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Analysis of Climate Change Performances of G7 Group Countries: An Application Using the MEREC-based RAFSI Method

Furkan Fahri ALTINTAŞ[1]

Abstract

The activities of major economies regarding climate change can influence the global climate, the global economy, and the climate change strategies of other countries. In this context, analyzing the climate change performance of G7 countries is considered important. In this research, the climate change performances of G7 countries for the year 2023 were measured using the MEREC-based RAFSI method, based on the Climate Change Performance Index (CCPI) criteria. According to the findings, the most significant climate change criteria for G7 countries within the scope of the MEREC method were identified as Greenhouse Gases Emissions and Climate Policy. According to the MEREC-based RAFSI method, the climate change performance values of the countries were ranked as follows: Germany, the UK, France, Italy, the USA, Japan, and Canada. Furthermore, it was observed that the countries with performance values above the average climate change performance value were Germany, the UK, France, and Italy. Consequently, for the improvement of global climate change and contributions to the global economy, it is assessed that G7 countries need to show development particularly in Greenhouse Gas Emissions and Climate Policy criteria, and that the USA, Japan, and Canada need to undertake activities to enhance their climate change performance. From a methodological perspective, it was concluded that the MEREC-based RAFSI method is sensitive in measuring the climate change performances of countries according to sensitivity analysis, credible and reliable according to comparative analysis, and robust and stable according to simulation analysis. Therefore, based on the results of sensitivity, comparative, and simulation analyses, it was determined that the climate change performances of countries can be measured with MEREC based RAFSI in the scope of the CCPI.

Keywords: Climate Performance, G7, MEREC, MEREC based RAFSI.

1. Assoc. Prof. Dr., Gendarmerie General Command,
furkanfahrialtintas@yahoo.com,
https://orcid.org/0000-0002-0161-5862

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1. INTRODUCTION

Climate change is a universal issue that deeply affects our planet's ecosystems, biodiversity, and human life, leading to severe consequences such as global warming and extreme weather events (Smerdon, 2018; Rebonato, 2024). In this context, the performance of countries in combating climate change impacts not only their national boundaries but also global sustainability and the quality of life for future generations (Leckie, 2018; Briggle, 2024). The effectiveness of countries' climate policies and the success of their implementations are of great importance both environmentally and economically. The comprehensive and determined execution of these efforts has become a critical necessity for the future of our planet (Pogue, 2021; Hulme, 2022).

In the context of the relationship between climate change and economic size, the strategies and activities of major economies regarding climate change can influence global climate change and the climate change policies of other countries. Therefore, analyzing the climate change performances of major economies is considered important (Wu et al., 2021). In this regard, the climate change performances of the world's largest economies, the G7 countries, were measured using the MEREC-based RAFSI method, based on the most recent and up-to-date 2023 Climate Change Performance Index (CCPI) criteria.

The first aim of the research is to calculate the weights of climate change criteria for each country using the MEREC method. The second aim is to measure the climate change performances of countries using the MEREC-based RAFSI method. Through these analyses, it was determined which CCPI criteria countries should prioritize to contribute to the improvement of climate change and the global economy, and which country or countries need to enhance their climate change performances. Thirdly, the research explains the extent to which the climate change performances of countries can be measured using the MEREC-based RAFSI method within the scope of the CCPI. In this context, the literature section of the research explains the importance of climate change for countries and the relationship between climate change and economic growth. The methodology section specifies the data set and analysis of the research, along with the MEREC and RAFSI methods. Finally, the findings are discussed in the results section, and conclusions are drawn based on the identified quantitative values.

2. LITERATURE

2.1. Climate Change and Its Importance for Countries

Climate change, in its most general definition, is characterized as a long-lasting shift in average weather conditions or climate variability (Mohanty & Mohanty, 2009). More specifically, climate change is defined as an irreversible alteration in climate due to carbon emissions (Solomon et al., 2009). From another perspective, climate change refers to a shift in the state of the climate, identifiable through statistical tests by changes in the average and/or variability of its attributes, and lasting for an extended period, usually decades or longer (Intergovernmental Panel on Climate Change [IPCC)], 2007).

The adverse effects of climate change have a multifaceted nature. Environmentally, climate change contributes to air pollution, disasters, droughts, floods, sudden weather changes, global warming, an increase in forest fires, the melting of glaciers, rising sea levels, increased carbon dioxide levels, ecosystem disruption, biodiversity loss, and irregular animal migration (Corell, 2006; Matawal & Maton, 2013; Chakraborty et al., 2014; Ching-Ruey, 2020; Hamza et al., 2020; Yakovlev & Belyaev, 2023). Socially, climate change plays a role in the decline of food security quality and agricultural productivity, the spread of diseases, and the weakening of the economic structure (Patz et al., 2014; Naceur & Rahmani, 2023; Rahman et al., 2014).

With the adverse impacts of climate change, the climate change performance of countries has gained importance. By being aware of their climate change performance, countries can identify shortcomings, enhance their performance, and ensure the sustainability of their current performance through strategies, policies, and activities for both the present and future periods. Additionally, countries monitor each other's climate change performance. To address deficiencies or further develop themselves, countries can establish collaborations and partnerships with those that have a good climate change performance. Therefore, countries consistently need metrics, scales, or indices that measure their climate change performance on an international level (Bernauer & Böhmelt, 2013).

The only scale that measures the climate change performance of countries on an international level is the Climate Change Performance Index (CCPI) (Burck et al., 2006; Harmeling, 2011). The CCPI is an index created to measure the climate change performance of countries. This index provides the opportunity to compare the climate change performances of countries. The CCPI primarily consists of the following criteria: Greenhouse Gases Emissions, Renewable Energy, Energy Use, and Climate Policy (Burck et al., 2024).

2.2. Climate Change and Its Relationship with Economic Growth

A review of the literature reveals that the impact of climate change on economic growth has been evaluated as highly variable. This is because the relationship between economic size and climate change can differ depending on a country's economic structure, geographic location, average seasonal fluctuations, and climate culture (Mendelsohn, 2009). On the other hand, innovation activities and technological advancements made by countries as part of measures against climate change can contribute to their economic growth (Fankhauser & Tol, 2005). However, in the context of climate change, environmental sustainability, the increasing prominence of global warming, and the pursuit of economic growth by world economies require more stable and sustainable economies to reduce greenhouse gas emissions (Ismail, 2018; Sachs et al., 2023).

In the literature, many studies have investigated the relationship between climate change and economic growth. In this context, Dell et al. (2008) found that rising temperatures due to climate change significantly reduce economic growth only in poor countries. Roson and Mensbruggle (2010) assessed that in the long term, rising sea levels, increasing heat, and humidity within the framework of climate change could have adverse effects on countries' tourism and agriculture sectors. Gulzar and Aziz (2013) examined the impact of climate change on economic growth for Asian countries. The researchers found that in the short and long term, increased rainfall and temperatures in Asian countries limit economic growth. Soliman et al. (2014) found that climate change does not contribute to economic growth in Arab countries. Hayaloğlu (2018) observed that, based on data for the ten countries most affected by climate change according to the Global Climate Change Risk Index from 1990-2016, climate change generally has negative impacts on economic growth and agricultural value added in these countries. Akyol (2022) determined that in newly industrialized countries, average annual temperatures and carbon dioxide emissions have a positive effect on economic growth within the context of climate change. Benhamed et al. (2023) found, using data from countries on different continents, that climate change generally does not affect economic growth. However, the authors identified that climate change has negative long-term effects on economic growth only in the hottest countries. Kızılkaya and Mike (2023) concluded in their study that climate change could have negative long-term effects on Türkiye. Petrović (2023) analyzed the relationship between climate change (temperature and carbon emissions) and economic growth using data from countries on different continents. This analysis found that climate change promotes economic growth. Stern and Stiglitz (2023) emphasized that the negative impacts of climate change on economic growth can be mitigated through innovation, artificial intelligence, advanced technologies, and green growth. Ullaha et al. (2024) concluded that, in general, climate change accelerates economic growth in Asian countries.

A review of the literature on countries' climate change performance reveals that Keleş and Ersoy (2023) examined the climate change performance of G20 countries for the years 2019-2023 using LOPCOW-based SPOTIS, WISP, and RSMVC MCDM methods. Within the framework of the G20 countries encompassing the G7 countries, the climate change performances of these countries were ranked as follows: according to the LOPCOW-based SPOTIS method, UK, Germany, Italy, France, Japan, the USA, and Canada; according to the LOPCOW-based WISP method, Germany, the UK, Italy, France, the USA, Japan, and Canada; and finally, according to the LOPCOW-based RSMVC method, UK, Germany, Italy, France, the USA, Japan, and Canada. According to Burck et al. (2024), the climate change performance for the year 2023 is ranked as Germany, the UK, France, Italy, the USA, Japan, and Canada. Additionally, the average climate change performance of these countries was measured, and it was observed that the countries with performance above the average were Germany, the UK, France, and Italy. Puška et al. (2024) assessed the climate change performance of European countries using the fuzzy MABAC method. The study identified Denmark, Estonia, and the Netherlands as the top-performing countries. Among the G7 nations, Germany ranked 5th, France 17th, and Italy 20th. Köse et al. (2024) evaluated the climate change performance of G20 countries using the MEREC-based PROMETHEE method. In their study, the performance rankings of the G7 countries within the G20 were as follows: the United Kingdom, Germany, Italy, France, Japan, Canada, and the United States. Gökgöz and Yalçın (2021) measured the climate change performance of EU countries using the CRITIC-based TOPSIS and COPRAS methods. Their findings indicated that Nordic and Baltic countries outperformed other European nations in terms of climate change performance.

