48(6), 2145-2160. <https://doi.org/10.1016/j.ijhydene.2022.10.101>
- Karadağ, M. M. (2025). An in-depth evaluation of the financial performance of Turkish Football Clubs using entropy-based RAWEC, FUCA, and SAW methodologies. *Journal of Physical Education & Sport*, 25(3), 661-671. <http://dx.doi.org/10.7752/jpes.2025.03071>
- Karahan, M., Yıldırım, Z., & Yıldırım, T. (2025). Comparative analysis of Turkey's environmental performance with Eastern European countries according to international EPI 2022 data. *Green Technologies and Sustainability*, 3(1), 100116. <https://doi.org/10.1016/j.grets.2024.100116>
- Keleş, N. (2024). Çevresel performans indeksi değerlendirmesinde kullanılan kriter ağırlıklarının objektif yöntemlerle belirlenmesi: OECD ülkeleri örneği. *İstanbul Gelişim Üniversitesi Sosyal Bilimler Dergisi*, 11(2), 632-651.
- Keleş, N., & Ersoy, N. (2023). Analyzing climate change performance over the last five years of G20 countries using a multi-criteria decision-making framework. *Dokuz Eylül University Journal of Faculty of Business*, 24(2), 13-34. <https://doi.org/10.24889/ifede.1284974>
- Köse, E., Aksoy, E., & Gürbüz, C. (2024). An analysis of climate change performances of the G-20 countries. *Uluslararası İşletme, Ekonomi ve Yönetim Perspektifleri Dergisi*, 8(1), 75-102. <http://dx.doi.org/10.29228/ijbemp.7>
- Lukić, R. (2025). Analysis of climate change performance of G7 countries based on AHP-CODAS methods. *The Holistic Approach To Environment*, 15(2), 47-56. <https://doi.org/10.33765/thate.15.2.1>

- Malefaki, S., Markatos, D., Filippatos, A., & Pantelakis, S. (2025). A comparative analysis of Multi-Criteria Decision-Making methods and normalization techniques in holistic sustainability assessment for engineering applications. *Aerospace*, 12(2), 100. <https://doi.org/10.3390/aerospace12020100>
- Mathew, M., & Sahu, S. (2018). Comparison of New multi-criteria decision making methods for material handling equipment selection. *Management Science Letters*, 8(3), 139-150. <http://dx.doi.org/10.5267/j.msl.2018.1.004>
- Mohaghar, A., Amiri, K., Ghasemi, R., & Azani, M. (2018). Prioritizing the OECD countries based on Environmental Performance Index indicators. In *International Conference on Law, Management, Business, Economics and CSR (Dubai, 2018)*.
- Mohamed, M., Salam, A., & Ye, J. (2024). Selection of sustainable material for the construction of drone aerodynamic wing using Neutrosophic RAWEC. *Systems Assessment and Engineering Management*, 1, 54-72. <https://doi.org/10.61356/j.saem.2024.1295>
- Nedeljković, M., Puška, A., Pamučar, D., & Marinković, D. (2024). Selection of agricultural product sales channels using fuzzy double MEREC and fuzzy RAWEC method. *Agriculture and Forestry*, 70(3), 45-58. <http://dx.doi.org/10.17707/AgricultForest.70.3.03>
- Olafsson, S., Cook, D., Davidsdottir, B., & Johannsdottir, L. (2014). Measuring countries' environmental sustainability performance: A review and case study of Iceland. *Renewable and Sustainable Energy Reviews*, 39, 934-948. <https://doi.org/10.1016/j.rser.2014.07.101>
- Pala, O. (2024). Assessment of the social progress on European Union by logarithmic decomposition of criteria importance. *Expert Systems with Applications*, 238, 121846.
