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RESEARCH ARTICLE ARAŞTIRMA MAKALESİ

Analysis of the ocean and marine health performances of 18 countries in the G20 countries: An application using the CEBM-based TOPSIS method

G20 ülkeleri içinde 18 ülkenin okyanus ve deniz sağlığı performanslarının analizi: CEBM tabanlı TOPSIS yöntemi ile bir uygulama

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Abstract: This study investigates the critical role of G20 nations in maintaining ocean health, given the significant influence their economic activities have on global maritime ecosystems. Employing the most recent Ocean Health Index (OHI) data (2023) and the CEBM-TOPSIS Multi-Criteria Decision Making (MCDM) method, the research assesses the ocean health performance of 18 countries G20 countries. The CEBM analysis identifies biodiversity, carbon sequestration capacity, fisheries sustainability, water quality, and coastal protection as the most important OHI criteria, respectively. According to the CEBM-TOPSIS method, Russia, Brazil, and France are the top three countries with the highest ocean health performance, while China, India, and South Africa are ranked lowest among the first three countries. Notably, the average performance score indicates that Russia, Brazil, France, the United Kingdom, Australia, Mexico, South Korea, the United States, Germany, Saudi Arabia, and Canada all exceed the average. This suggests a need for improvement among G20 countries with below-average performance to ensure a more substantial contribution to the global economy and interconnected dimensions. Finally, sensitivity, comparison, and simulation analysis validate the CEBM-TOPSIS MCDM method as a reliable tool for evaluating national ocean health performance.

Keywords: CEBM, CEBM based TOPSIS, G20, large economies, ocean/marine health performance, ocean/marine pollution

Öz: Bu çalışma, ekonomik faaliyetlerinin küresel deniz ekosistemleri üzerindeki önemli etkisini göz önünde bulundurarak, G20 ülkelerinin okyanus sağlığını korumadaki kritik rolünü araştırmaktadır. En yeni Okyanus Sağlık Endeksi (OHI) verilerini (2023) ve CEBM-TOPSIS Çok Kriterli Karar Verme (MCDM) yöntemini kullanan bu çalışma, 18 tane G20 ülkesinin okyanus sağlığı performansını değerlendirmektedir. Yapılan CEBM analizi sonucunda en önemli OHI kriterleri sırasıyla; biyoçeşitlilik, karbon tutma kapasitesi, balıkçılık sürdürülebilirliği, su kalitesi ve kıyı korumayı belirlemektedir. CEBM-TOPSIS analiz sonucuna göre, okyanus sağlığı performansı en yüksek olan ülkeler sırasıyla Rusya, Brezilya ve Fransa, en düşük ülkeler ise Çin, Hindistan ve Güney Afrika'nın ise en düşük ilk üç sırada yer aldığını ortaya koymaktadır. Ayrıca, Rusya, Brezilya, Fransa, Birleşik Krallık, Avustralya, Meksika, Güney Kore, ABD, Almanya, Suudi Arabistan ve Kanada'nın ortalama puanlarının ortalama değerleri aştığı belirlenmiştir. Bu sonuç, küresel ekonomiye ve birbiriyle bağlantılı paydaşlara (Boyut yerine başka geniş bir ifade kullanılabilir) daha etkin katkılar sağlamak için ortalama altında performans gösteren G20 ülkelerinin deniz sağlığı performanslarının iyileştirilmesinin gerektiğini gözler önüne sermektedir. Buna benzer şekilde düzenlenebilir. Son olarak, bu çalışma kapsamında yapılan duyarlılık, karşılaştırma ve simülasyon sonuçları, CEBM-TOPSIS MCDM yönteminin ülkelerin veya ülke bazında okyanus/deniz sağlığı için güvenilir bir araç olarak doğrulamaktadır.

Anahtar kelimeler: CEBM, CEBM tabanlı TOPSIS, G20, büyük ekonomiler, okyanus/deniz sağlığı performansı, okyanus/deniz kirlenmesi

INTRODUCTION

Marine and ocean/marine pollution pose a critical global environmental challenge with far-reaching implications for ecosystems, human health, economies, biodiversity, and food security. Recognizing this, international collaboration and effective policies are essential for the sustainable management of seas and oceans (Karim, 2015). Monitoring the marine health performance of countries is crucial to prevent pollution and ecosystem degradation, fostering global cooperation and transparency.