One of the most significant causes of climate change is carbon emissions. Excessive carbon emissions lead to increased temperatures, resulting in seasonal fluctuations and ecological disruptions (Sachs et al., 2023). Globally, between 1970 and 2016, approximately 39% of the world's carbon emissions were attributed to the G7 countries (Graphwise, 2024). The activities, strategies, and methods of large economies regarding climate change can influence global climate change policies and the climate change plans of other countries (Wu et al., 2021). Additionally, in 2023, the climate change policies of the G7 countries have had an impact on the global reduction of carbon emissions (International Energy Agency [IEA], 2023). In this context, analyzing the climate change performance of the G7 countries can be considered important (Wu et al., 2021). The G7 countries, possessing economic power that significantly impacts global climate change, bear extensive responsibilities in combating climate change, encompassing both historical and contemporary contexts. These responsibilities are directly correlated with economic development, greenhouse gas emissions, financial contributions, and environmental sustainability objectives (Kirton & Kokotsiz, 2015). Throughout history, the G7 countries have been responsible for a significant share of global greenhouse gas emissions, particularly since the Industrial Revolution. Countries such as the United States, Canada, Germany, France, Italy, Japan, and the United Kingdom, as highly industrialized nations, have historically emitted substantial amounts of carbon dioxide (CO_2). Consequently, the responsibility of G7 countries in addressing climate change is not only linked to their current emission levels but also to the long-term impact of their accumulated greenhouse gas emissions (Jakob & Gardiner, 2022). Moreover, G7 countries have a responsibility to provide financial and technological support to developing nations in their efforts to combat and adapt to climate change. Given their advanced infrastructure and technological capacity, these countries can play a leading role in developing technological innovations and promoting low-carbon solutions in the fight against climate change (Koirala et al, 2024). Additionally, G7 nations must increase the financial commitments they have pledged to developing countries for climate financing. Under the framework of the Paris Agreement, the commitment of developed nations to provide a certain amount of climate finance annually serves as a concrete example of this responsibility (The United Nations Framework Convention on Climate Change [UNFCCC], 2021). Numerous academic studies emphasize that while wealthy nations have contributed extensively to carbon emissions since the Industrial Revolution, developing countries have made relatively lower contributions. This disparity highlights the necessity of considering historical emissions within a framework of climate justice (Roberts & Parks, 2006). In terms of greenhouse gas emissions, G7 countries are among the largest contributors to global emissions and, therefore, play a crucial role in combating climate change. These nations bear the responsibility of reducing their global carbon footprints and achieving climate targets. Numerous scientific reports emphasize that these countries should take the lead in aligning with the Paris Agreement, which aims to limit global warming to 1.5°C (Intergovernmental Panel on Climate Change [IPCC)], 2018). Furthermore, it is of great importance that G7 countries accelerate their energy transition processes by shifting toward renewable energy sources and reducing their dependence on fossil fuels. In terms of global climate policies, G7 countries possess the leadership capacity to shape climate change policies on a global scale. These nations have a responsibility to ensure environmental justice both within their own borders and at the international level when formulating climate policies (Kirton et al., 2018). In this context, it is expected that G7 countries will strengthen international cooperation in the fight against climate change and contribute positively to both their domestic policies and global negotiations. These countries can particularly take the lead in limiting greenhouse gas emissions through market-based solutions, such as carbon taxation. In conclusion, G7 countries bear a significant responsibility in the global fight against climate change. This responsibility is not limited solely to their current greenhouse gas emissions but is also directly linked to their historical emissions and the support they provide to developing countries (National Academy of Science, 2014). It is essential for G7 nations to take the lead in combating climate change, develop effective policies on a global scale, and offer financial and technological assistance to developing nations. In this context, the climate policies of G7 countries should be addressed not only from an environmental perspective but also within the framework of social and economic sustainability. As long as climate change performance does not improve, sustainability cannot be ensured in any economy-related aspect. Consequently, this situation may negatively impact the global economy, potentially leading to economic stagnation for both developed and developing countries. Accordingly, the G7 countries, as the most significant economic actors, recognize the necessity of enhancing their climate change performance to ensure sustainability (National Academy of Science, 2014).

3. MATERIAL AND METHOD

3.1. Data Set and Analysis of the Research

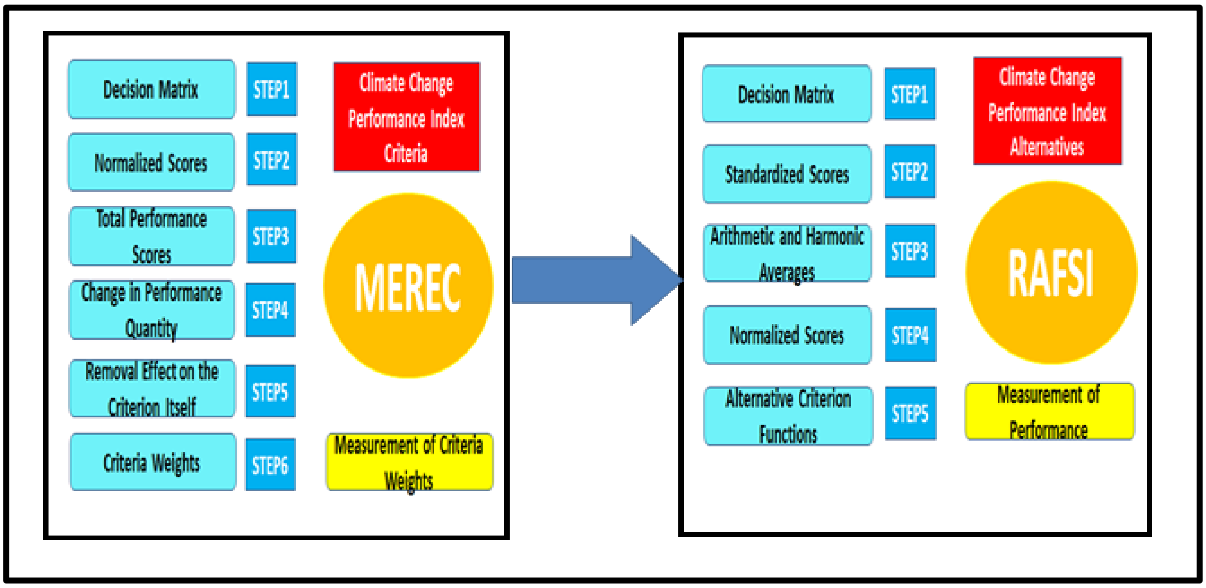
The research has compiled the CCPI criterion values for the G7 countries for the most recent year, 2023. For ease of reference, abbreviations of the CCPI criteria are shown in Table 1.

Table 1. Abbreviations of CCPI Criteria

CCPI Criteria	CCPI
Greenhouse Gases Emissions	CCPI1
Renewable Energy	CCPI2
Energy Use	CCPI3
Climate Policy	CCPI4

The primary objective of this research is to evaluate the climate change performance of G7 countries using the MEREC-based RAFSI method, employing the most recent and current CCPI (Climate Change Performance Index) criterion values. The selection of CCPI criterion data in this study is predicated on its contemporary structure and its capacity to comprehensively delineate the climate change performance of nations (Burck et al., 2024). The MEREC method, grounded in logarithmic measurement, demonstrates a superior capacity for elucidating the contribution of criteria weighting, particularly in datasets characterized by limited data points. Furthermore, from a mathematical standpoint, MEREC excels in the differentiation of criteria and the determination of their inherent characteristics. This method exhibits robust consistency in criteria weighting, ensuring a homogeneous weighting structure and mitigating the occurrence of extreme weight assignments, thereby affirming its strength and stability (Keshavarz-Ghorabaee et al., 2021). Conversely, the RAFSI method, notably through the integration of ideal and anti-ideal values via arithmetic and harmonic means, manifests a framework that comprehensively considers the strength of all values within the dataset. This methodology provides a more realistic framework for performance assessment (Žižović et al., 2020). Consequently, in consideration of the distinct characteristics of these methodologies, this study employs MEREC for criteria weighting and RAFSI for the evaluation of climate change performance among alternatives, specifically nations. In this context, the research model pertaining to this is illustrated in Figure 1.

Figure 1. Research Model



3.2. MEREC Method

MEREC (A New Method Based on The Removal Effects of Criteria) is one of the current objective criterion weighting methods, which considers changes in the total criterion weight by excluding and disabling criteria from consideration (Ayçin & Arsu, 2021). Accordingly, criteria that have a greater impact on decision alternatives have higher weights (Keshavarz-Ghorabaee et al., 2021).

Upon reviewing the MEREC literature, it has been observed that many researchers have utilized the MEREC method for measuring criterion weights. Consequently, some studies using the MEREC method are shown in Table 2.