- Pala, O., Atçeken, Ö., Omurtak, H., Şimşir, B. (2024). BİST çimento sektöründe LODECI ve CRADIS ile finansal performans analizi. *Alanya Akademik Bakış*, 8(3), 956-970. <https://doi.org/10.29023/alanyaakademik.1452960>
- Pamučar, D., & Čirović, G. (2015). The selection of transport and handling resources in logistics centers using multi-attributive border approximation area comparison (MABAC). *Expert Systems with Applications*, 42(6), 3016-3028. <https://doi.org/10.1016/j.eswa.2014.11.057>
- Puška, A., Hodžić, I., Štilić, A., & Murtić, S. (2024). Evaluating European Union countries on climate change management: A fuzzy MABAC approach to the climate change performance index. *Journal of Green Economy and Low-Carbon Development*, 3(1), 15-25. <https://doi.org/10.56578/jgelcd030102>
- Puška, A., Štilić, A., Pamučar, D., Božanić, D., & Nedeljković, M. (2024). Introducing a novel multi-criteria ranking of alternatives with weights of criterion (RAWEC) model. *MethodsX*, 12, 102628. <https://doi.org/10.1016/j.mex.2024.102628>
- Senir, G. (2024). Evaluation of the environmental sustainability performance of Eastern European countries with integrated MCDM methods. *International Journal of Agriculture Environment and Food Sciences*, 8(2), 378-391.
- Shah, W. U. H., Zhang, X., Yasmeen, R., & Padda, I. U. H. (2023). Green transition and economic growth in G20 countries: Evidence from disaggregated energy sources. *Environmental Science and Pollution Research*, 30(40), 92206-92223. <https://doi.org/10.1007/s11356-023-28781-6>
- Shamsi, M., Zakerinejad, M., & Zareifard, M. R. (2025). Optimal, reliable, and sustainable technology selection for mining overburden waste utilization using green & climate-smart mining (GCSM): A hybrid fuzzy multi-criteria decision-making tool. *Journal of Environmental Chemical Engineering*, 13(3), 116118.
- Sikder, A., Inekwe, J., & Bhattacharya, M. (2019). Economic output in the era of changing energy-mix for G20 countries: New evidence with trade openness and research and development investment. *Applied Energy*, 235, 930-938. <https://doi.org/10.1016/j.apenergy.2018.10.092>
- Terra dos Santos, L. C., Frimaio, A., Giannetti, B. F., Agostinho, F., Liu, G., & Almeida, C. M. (2023). Integrating environmental, social, and economic dimensions to monitor sustainability in the G20 countries. *Sustainability*, 15(8), 6502. <https://doi.org/10.3390/su15086502>
- Trung, D. D., Ašonja, A., Van Duc, D., Bao, N. C., & Son, N. H. (2025). Comparison of RAWEC and AROMAN methods in material selection for manufacturing or maintenance. In H. Glavaš, M. Hadzima-Nyarko, N. Ademović, & T. Hanák (Eds.), *33rd International Conference on Organization and Technology of Maintenance (OTO 2024)* (Lecture Notes in Networks and Systems, Vol. 1242, pp. 190–200). Springer, Cham. https://doi.org/10.1007/978-3-031-80597-4_15

- Tufan, D., & Ulutaş, A. (2026). Supplier selection in the food sector: An integrated approach using LODECI and CORASO methods. *Spectrum of Decision Making and Applications*, 3(1), 40-51.
- Yalçın, G. C., Kara, K., & Senapati, T. (2024). A hybrid spherical fuzzy logarithmic decomposition of criteria importance and alternative ranking technique based on adaptive standardized intervals model with application. *Decision Analytics Journal*, 11, 100441.
- Yale Center for Environmental Law and Policy. (2020). *Environmental Performance Index (EPI) 2020 Report*. Yale University. <https://epi.yale.edu>
- Yürüyen, A. A., & Ulutaş, A. (2024). Assessing the urban competitiveness of european cities using LOPCOW-RAWEC methodologies. *International Journal of Knowledge and Innovation Studies*, 2(3), 179-189. <https://doi.org/10.56578/ijkis020305>
- Zhou, P., Poh, K. L., & Ang, B. W. (2007). A non-radial DEA approach to measuring environmental performance. *European Journal of Operational Research*, 178(1), 1-9. <https://doi.org/10.1016/j.ejor.2006.04.038>
- Zolfani, S. H., Pourhossein, M., Yazdani, M., & Zavadskas, E. K. (2018). Evaluating construction projects of hotels based on environmental sustainability with MCDM framework. *Alexandria Engineering Journal*, 57(1), 357-365. <https://doi.org/10.1016/j.aej.2016.11.002>