The escalating use of seas and increasing global interconnections between countries have elevated marine and ocean health as a critical global concern (Kennish, 1997; Neto et al., 2017; Krushelnytska, 2018; Cusine and Grant, 2019; Pei and Junaid, 2019; Yao et al., 2023). However, the presence of harmful substances endangering ecological balance impedes the sustainability of ocean/marine health, leading to declining water quality and atmospheric/climatic changes (Arias and Marcovecchio, 2018; Niceforo, 2019).

Internationally, ocean/marine pollution is defined by the United Nations Convention on the Law of the Sea as any human activity that introduces substances or energy into the marine environment, causing deleterious effects such as harm to living resources and marine life, impairment of water quality for human use, and interference with legitimate sea uses (Proelß, 2017). Ocean/marine pollutants include nutrients, sediments, pathogens, alien species, persistent toxins (PCBs, heavy metals, DDT), oil, plastics, radioactive substances, thermal, and noise (Potters, 2013). The literature classifies factors influencing ocean/marine pollution, such as land-based activities, industrial waste disposal, radioactive pollution, ship-borne pollutants, and mineral exploitation (Hardy, 1971; Tornero and Hanke, 2016). Specific pollutants in oceans and marines include POPs, EDCs, mercury, heavy metals, pesticides, pharmaceuticals, oil, plastic wastes, BPA, phthalates, personal care products, and industrial/agricultural emissions. Understanding these pollutants is crucial for collaborative policies to achieve sustainable marine and ocean health (Lloyd-Smith and Immig, 2018).

Countries depend on oceans for fisheries, tourism, transportation, water supply, and wastewater discharge, necessitating the evaluation of marine health performance to ensure economic benefits. The Ocean Health Index (OHI) is the sole metric measuring countries' ocean/marine health performance, emphasizing sustainability in food, cultural, economic, and social aspects.

OHI raises awareness and aids countries in planning pollution protection strategies, comprising 10 components and 8 sub-components measured through arithmetic means (Halpern et al., 2012). The explanations of the components and sub-components are shown in Table 1.

Table 1. OHI components and sub-components (Rintaka et al., 2023; Ocean Health Index, 2023)

Components	Sub-Components	Explanation
Food Provision	Wild Caught Fisheries	Measures the sustainability of wild-caught and farmed seafood.
	Mariculture	Measures the sustainability of farmed seafood.
Artisanal Fishing Opportunities	------	Measures the level of opportunity for people to fish for subsistence or local-scale fishing.
Natural Products	------	Measures how well countries maximize the sustainable harvest of non-food marine resources.
Carbon Storage	------	Measures the amount of carbon storage provided by oceans.
Coastal Protection	------	Measures the level of coastal protection.
Livelihoods and Economies	Livelihoods	Measures the quality and quantity of ocean-related jobs.
	Economies	Measures the value of income generated from the ocean.
Tourism and Recreation	------	Measures the level of sustainable tourism.
Sense of Place	Iconic Species	Measures the level of protection of important marine species.
	Lasting Special Places	Measures the level of protection of culturally significant marine places.
Clean Waters	------	Measures the performance of countries in providing clean water.
Biodiversity	Habitat	Measures the performance of countries in protecting the natural habitats of marine species.
	Species	Measures the performance of countries in protecting marine species.

Rapid economic growth, industrialization, and rising consumption intensify ocean/marine pollution through industrial waste, pesticides, carbon emissions, and plastic waste. These factors threatens ecosystems, marine life, and human health. Sustainable development, integrating economic growth with environmental protection, offers mitigation strategies. Further research and policy development are crucial (Sachs et al., 2023).

Reducing ocean/marine pollution drives economic growth through new opportunities, innovation, and solutions to global challenges like food security and resource availability (Mitra et al., 2021). Conversely, inaction incurs greater costs, harming sectors like tourism, fisheries, health, and coastal development (Diez et al., 2019). In the second dimension, Economic growth often correlates with increased ocean/marine pollution, as seen across various studies (Zhang and Chen, 2022; Li, 2024). Marine resource depletion further emphasizes the need for innovative solutions.