Table 2. MEREC Literature

Author(s)	Method(s)	Theme
Shanmugasundar et al. (2022)	MEREC-CODAS, COPRAS, COCOSO, MABAC and VIKOR	Assessment of ideal spray-painting robot
Ulutaş et al. (2022)	MEREC-WISP S	Analysis of pallet truck selection
Banik et al. (2023)	MEREC-GRA	Analysis of pentagonal neutrosophic environment
Bektaş (2023)	MEREC-MABAC	Evaluation of financial performance of energy companies
Narang et al. (2023)	fuzzy extension of MEREC	Evaluation of parabolic measure
Popović et al. (2022)	MEREC-COBRA	Selection of e-commerce development strategy
Pucar et al. (2023)	MEREC-CRADIS	Assessment of learning management systems
Sümerli Sarıgül et al. (2023)	MEREC-MARCOS, COCOSO	Assessment of airport service quality
Risti et al. (2024)	MEREC-MARCOS	Analysis of urban of pedestrian crossings
Zhai et al. (2022)	MEREC-Pythagorean fuzzy sets	Evaluation of the agriculture supply chain risks

Regarding this matter, the application steps of the aforementioned method are explained below (Keshavarz-Ghorabaee et al., 2021; Keleş, 2023).

Step 1: Formation of the Decision Matrix

$i = 1,2,3 \dots m, m$: number of decision alternatives

$j = 1,2,3, \dots n, n$: number of criteria

d_{ij} = It denotes the value corresponding to alternative i for criterion j.

d_{ij}^{*}= It denotes the normalized value corresponding to alternative i for criterion j.

D: Decision matrix

The decision matrix is ensured by Equation 1

$$D = \left[d_{ij}\right]_{mxn} = \begin{bmatrix} x_{11} & x_{12} & \cdots & x_{1n} \\ x_{21} & x_{22} & \cdots & x_{2n} \\ \vdots & \vdots & \vdots & \vdots \\ x_{m1} & x_{m2} & \cdots & x_{mn} \end{bmatrix} \tag{1}$$

Second Step: Measurement of Normalized Values of the Decision Matrix

for benefit-oriented criteria:

$$d_{ij}^{*}=\frac{mind_{ij}}{d_{ij}} \tag{2}$$

for cost-oriented criteria

$$d_{ij}^{*}=\frac{d_{ij}}{makd_{ij}} \tag{3}$$

Third Step: Measurement of the Total Performance Values of Decision Alternatives

$$S_i=In(1+(\frac{1}{m}\sum_{j}\left|In(d_{ij})\right|)) \tag{4}$$

Fourth Step: Calculation of the Change in Performance Quantity of Decision Alternatives without Considering the Value of Each Decision Alternative

$$S_{ij}^{'}=In(1+(\frac{1}{m}\sum_{k,k\neq j}\left|In(d_{ik}^{*})\right|)) \tag{5}$$

Fifth Step: Calculation of the Sum of Absolute Deviations (Calculation of the Removal Effect on the Criterion Itself)

$$E_j=\sum_{i}\left|S_{ij}^{'}-S_i\right| \tag{6}$$

Sixth Step: Calculation of Criterion Weights

$$w_j=\frac{E_j}{\sum_k E_k} \tag{7}$$

3.3. RAFSI Method

RAFSI (Ranking of Alternatives through Functional Mapping of Criterion Sub-intervals into a Single Interval) method does not apply the classic normalization process but instead introduces an original standardization method that transforms data changes in any range of the decision matrix, meeting the conditions for ideal decision making (Žižović et al., 2020). The method allows for adjustment to a different criterion weight through component functions and component sub-intervals within the decision matrix, particularly achieving heterogeneous criterion weights based on arithmetic and harmonic means of the components' properties. Additionally, the method permits subjective reasoning of decision-makers in calculating ideal and anti-ideal values, distinguishing RAFSI's significant feature from other MCDM methods (Demir, 2021). Studies using the RAFSI method can be found in the literature, and relevant research is detailed in Table 3.

Table 3. RAFSI Literature

Author(s)	Method(s)	Theme
Pamucar et al. (2021)	FUCOM-RAFSI	Evaluation of ports
Alossta et al. (2021)	AHP-RAFSI	Analysis of resolving a location
Božanić et al. (2021)	D NUMBERS – FUCOM – FUZZY RAFSI	Evaluation of construction machines
Gokasar et al. (2023)	Type-2 neutrosophic numbers based RAFSI	Assessment of alternatives of introducing electric vehicles
Deveci et al. (2023)	LMAW-RAFSI	Analysis of optimal e-scooter parking locations
Deveci et al. (2022)	LAAW-RAFSI	Selection of floating photovoltaic site
Bisht & Pal (2024)	Fuzzy modified RAFSI	Analysis of five stocks under the national stock exchange
Deveci et al. (2024)	Fuzzy trigonometric based OPA and RAFSI	Evaluation of aircraft type selection
Ali et al. (2024)	CRITIC-RAFSI	Impact of financial risks on the financial sustainability

In this context, the application steps of the RAFSI method are outlined below in bullet points (Žižović et al., 2020).

First Step: Formation of the Decision Matrix and Determination of Ideal and Anti-ideal Values

$i: 1, 2, 3, \ldots, m$ represents the decision alternatives, N denotes the decision matrix, and d_{ij} specifies the $i-th$ decision alternative on the $j-th$ component. Subsequently, by ensuring the condition $\sum_{j=1}^{n} w_j=1$ and considering the utility and cost orientations of the components, the decision matrix in Equation 8 is formed.

$$N=\left[n_{ij}\right]_{mxn}=\begin{bmatrix} n_{11} & n_{12} & \cdots & n_{1n} \\ n_{21} & n_{22} & \cdots & n_{2n} \\ \vdots & \vdots & \vdots & \vdots \\ n_{m1} & n_{m2} & \cdots & n_{mn} \end{bmatrix} \tag{8}$$

In the context of determining ideal and anti-ideal values, for each component $C_j(j=1,2,....n)$, two values are identified by the decision maker: a_{Ij} (ideal value of criterion C_j) and a_{Nj} (anti-ideal value of criterion C_j). For benefit-oriented criteria, $a_{Ij}>a_{Nj}$ and for cost-oriented criteria, $a_{Ij}<a_{Nj}$ determined.

Second Step: Mapping Decision Matrix Values to Component Weights (Establishing the Standard Decision Matrix).

Firstly, Equation 9 is applied for benefit-oriented components.

$C_j \in$

$$\left[a_{Nj}, a_{Ij}\right] \tag{9}$$

Equation 10 is applied for cost-oriented components.

$C_j \in$

$$\left[a_{Ij}, a_{Nj}\right] \tag{10}$$

The transfer of all components of the decision matrix to the component range is achieved with a number sequence in interval k by transferring $k-1$ points between the minimum and maximum values of component weights, as specified by Equation 11.

$$n_1 < n_2 \leq n_3 \leq n_4 \leq n_5 \leq n_6 .... \leq n_{2k-1} \leq n_{2k} \tag{11}$$

The component weight is constant for all components and has fixed points. The maximum value is n_{2k} for benefit (a_{Ij}) and cost (a_{Nj}) directional components. In contrast, the minimum value is n_1 for benefit (a_{Nj}) and cost (a_{Ij}) directional components. It is recommended that the ideal value should be 6 times better than the anti-ideal value. Therefore, if $n_1 = 1$, then $n_{2k} = 6$ should be applicable. Additionally, it is suggested that for $n_1 = 1$, values such as $n_{2k} = 9$ can also be used. Subsequently, a function $f_s(x)$ is defined that maps the sub-interval component weight to $[n_1, n_{2k}]$. The function $f_s(x)$ is elaborated in Equation 12.

$$f_s(x) = \frac{n_{2k} - n_1}{n_{Ij} - a_{Nj}} . x + \frac{a_{Ij} . n_1 - a_{Nj} . n_{2k}}{a_{Ij} - a_{Nj}} \tag{12}$$

Equation 12 specifies the relationship indicating the preference quantity of n_{2k} and n_1 over the ideal to anti-ideal values. The determination of numbers (a_{Ij}) and (a_{Nj}) defines the criterion weight values and the extreme points of criterion weight. Within the scope of the research, the definitions of (a_{Ij}) and (a_{Nj}) are established through the extreme points of criterion weight. Thus, ensuring all values in the matrix are mapped to the $[n_1, n_{2k}]$ interval, the standardized decision matrix $S = \left[S_{ij}\right]_{mxn} mxn$ is obtained where $i = 1,2, \dots m$ and $j = 1,2, \dots n$. Following the functional mapping of initial decision matrix (N) values to the $[n_1, n_{2k}]$ criterion weight, S_{ij} is established for each i and j as $n_1 < S_{ij} < n_{2k}$.

$$S = \left[S_{ij}\right]_{mxn} = \begin{bmatrix} S_{11} & S_{12} & \cdots & S_{1n} \\ S_{21} & S_{22} & \cdots & S_{2n} \\ \vdots & \vdots & \vdots & \vdots \\ S_{m1} & S_{m2} & \cdots & S_{mn} \end{bmatrix} \quad i=1,2,....m \;\; j=1,2,...n \tag{13}$$

In Equation 13, the values of matrix S, denoted as S_{ij}, are determined by $S_{ij} = f_{A_i}(C_j)$. For benefit-oriented components, if there exists an a_{xj} that satisfies the condition $a_{xj} > a_{ij}$, then there exists

$f(a_{xj}) = f(a_{ij})$. Similarly, for cost-oriented components, if there exists an a_{xj} that satisfies the condition $a_{xj} < a_{ij}$, then there exists $f(a_{xj}) = f(a_{ij})$.

Third Step: Measurement of Arithmetic and Harmonic Averages

The arithmetic mean for the maximum and minimum series of n_{2k} and n_1 values is calculated using Equation 14, and the harmonic mean is calculated using Equation 15.

$$A=\frac{n_1+n_{2k}}{2} \tag{14}$$

$$H=\frac{2.\, n_{2k}.\, n_1}{n_{2k}+ n_1} \tag{15}$$

Fourth Step: Formation of the Normalized Decision Matrix

The normalization process of the S matrix values utilizes Equation 16 for benefit-oriented components and Equation 17 for cost-oriented components, ensuring normalization within the [0,1] range, resulting in the normalized decision matrix provided by Equation 18.

$$\hat{S}_{ij}=\frac{s_{ij}}{2A} \tag{16}$$

$$\hat{S}_{ij}=\frac{H}{2s_{ij}} \tag{17}$$

$$(\hat{S}) = [\hat{S}_{ij}]_{mxn}=\begin{bmatrix} \hat{S}_{11} & \hat{S}_{12} & \cdots & \hat{S}_{1n} \\ \hat{S}_{21} & \hat{S}_{22} & \cdots & \hat{S}_{2n} \\ \vdots & \vdots & \vdots & \vdots \\ \hat{S}_{m1} & \hat{S}_{m2} & \cdots & \hat{S}_{mn} \end{bmatrix} \; i=1,2,....m \;\; j=1,2,...n \tag{18}$$

Equation 18 is derived using Equation 19 for benefit-oriented components and Equation 20 for cost-oriented components.

$$0<\frac{n_1}{2A}\leq\hat{s}_{ij}\leq\frac{H}{2n_1} < 1 \tag{19}$$

$$0<\frac{H}{2n_{2k}}\leq\hat{s}_{ij}\leq\frac{H}{2n_1} < 1 \tag{20}$$

Fifth Step: Determination of Alternative Criterion Functions

Equations 21 are used to determine $(V(A_i))$. Subsequently, these values are ranked in descending order to arrange the performance of decision alternatives from best to worst.

$$V(A_i)=w_1.\, \hat{S}_{i1}+w_2.\, \hat{S}_{i2}+...+w_n.\, \hat{S}_{in} \tag{21}$$

4. FINDINGS

4.1. Computational Analysis

In the study, initially, the weights (importance degrees) of CCPI components (criteria) using the MEREC method were calculated for G7 countries. In this regard, in the first step of the MEREC method, Decision Matrix was formed with Equation 1. In the second step of the method, Equation 2 was applied to normalize the values of the Decision Matrix. Accordingly, the values of the Decision Matrix and the normalized Decision Matrix are presented in Table 4.

Table 4. Decision ($\boldsymbol{D}$) and Normalized Matrix ($\boldsymbol{d_{ij}^{*}}$)

Decision Matrix				
Text	CCPI1	CCPI2	CCPI3	CCPI4
Canada	14.59	3.4	4.04	9.52
France	27.02	4.55	12.84	12.71
Germany	28.47	7.38	14.54	15.39
Italy	23.2	7.38	13.52	6.49
Japan	21.42	5	13.15	2.5
UK	30.95	5.2	16.63	9.58
USA	16.88	3.03	6.69	16.2
Normalized Scores				
Text	CCPI1	CCPI2	CCPI3	CCPI4
Canada	1.000	0.891	1.000	0.263
France	0.540	0.666	0.315	0.197
Germany	0.512	0.411	0.278	0.162
Italy	0.629	0.411	0.299	0.385
Japan	0.681	0.606	0.307	1.000
UK	0.471	0.583	0.243	0.261
USA	0.864	1.000	0.604	0.154

In the third step of the MEREC method, Equation 4 was used to calculate the total performance values (S_i) of decision alternatives, in the fourth step followed by Equation 5 to measure changes in countries' performances ($S_{ij}^{'}$) by subtracting the values of all criteria.

Table 5. S_i and S'_{ij} Scores

Countries	S_i	S'_{ij}			
		CCPI1	**CCPI2**	**CCPI3**	**CCPI4**
Canada	0.445	0.445	0.000	0.445	0.109
France	1.314	0.704	1.150	0.942	0.879
Germany	1.492	0.942	1.217	1.152	1.094
Italy	1.356	1.023	1.123	0.983	1.014
Japan	1.120	0.986	1.084	0.634	0.823
UK	1.424	0.919	1.292	1.008	1.017
USA	16.88	3.03	6.69	16.2	

In the fifth step of the method, Equation 6 was utilized to calculate the sum of absolute deviations (E_j) of the criteria, and in the sixth step, Equation 7 was employed to determine the weights of the criteria. The computed values are presented in Table 6 accordingly.

Table 6. E_j and w Scores

Countries	**CCPI1**	**CCPI2**	**CCPI3**	**CCPI4**
Canada	0.000	0.445	0.000	0.336
France	0.611	0.164	0.372	0.435
Germany	0.550	0.275	0.340	0.398
Italy	0.333	0.233	0.373	0.342
Japan	0.134	0.036	0.486	0.297
UK	0.505	0.133	0.416	0.408
USA	0.709	0.223	0.251	0.548
E_j	2.842	1.509	2.238	2.764
w	0.304	0.161	0.239	0.295
w Mean	0.250			
Rank	1	4	3	2

Upon reviewing Table 6, the weight values of the CCPI criteria are ranked as CCPI1, CCPI4, CCPI3, and CCPI2 across countries. Additionally, based on Table 6, noticeable differences are observed among CCPI3 and CCPI2 in terms of the higher weight values attributed to CCPI1 and CCPI4 criteria. Furthermore, the average weight value of CCPI criteria across countries has been calculated, revealing that CCPI1 and CCPI4 criteria have weights higher than the average value.

In the study, secondly, using the MEREC-based RAFSI method, countries' performances on climate change have been calculated. In this context, initially within the RAFSI method, Equation 8 was employed to determine the ideal and anti-ideal values for the decision matrix and criteria. The decision matrix in question was previously constructed via Equation 1 within the MEREC method and presented in Table 3. Accordingly, the ideal and anti-ideal values for the criteria are indicated in Table 7.

Table 7. Ideal (a_{Ij}) and Anti-ideal Scores (a_{Nj})

Criteria	Ideal Values	Anti-ideal Values	Description
CCP1	14.59	30.95	CCP∈ (30.95;14.59)
CCP2	3.03	7.38	CCP∈ (7.38;3.03)
CCP3	4.04	16.63	CCP∈ (16.63;4.04)
CCP4	2.5	16.2	CCP∈ (16.2;2.5)

In the second step of the method, Equations 9, 10, 11, 12, and 13 were utilized to construct the standard decision matrix for the criteria, and the values of the constructed standard decision matrix are detailed in Table 8.

Table 8. Standard Decision Matrix ($\boldsymbol{S}$)

Countries	CCPI1	CCPI2	CCPI3	CCPI4
Canada	1.000	1.425	1.000	3.562
France	4.799	2.747	4.495	4.726
Germany	5.242	6.000	5.170	5.704
Italy	3.631	6.000	4.765	2.456
Japan	3.087	3.264	4.618	1.000
UK	6.000	3.494	6.000	3.584
USA	1.700	1.000	2.052	6.000

In the third step of the RAFSI method, the arithmetic mean value was determined using Equation 14, and the harmonic mean value was determined using Equation 15, with the respective arithmetic and harmonic mean values presented in Table 9.

Table 9. Means Score

Means	Measures
Arithmetic Mean	$A = \frac{1+6}{2} = 3.5$
Harmonic Mean	$H = \frac{2}{\frac{1}{6}+\frac{1}{1}} = 1.71$

In the fourth step, the normalized decision matrix values are calculated using Equations 16, 18, and 19. The calculated normalized values are explained in Table 10.

Table 10. Normalized Decision Matrix $(\hat{S})$

Countries	CCPI1	CCPI2	CCPI3	CCPI4
Canada	0.143	0.204	0.143	0.509
France	0.686	0.392	0.642	0.675
Germany	0.749	0.857	0.739	0.815
Italy	0.519	0.857	0.681	0.351
Japan	0.441	0.466	0.660	0.143
UK	0.857	0.499	0.857	0.512
USA	0.243	0.143	0.293	0.857

In the final step of the method, Equation 21 is used to calculate the criterion functions (Countries' climate change performances). In this context, countries' climate change performances are detailed in Table 11.