G20 countries, being major economies, significantly contribute to global ocean/marine pollution, with the top plastic waste producers and rivers carrying plastic waste located within the G20 (World Ocean Initiative, 2024). Recognizing this, G20 countries have developed action plans and initiatives, such as the Marine Litter Action Plan and the Osaka Blue Ocean Vision, to address ocean/marine pollution comprehensively (Ministry of Foreign Affairs of Japan, 2017; Kojima et al., 2022). The policies and actions of G20 countries in this regard have global implications for human health, economic development and growth, social well-being, biodiversity, and food security (OECD, 2019). Therefore, it can be considered relevant to analyze the ocean/marine performance of G20 countries. According to the Ocean Health Index (OHI) report for the year 2023, it has been determined that among the G20 countries, the top three countries with the highest ocean/sea health performance are Russia, Brazil, and Australia, while the bottom three countries with the lowest performance are India, China, and South Africa. Furthermore, as per the Ocean Health Index (2023) report, countries with ocean/sea health performance scores above the average include Russia, Brazil, Australia, Germany, South Korea, France, the United Kingdom, Mexico, and Saudi Arabia. Conversely, it has been observed that Türkiye and the United States are closely aligned with the average ocean/sea health performance value of the G20 countries (Ocean Health Index, 2023).

Monitoring the marine health performance of countries is crucial to prevent pollution and ecosystem degradation, fostering global cooperation and transparency. The interplay between economic growth and ocean/marine pollution emphasizes the importance of evaluating the ocean/marine health performance of the G20 countries, as they represent the world's major economies (Ullah et al., 2023). Therefore, it is important for countries to prioritize specific ocean/sea health performance criteria in order to contribute to global ocean/sea health and economic development. Identifying the ocean/marine health performance criteria that major economies should prioritize, and determining which major economies need to improve their ocean/marine health performance, is crucial (Mitra et al., 2021).

Methodologically, the CEBM method is effective in measuring the weights of criteria in a non-linear structure. CEBM (Cubic Effect Based Measurement) is a novel method for weighting criteria. It captures complex relationships by analyzing cubic interactions between them, using integral calculus and normalized data. This functional approach offers a distinct advantage and leads to more effective outcomes for complex problems compared to other methods (Altıntaş, 2023). On the other hand, the TOPSIS method is a reliable approach for measuring the performance of alternatives and is frequently utilized for this purpose. TOPSIS (Technique for Order Preference by Similarity to Ideal Solution) was introduced to the MCDM literature in 1980 by Hwang and Yoon (1981). In TOPSIS, alternatives are assessed based on two key points: the positive ideal solution and the negative ideal solution (Ayçin, 2019). The positive ideal solution maximizes benefit criteria and minimizes cost criteria. Conversely, the negative ideal solution minimizes benefit criteria and maximizes cost criteria (Paksoy, 2017). According to the method, as a decision point moves away from the negative ideal solution, it approaches the positive ideal solution. Consequently, a decision point that moves closer to the positive ideal solution and farther from the negative ideal solution gains an advantage over other decision points in the ranking (Aktaş et al., 2015). A review of the literature reveals that the TOPSIS method is frequently utilized to evaluate the performance of decision alternatives and in selection problems. The current literature on the TOPSIS method is presented in Table 2.