Table 11. Climate Change Performance Score $V(A_i)$

Countries	CCPI1	CCPI2	CCPI3	CCPI4	Sum	Rank
Canada	0.043	0.033	0.034	0.150	0.261	7
France	0.208	0.063	0.154	0.200	0.625	3
Germany	0.228	0.138	0.177	0.241	0.783	1
Italy	0.158	0.138	0.163	0.104	0.563	4
Japan	0.134	0.075	0.158	0.042	0.409	6
UK	0.260	0.081	0.205	0.151	0.697	2
USA	0.074	0.023	0.070	0.253	0.420	5
		Mean			0.537	---

Upon reviewing Table 11, countries' climate change performances are ranked as Germany, the UK, France, Italy, the USA, Japan, and Canada. Furthermore, upon examining Table 11, countries' average climate change performance based on the MEREC-based RAFSI method has been calculated, identifying Germany, the UK, France, and Italy as the countries with performance above the average.

4.2. Sensibility Analysis

In this study, we conducted a sensitivity analysis to evaluate the methodological robustness of the LOPCOW-based DNMA method. Sensitivity analysis, within the framework of MCDM (Multi-Criteria Decision Making), involves applying various weighting techniques to a single dataset. This approach allows for a comparative evaluation of the resulting values and rankings of decision alternatives' performance. We anticipate a divergence in the performance rankings of the identified decision alternatives, ensuring the sensitivity of the chosen weight coefficient calculation method. This divergence is expected when comparing the performance rankings of decision alternatives obtained through the application of alternative methods (Gigovič, et al., 2016). In this specific context, Table 12 presents the values obtained by applying various weighting methods to the CCPI criteria for different countries.

Table 12. Weight Values of Criteria According to Weighting Methods

Countries	CCPI1	CCPI2	CCPI3	CCPI4
ENTROPY	0.114	0.184	0.287	0.415
Rank	4	3	2	1
CRITIC	0.185	0.227	0.222	0.367
Rank	4	2	3	1
SD	0.249	0.268	0.242	0.240
Rank	2	1	3	4
SVP	0.436	0.036	0.244	0.284
Rank	1	4	3	2
LOPCOW	0.239	0.191	0.292	0.278
Rank	3	4	1	2

In the continuation of the sensitivity analysis, the climate change performances of the countries are ranked according to the RAFSI method based on ENTROPY, CRITIC, SD, SVP, and LOPCOW, taking into account the criterion weights calculated by the objective weighting methods shown in Table 12. The determined rankings are presented in Table 13.

Table 13. Climate Change Performance and Rankings of Countries According to the RAFSI Method Based on ENTROPY, CRITIC, SD, SVP, and LOPCOW

Countries	ENTROPY RAFSI		CRITIC RAFSI		SD RAFSI		SVP RAFSI		LOPCOW RAFSI	
	Score	Rank	Score	Rank	Score	Rank	Score	Rank	Score	Rank
Canada	0.306	7	0.291	7	0.247	7	0.249	7	0.256	7
France	0.615	3	0.606	3	0.594	4	0.662	3	0.614	3
Germany	0.793	1	0.795	1	0.791	1	0.769	1	0.785	1
Italy	0.558	4	0.570	4	0.608	3	0.523	4	0.584	4
Japan	0.385	6	0.386	6	0.429	5	0.411	6	0.427	5
UK	0.648	2	0.649	2	0.678	2	0.746	2	0.693	2
USA	0.494	5	0.457	5	0.376	6	0.426	5	0.409	6

When examining Table 12 and Table 13 together, it is observed that the rankings of countries' climate change protection performances are consistent according to the RAFSI method based on MEREC, ENTROPY, CRITIC, and SVP. In contrast, the performance rankings identified using the MEREC-based RAFSI method differ from those determined using the SD and LOPCOW-based RAFSI methods. Consequently, it is assessed that the measurement of countries' climate change performances using the MEREC-based RAFSI method is sensitive within the context of CCPI.

4.3. Comparative Analysis

The comparative analysis evaluates the relationships and positions of the proposed approach in comparison to other methodologies used for calculating MCDM methods. The proposed method should demonstrate credibility, reliability, and consistency with other methodologies, while also showing a favorable and statistically significant correlation with various weight coefficient methodologies (Keshavarz-Ghorabaee et al., 2021). Consequently, the climate change performances of the countries were first measured using MEREC-based WASPAS, ARAS, TOPSIS, WPA, and GRA methods. The performance values and rankings of the countries according to these methods are presented in Table 14.

Table 14. Climate Change Performance Scores of Countries According to MEREC-Based MCDM Methods

Countries	MEREC ARAS		MEREC WASPAS		MEREC TOPSIS	
	Score	Rank	Score	Rank	Score	Rank
Canada	0.452	7	0.356	7	0.010	7
France	0.780	3	0.663	4	0.734	3
Germany	0.931	1	0.770	2	0.846	2
Italy	0.695	4	0.699	3	0.589	4
Japan	0.543	6	0.620	5	0.499	5
UK	0.823	2	0.775	1	0.943	1
USA	0.634	5	0.419	6	0.160	6

Countries	MEREC WPA		MEREC GRA		MEREC MARCOS	
	Score	Rank	Score	Rank	Score	Rank
Canada	0.500	7	0.238	7	0.354	7
France	0.834	4	0.425	4	0.706	4
Germany	0.944	2	0.574	2	0.835	2
Italy	0.872	3	0.478	3	0.750	3
Japan	0.794	5	0.372	5	0.654	5
UK	0.945	1	0.624	1	0.844	1
USA	0.579	6	0.258	6	0.422	6

When Table 11 and Table 14 are examined together, it is observed that the performance values of countries under the MEREC-based RAFSI method are consistent only with the MEREC-based ARAS method. The visual representations of the MEREC-based MCDM methods are presented in Figures 2, 3, and 4.

Figure 2. Position of MEREC based RAFSI

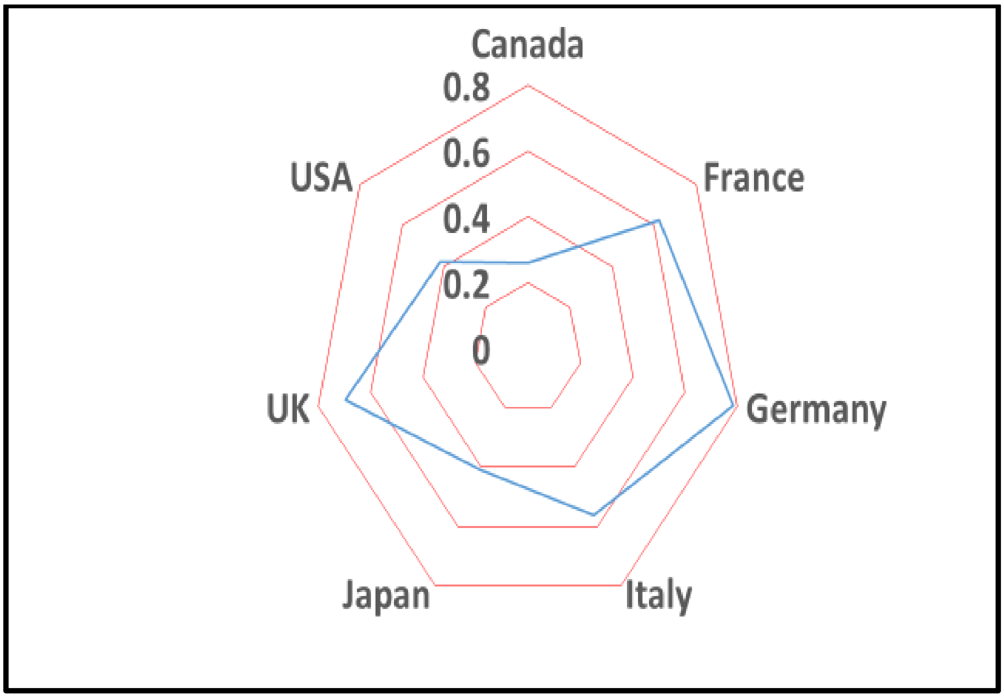


Figure 3. Position of MEREC based MCDM Positions-1

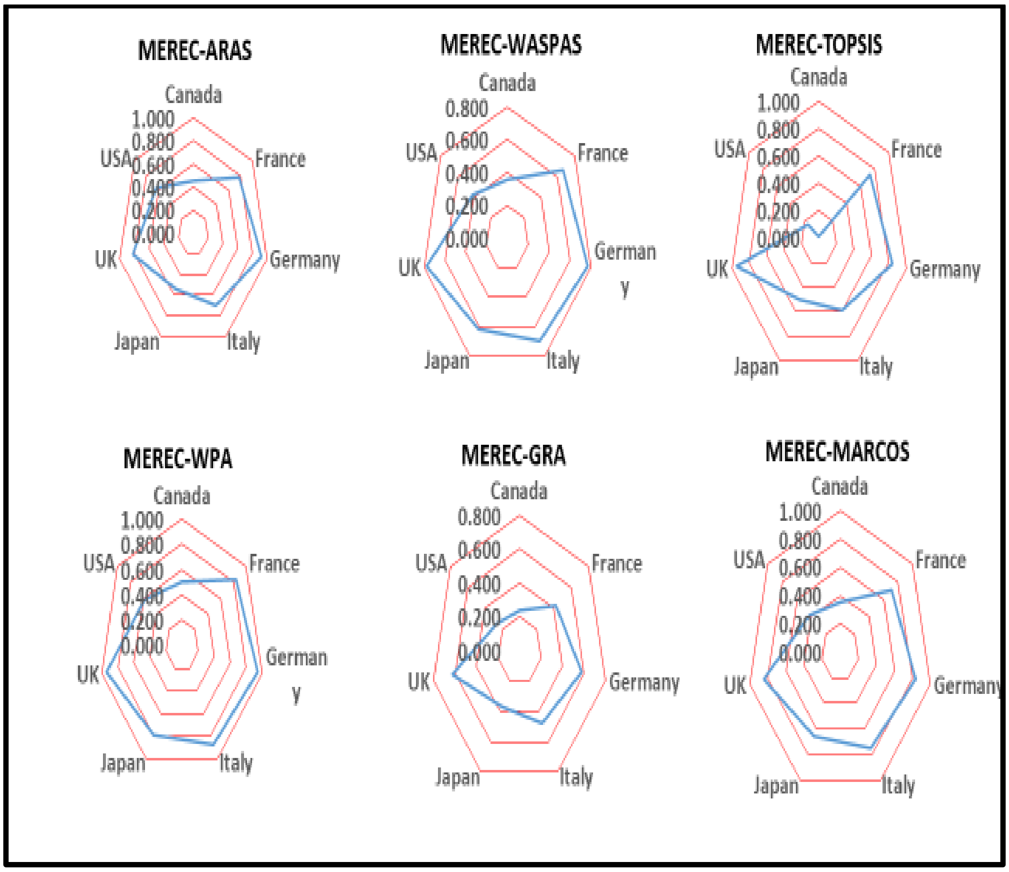
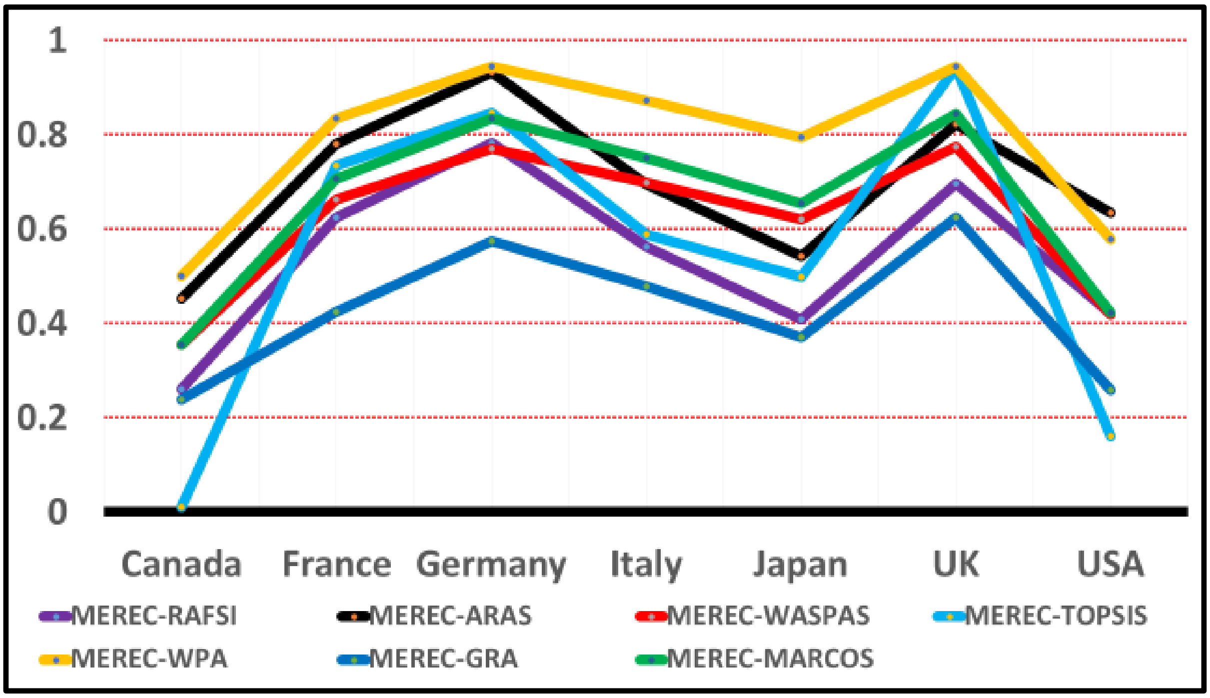


Figure 4. Position of MEREC based MCDM Positions-2



When Figures 2, 3, and 4 are evaluated together, it is observed that the fluctuations in the climate change performance values of countries calculated using the MEREC-based RAFSI method are generally consistent with the fluctuations in the performance values of countries measured by other MCDM methods. Consequently, it is concluded that there are positive, significant, and high or very high correlations between the climate change performance values of countries calculated using the MEREC-based RAFSI method and those measured by other MCDM methods.

In Walters' (2009) study, Keshavarz-Ghorabaee et al. (2021) stated that a Pearson correlation ranging from 0.400 to 0.600 between the MEREC method and other methods (SD, ENTROPY, and CRITIC) indicates a moderate level of relationship between the variables. If the correlation exceeds 0.600, the relationship is considered statistically significant. Accordingly, the correlation values between the MCDM methods are shown in Table 15.

Table 15. Correlations Among the MCDM Methods

MCDM METHODS	MEREC ARAS	MEREC WASPAS	MEREC TOPSIS	MEREC WPA	MEREC GRA	MEREC MARCOS
MEREC RAFSI	0.823**	0.999**	0.977**	0.999**	0.963**	0.927**

Note: **p<.01

Upon examining Table 15, it is observed that the correlation values between the climate change performance scores of countries calculated using the MEREC-based RAFSI method and those calculated using other MEREC-based MCDM methods are all significant, positive, and high. In this context, it is concluded that the MEREC-based RAFSI method is credible and reliable for measuring countries' climate change performance within the scope of the CCPI.

4.4. Simulation Analysis

To assess the robustness and stability of the proposed method's results, a simulation analysis will be conducted. This analysis will involve generating various scenarios by applying different values to decision matrices. A reliable method should demonstrate increasing divergence in its results compared to other methods as the number of scenarios increases. Subsequently, the average variance of criterion weights determined by the proposed method across the scenarios should be notably higher than that of at least one other objective weighting method. This would indicate the superior ability of the proposed method to differentiate between the relative importance of criteria. Finally, the analysis should establish consistency in the variance of criterion weights across all methods within each individual scenario (Keshavarz-Ghorabaee et al., 2021). In this context, Table 16 presents the correlation coefficients between the MEREC-based RAFSI method and other MEREC-based MCDM methods, calculated based on the initial 10 scenarios of the simulation analysis.

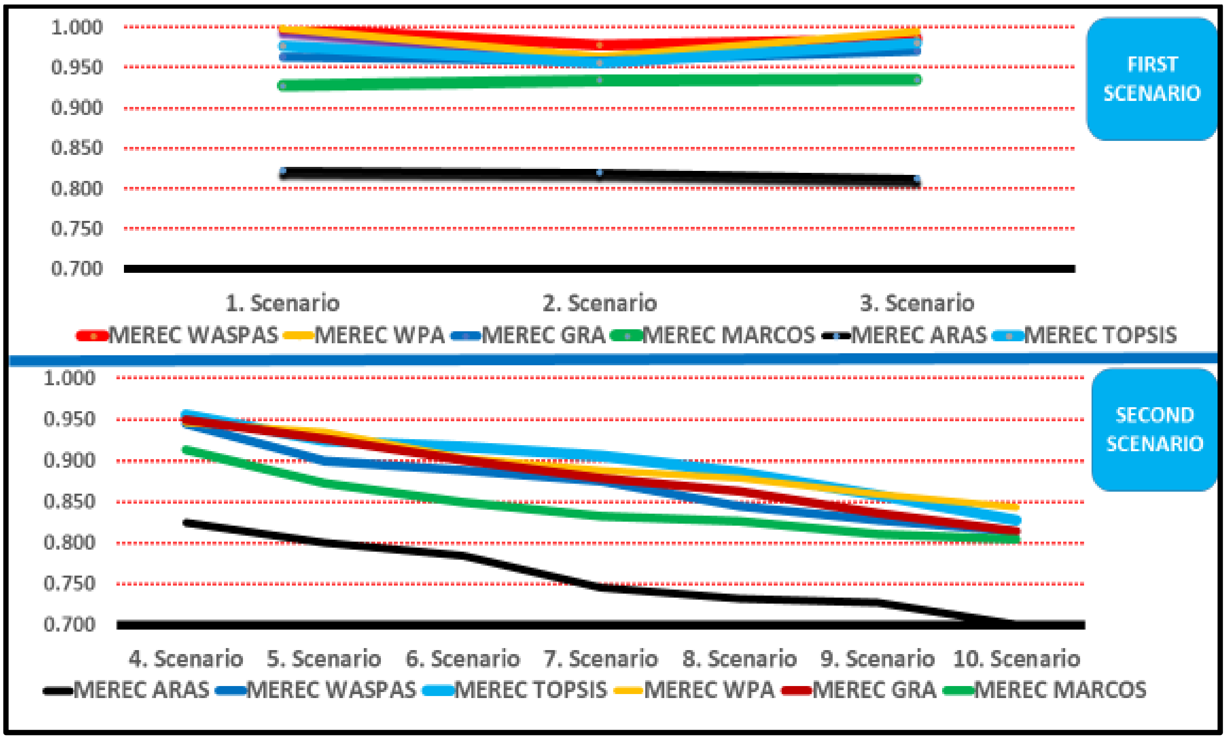
Table 16. Correlations Scores between MEREC-based RAFSI and Other MCDM Methods