Table 2. TOPSIS literature

Author(s)	Method(s)	Theme
Korucuk et al. (2022)	FFS–TOPSIS	Evaluation green approaches and digital marketing strategies
Asadabadi et al. (2023)	BWM based TOPSIS	Supplier selection to support environmental sustainability
Badi et al. (2023)	Grey TOPSIS	Solar farm location selection
Das and Kumar (2023)	TOPSIS	Assessment of electric two-wheeler ecosystem
Korucuk et al. (2023)	BN-TOPSIS	Assessment of agile supply chain management
Singh et al. (2023)	AHP based TOPSIS	Selecting parameter-influencing testing
Tanveer et al. (2023)	Fuzzy TOPSIS	Selecting digital technologies in circular supply chains
Yavari et al. (2023)	Genetic Algorithm and TOPSIS	Selection of optimal well trajectory
Zhao et al. (2023)	GRA and TOPSIS	Social and economic impact assessment of coal power
Zhu et al. (2023)	SWOT and TOPSIS	Investigation of West Lake ecotourism capabilities
Dharmawan (2024)	TOPSIS	Assessing teachers performance
Kolsara (2024)	TOPSIS	Project proposal selection

In this context, the study assessed the ocean/marine health performance of 18 countries G20 countries in 2023 using the Ocean Health Index (OHI) criteria and the CEBM-based TOPSIS method. Three key findings emerged from the quantitative analysis. Firstly, the study identified priority OHI criteria for countries to enhance their overall marine health performance, contributing to global economic and related dimensions. Secondly, it pinpointed countries that need to improve their marine health performance to make more significant contributions to the global economy. Lastly, the study evaluated the applicability of the CEBM-based TOPSIS method within the OHI framework for measuring countries' ocean/marine health performance. The methodology details the research analysis and dataset, and the results section provides insights and discussions based on the quantitative findings.

MATERIALS AND METHODS

Dataset and analysis of the research

The research dataset consists of the OHI criteria data for the year 2023, which is the latest and most up-to-date data for 18 countries in the G20 group. The weights (importance levels) of the OHI criteria for each country were measured using the CEBM method, and the ocean/marine health performance of the countries was measured using the CEBM-based TOPSIS method. As It is known, the G20 group consists of 19 countries and the European Union as an organization (Öztaş and Öztaş, 2024). Japan was not included in the study because the numerical performance value of the Tourism and Recreation criterion was not available in the OHI report for Japan. For convenience, the abbreviations of the OHI criteria are shown in Table 3.

Table 3. Abbreviations of OHI components (Ocean Health Index, 2023)

Components	Abbreviations
Food Provision	OHI1
Artisanal Fishing Opportunities	OHI2
Natural Products	OHI3
Carbon Storage	OHI4
Coastal Protection	OHI5
Livelihoods and Economies	OHI6
Tourism and Recreation	OHI7
Sense of Place	OHI8
Clean Waters	OHI9
Biodiversity	OHI10

The CEBM method, known for its interactive nature and non-linear structure based on cubic functions, proves effective in solving complex problems, setting it apart from other criteria weighting methods (Altıntaş, 2023). The TOPSIS method, widely utilized in decision and selection problems, gains popularity due to its simultaneous evaluation of ideal and non-ideal solutions, mathematical simplicity, algorithm clarity, and adaptability to different weighting methods (Çakır and Perçin, 2013; Öztel and Alp, 2020). Leveraging the advantages of MCDM methods, this study employed CEBM to determine OHI criterion weights and CEBM-based TOPSIS to measure ocean/marine health performance.

This research stands out as the first to utilize MCDM methods to elucidate the ocean/marine health performance of G20 countries. The novelty is further emphasized by the application of the CEBM-based TOPSIS method in decision alternative performance measurement, contributing to both ocean/marine health and MCDM literature.

CEBM method

Step 1: Retrieving the Decision Matrix (Altıntaş, 2023)

i: 1, 2, 3...n, where n represents the number of decision alternatives

j: 1, 2, 3...m, where m represents the number of criteria

D: Decision matrix

C: Criterion

d_{ij}: The decision matrix is constructed according to Equation 1, where "i_j" represents the $i-th$ decision alternative on the $j-th$ criterion.

$$D = [d_{ij}]_{nxm} = \begin{bmatrix} C_1 & C_2 & \cdots & C_m \\ x_{11} & x_{12} & & x_{1m} \\ x_{21} & x_{22} & \cdots & x_{2m} \\ \vdots & \vdots & \vdots & \vdots \\ x_{n1} & x_{n2} & \cdots & x_{nm} \end{bmatrix} \quad (1)$$

Step 2: Establishment of Decision Matrix Normalization (d_{ij}^*) (Altıntaş, 2023)