MCDM METHODS	MEREC ARAS	MEREC WASPAS	MEREC TOPSIS	MEREC WPA	MEREC GRA	MEREC MARCOS
1. Scenario	0.823**	0.999**	0.977**	0.999**	0.963**	0.927**
2. Scenario	0.820**	0.978**	0.956**	0.963**	0.958**	0.934**
3. Scenario	0.813**	0.985**	0.980**	0.995**	0.971**	0.935**
MCDM METHODS	**MEREC ARAS**	**MEREC WASPAS**	**MEREC TOPSIS**	**MEREC WPA**	**MEREC GRA**	**MEREC MARCOS**
4. Scenario	0.825**	0.945**	0.955**	0.946**	0.949**	0.913**
5. Scenario	0.800**	0.900**	0.924**	0.935**	0.926**	0.873**
6. Scenario	0.784**	0.888**	0.916**	0.903**	0.901**	0.849**
7. Scenario	0.745**	0.875**	0.905**	0.888**	0.879**	0.833**
8. Scenario	0.732**	0.845**	0.886**	0.879**	0.863**	0.827**
9. Scenario	0.727**	0.828**	0.858**	0.859**	0.836**	0.811**
10. Scenario	0.700**	0.814**	0.828**	0.843**	0.814**	0.805**
Mean	0.777	0.906	0.919	0.921	0.906	0.871**

Note: **p<.01

Table 16 divides the 10 scenarios into two groups. The first group consists of the initial 3 scenarios, while the second group includes the remaining scenarios. Upon reviewing Table 16, it is observed that as the number of scenarios increases, the correlation values between the MEREC-based RAFSI method and other methods decrease. This trend is illustrated in Figure 5.

Figure 5. Correlation Positions of MEREC-based RAFSI Among the Other MEREC-based MCDM



Upon inspection of Figure 5, it becomes apparent that the MEREC-based DNMA method exhibits increasing divergence and separation from other MEREC-based MCDM methods as the number of scenarios grows. This observation suggests that the distinctive characteristics of the MEREC-based RAFSI method become more accentuated with an increase in scenarios. Absolutely, here's the revised text in English:

To further investigate the simulation results, ADM (ANOM for variances with Levene) analysis was employed to assess the consistency of variances in the criterion weights of the MEREC-based RAFSI method across different scenarios. This method offers a visual representation to evaluate the homogeneity of variances. The graphical output comprises three key elements: a central line representing the overall mean ADM, flanked by upper decision limits (UDL) and lower decision limits (LDL). If a group's (cluster's) standard deviation falls outside these decision limits, it signifies a statistically significant deviation from the overall mean ADM, implying heterogeneity in variances. Conversely, when the standard deviations of all groups remain within the UDL and LDL boundaries, it confirms the homogeneity of variances (Keshavarz-Ghorabaee et al., 2021). Within the framework of this analysis, the variance values for the performance scores of countries, as assessed by the MEREC-based RAFSI method, were calculated for each scenario. These variance values for the various methods within each scenario are subsequently presented in Table 17 (next page).

In analyzing Table 17, the MEREC-RAFSI method displays a higher average variance across the scenarios compared to the MEREC-ARAS, MEREC-WASPAS, MEREC-WPA and MEREC-GRA methods. This finding suggests that the MEREC-RAFSI method exhibits greater discriminatory power in differentiating between criteria. Additionally, the ADM analysis for the MEREC-RAFSI method within the scenarios is presented visually in Figure 6.

Table 17. Variance Values of MCDM Methods in scope of Scenarios

Scenarios	MEREC RAFSI	MEREC ARAS	MEREC WASPAS	MEREC TOPSIS	MEREC WPA	MEREC GRA	MEREC MARCOS
1. Sce.	0.028482	0.023251	0.024832	0.106795	0.028759	0.021784	0.035794
2. Sce.	0.031321	0.020187	0.020965	0.102831	0.025026	0.018051	0.032061
3. Sce.	0.027098	0.024893	0.025379	0.105874	0.029073	0.022447	0.035937
4. Sce.	0.030744	0.021562	0.022146	0.104147	0.02634	0.019118	0.033304
5. Sce.	0.024917	0.019976	0.019713	0.101982	0.024617	0.017685	0.031571
6. Sce.	0.033186	0.025128	0.024285	0.107055	0.028882	0.022112	0.036074
7. Sce.	0.026563	0.022245	0.023052	0.103418	0.027509	0.019789	0.034341
8. Sce.	0.029899	0.020719	0.021529	0.105542	0.025776	0.018456	0.032618
9. Sce.	0.032635	0.024572	0.025046	0.106329	0.029191	0.022581	0.035525
10. Sce.	0.025372	0.021091	0.022783	0.102266	0.026442	0.019423	0.033092
Mean	0.029022	0.0223624	0.022973	0.1046239	0.0271615	0.0201446	0.0340317

Figure 6. ADM Visual

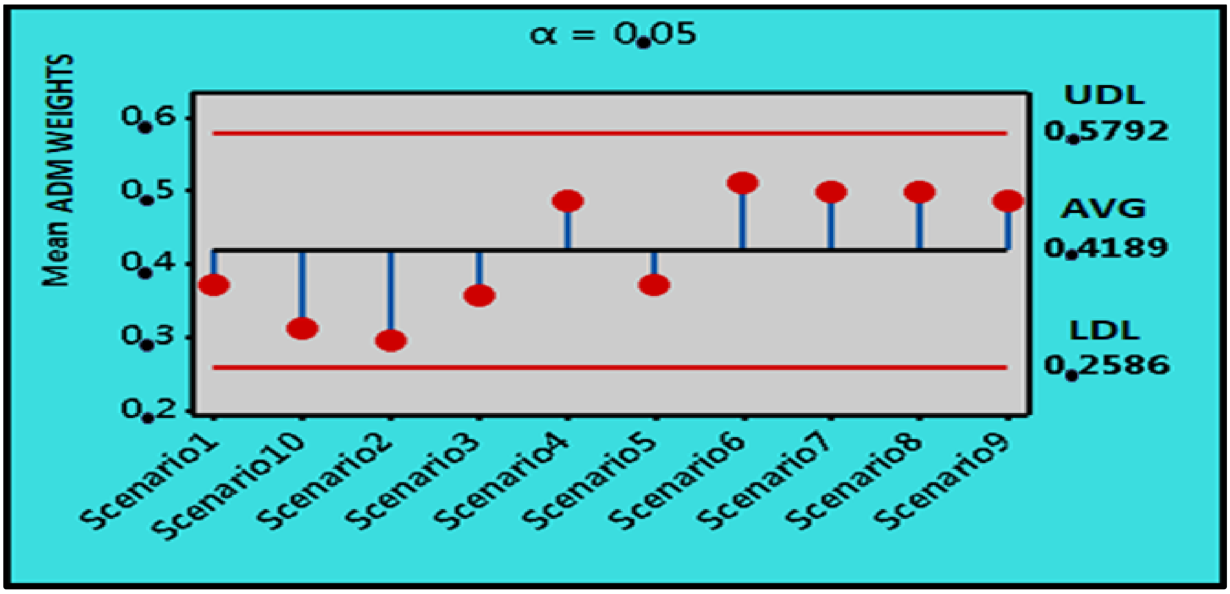


Figure 6 depicts a homogenous range for the calculated ADM values across all scenarios. Notably, all values fall within the pre-defined Upper Decision Limit (UDL) and Lower Decision Limit (LDL). This observation suggests consistent weight variances across the scenarios. Levene's Test, whose key statistics are presented in Table 18, further corroborates this finding.

Table 18. Variance Values of MCDM Methods in scope of Scenarios

Levene Statistic	df1	df2	Sig.
0.256	2	10	0.178

Note: *p<.05

Upon examining Table 18, it is observed that the Levene Statistic value is 0.256, and the significance value is greater than 0.05, indicating that the variances are homogeneous. Consequently, when the simulation analysis results are collectively considered, it is concluded that the MEREC-based RAFSI method is robust and stable for measuring countries' climate change performance within the scope of the CCPI.

5. CONCLUSION

Climate change presents new opportunities for major economies. Investing in areas such as renewable energy, energy efficiency, and sustainable infrastructure promotes economic development, creates new job opportunities, and enhances competitiveness. At the same time, investing in the necessary infrastructure and technologies to adapt to the effects of climate change also strengthens long-term economic resilience. Therefore, it can be considered important to analyze the climate change performance of major economies. In this context, the study measures the climate change performance of the G7 countries, which have the largest economies in the world, using the most recent and updated CCPI criteria values for the year 2023. This measurement is conducted through the MEREC-based RAFSI method.

The research first calculated the weights of CCPI criteria for countries using the MEREC method, ranking these criteria weights as CCPI1 (Greenhouse Gases Emissions), CCPI4 (Climate Policy), CCPI3 (Energy Use), and CCPI2 (Renewable Energy). It was observed that CCPI1 and CCPI4 criteria significantly differed from other criteria in terms of having higher weight values, surpassing the average weight values significantly.

In the study, secondly, countries' climate change performances were measured using the MEREC-based RAFSI method, and the measured values were ranked. According to the findings, countries' climate change performance scores were ranked as Germany, the UK, France, Italy, the USA, Japan, and Canada. Additionally, the average climate change performance of countries was calculated using the MEREC-based RAFSI method, and it was found that Germany, the UK, France, and Italy exceeded the average performance value.

In the study, thirdly, sensitivity, comparative, and simulation analyses were conducted within the framework of the management scope to assess countries' climate change performances based on the CCPI criteria using the MEREC-based RAFSI method. Regarding sensitivity analysis, it was observed that the rankings of countries' climate change performance determined by the MEREC-based RAFSI method differed from those determined by the SD and LOPCOW-based RAFSI methods, indicating that the MEREC-based RAFSI method is sensitive in measuring countries' climate change performances within the CCPI context. In terms of comparative analysis, it was found that the rankings of countries' climate change performances identified by the MEREC-based RAFSI method were different from those identified by the MEREC-based WASPAS, TOPSIS, WPA, GRA, and MARCOS methods. However, it was concluded that the climate change performance values of countries measured by the MEREC-based RAFSI method are significantly, positively, and highly correlated with those measured by all MEREC-based MCDM methods. Therefore, within the CCPI context, the MEREC-based RAFSI method was determined to be credible and reliable in measuring countries' climate change performances. In the Simulation Analysis, firstly, 10 scenarios (10 different decision matrices) were created, and it was observed that as the scenarios increased, the correlation coefficient between the climate change performance values of countries measured by the MEREC-based RAFSI method and those calculated by other MEREC-based MCDM methods decreased. Secondly, in the simulation analysis, under 10 scenarios, the average variance values of the MEREC-based RAFSI method were compared with those of other MEREC-based MCDM methods, and it was found that the average variance value calculated by the MEREC-based RAFSI method was higher than those of the MEREC-based ARAS, WASPAS, WPA, and GRA methods. Therefore, this result indicates that the MEREC-based RAFSI method distinguishes CCPI criteria more effectively compared to the MEREC-based ARAS, WASPAS, WPA, and GRA methods. Lastly, ADM analysis was conducted in the simulation analysis, leading to the conclusion that the variances were homogeneous. Therefore, based on the results of the simulation analysis, within the CCPI context, the MEREC-based RAFSI method was evaluated to be stable and robust in measuring countries' climate change performances.

Upon reviewing the literature, it is observed that studies measuring countries' climate change performances using various MCDM or other mathematical methods belong to Keleş and Ersoy (2023) and Burcks et al., (2024). In Keleş and Ersoy (2023), it was found that in the measurement of G7 countries' climate change performances using LOPCOW-based SPOTIS, WISP, and RSMVC methods, the top four positions were occupied by the UK, Germany, the UK, Italy, and France, while Japan, Canada, and the USA occupied the last three positions. In the current study, it was determined that in the ranking of G7 countries' climate change performances, the UK, Germany, the UK, Italy, and France occupied the top four positions, with Japan, Canada, and the USA occupying the last three positions. However, when comparing both studies, none of the climate change rankings identified in the current study showed consistency with the three different MCDM methods used in Keleş and Ersoy (2023). On the other hand, in the study by Burcks et al. (2024), the rankings of G7 countries' climate change performances were consistent with the rankings identified in the current study. Furthermore, according to the current study and Burcks et al. (2024), it was found that the G7 countries with climate change performance values above the average were Germany, the UK, France, and Italy. Consequently, considering the findings of the current study along with Keleş and Ersoy (2023) and Burcks et al. (2024), it is evaluated that Germany, the UK, France, and Italy demonstrate higher climate protection performance compared to the USA, Japan, and Canada. In both the present study and the research conducted by Köse et al. (2024), Germany, the UK, France, and Italy have demonstrated superior performance compared to the USA, Canada, and Japan. Notably, when comparing the findings of the present study with those of Puška et al. (2024), it has been observed that the performance rankings of Germany, France, and Italy are consistent with each other. Additionally, the study by Gökgöz and Yalçın (2021) indicates that non-G7 Northern European countries have exhibited better climate protection performance than the G7 countries analyzed in the present research.

In terms of recommendations, firstly, it is evaluated that G7 countries should implement policies, strategies, methods, management, and activities to enhance Greenhouse Gases Emissions and Climate Policy areas, which have values above the average, to improve global climate change and contribute to the global economy. Additionally, it is considered that G7 countries, including the USA, Japan, and Canada, which have climate change performances below the average, should demonstrate developments to enhance their climate change performances for improving global climate change and contributing to the global economy. Furthermore, in future studies, not only G7 countries but also countries belonging to other international economic organizations (such as BRICS, OECD, ASEAN, APEC, etc.) or those contributing the most to environmental carbon emissions could be examined for their climate change performances. In our study, expanding the applicability of the model not only within the current context but also to other international organizations, such as BRICS and ASEAN, represents a significant research direction. Given the varying socio-economic, environmental, and cultural characteristics of such organizations, further studies are needed to explore how the model can be adapted at the international level and how it may yield different results across diverse geographical regions. In this regard, future research may include case studies and comparative analyses to assess the model's performance within these organizations. Additionally, when considering the potential limitations of using the MEREC-RAFSI method in climate performance analysis, it is conceivable that these limitations could negatively impact the model’s accuracy and scope. However, several improvements can be suggested to overcome these limitations. For instance, enhancing the model to account for environmental factors in more detail, diversifying the datasets, and increasing the model's flexibility could be significant steps in addressing these limitations. Moreover, incorporating more data and an expanded model structure, particularly for complex issues such as climate performance, could improve the model's accuracy and provide more reliable results for future research. Countries can implement various measures to enhance their climate change performance and, consequently, contribute to global efforts in mitigating climate change. In this context, Canada can focus on improving CCPI1, CCPI2, and CCPI3 components, while Japan, the USA, France, the UK, and Germany should enhance their CCPI2 component. Lastly, Italy needs to focus on advancing its CCPI4 component. Regarding CCPI2, the relevant countries should adopt policies aimed at fostering the development of technology, infrastructure, investments, integration, and regulatory frameworks for renewable energy. These efforts would enhance the efficiency and sustainability of renewable energy utilization. For CCPI1, Canada must prioritize reducing greenhouse gas emissions by fundamentally transforming its energy consumption habits and production models. This involves reducing reliance on fossil fuels and transitioning toward cleaner energy sources, such as solar, wind, and hydroelectric power. Increasing investments in renewable energy and improving energy efficiency are crucial steps in this regard. In the transportation sector, expanding the use of electric vehicles and enhancing public transportation systems are key strategies. In the industrial sector, adopting cleaner production technologies and implementing effective waste management practices are essential. Similarly, the agricultural sector should embrace sustainable practices to preserve soil and water resources. Moreover, protecting forests and promoting reforestation efforts play a critical role in reducing atmospheric carbon dioxide levels. For these transitions to be effective, governments must introduce strong policies, enact necessary regulations, and raise public awareness. In essence, reducing greenhouse gas emissions requires a comprehensive transformation involving all sectors and individuals. Additionally, Canada should focus on optimizing energy use by prioritizing energy efficiency in both industrial and daily life applications. This can be achieved through investments in energy-saving technologies. Reducing dependence on fossil fuels and shifting toward environmentally friendly energy sources are also crucial. Expanding the use of renewable energy sources such as solar, wind, and hydroelectric power not only diversifies the energy supply but also minimizes environmental impacts. Furthermore, adopting smart grids and energy storage systems can optimize energy management and contribute to a more sustainable energy future. Lastly, increasing societal awareness of energy efficiency and renewable energy use can help individuals and institutions modify their energy consumption habits. Regarding climate policy, Italy must undergo a profound transformation in its energy sector to improve its climate policy framework. This transformation should involve increasing investments in renewable energy sources, such as solar and wind power, to reduce dependence on fossil fuels. Enhancing energy efficiency in buildings and industrial processes will lower overall energy consumption and significantly reduce greenhouse gas emissions. In the transportation sector, expanding the use of electric vehicles and improving public transportation systems will facilitate the transition to a more sustainable transportation model. To preserve its natural landscapes and strengthen carbon sinks, Italy must also prioritize forest conservation and afforestation initiatives. Lastly, Italy should actively participate in global climate change mitigation efforts and engage in international cooperation, which is essential for the success of an effective climate policy. Methodologically, countries' climate change performances can be measured using various

MCDM methods (such as EDAS, CODAS, DNMA, OPA, SECA, WISP, CRADIS, PSI, OWA Operator, TODIM, MULTIMOORA, MOOSRA, ROV, MAUT, MAIRCA, COCOSO, EDAS, COPRAS, etc.), and the rankings of countries' climate change performance values identified within these methods can be compared.

Ethics Committee approval was not required for this study.

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 article.

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