The decision matrix is normalized using the following equation. Equation 2 is applied for normalizing benefit criteria, while Equation 3 is utilized for the normalization of cost criteria.

$$d_{ij}^* = \frac{x_{ij} - x_j^{min}}{x_j^{max} - x_j^{min}} \quad (2)$$

$$d_{ij}^* = \frac{x_j^{max} - x_{ij}}{x_j^{max} - x_j^{min}} \quad (3)$$

Step 3: Obtaining of Cubic Equations (Altıntaş, 2023)

Utilizing SPSS assistance (CURVE ESTIMATION), cubic functions $(y = ax^3 + bx^2 + cx + d)$ are formulated for the variables, where the number of criteria, denoted as 'm', determines the quantity of $\left\{2.C(m,2) = 2.\frac{m!}{2!.(m-2)!}\right\}$ up to which the functions are generated, taking into account the cubic relationship between them.

$$(1)\ f(C_1) = C_2, f(C_1) = C_3, \dots\dots f(C_1) = C_m \quad (4)$$

$$(2)\ f(C_2) = C_1, f(C_2) = C_3, \dots\dots f(C_2) = C_m \quad (5)$$

$$(3)\ f(C_3) = C_1, f(C_3) = C_2, \dots\dots f(C_3) = C_m \quad (6)$$

$$\vdots \quad \vdots \quad \vdots$$

$$(m)\ f(C_m) = C_1, f(C_m) = C_2, \dots\dots f(C_m) = C_{m-1} \quad (7)$$

Step 4: Calculation of Cubic Impact Value between Criteria (Altıntaş, 2023)

During this phase, assessing the impact or modification of a dependent a criterion by an independent variable (another criterion) involves evaluating the independent variable's influence across its minimum and maximum values through definite integral calculation. In this context, the symbol "k" represents the cubic impact value of one criterion on the other. It is essential to verify the absolute values of the impact post-integral calculation.

$$(1)\ f(C_1) = C_2, \int_{C_{1min.}}^{C_{1maks.}} (f'(C_1))\, dx = |k_{C_1 \to C_2}| \quad (8)$$

$$(2)\ f(C_1) = C_3, \int_{C_{1min.}}^{C_{1maks.}} (f'(C_1))\, dx = |k_{C_1 \to C_3}| \quad (9)$$

$$(3)\ f(C_1) = C_4, \int_{C_{1min.}}^{C_{1maks.}} (f'(C_1))\, dx = |k_{C_1 \to C_4}| \quad (10)$$

$$\vdots \quad \vdots \quad \vdots$$

$$\left(\frac{m!}{(m-2)!}\right) f(C_m) = C_{m-1}, \int_{C_{mmin.}}^{C_{mmaks.}} (f'(C_m))\, dx = |k_{C_m \to C_{m-1}}| \quad (11)$$

The significance of the absolute value of the impact value of one criterion on another is highlighted. This is crucial in this approach, as the focus lies not on the direction of influence between criteria but rather on the magnitude of the influence.

Step 5: Calculation of the Total Cubic Impact Values of Each Criterion (T_c) (Altıntaş, 2023)

During this stage, the cubic impact values originating from a criterion on other criteria are aggregated to assess the comprehensive cubic impact value of a criterion on the remaining criteria.

$$(1)\ for\ C_1\ |k_{C_1 \to C_2}| + |k_{C_1 \to C_3}| + |k_{C_1 \to C_4}| \dots\dots + |k_{C_1 \to C_m}| = \left(\sum_{j=1}^{m-1} |k_{C_1 \to C_{j+1}}|\right) = T_{C_1} \quad (12)$$

$$(2)\ for\ C_2\ |k_{C_2 \to C_1}| + |k_{C_2 \to C_3}| + |k_{C_2 \to C_4}| \dots + |k_{C_2 \to C_m}| = \left(\sum_{j=0, j\neq 1}^{m-1} |k_{C_2 \to C_{j+1}}|\right) = T_{C_2} \quad (13)$$

$$(3)\ for\ C_3\ |k_{C_3 \to C_1}| + |k_{C_3 \to C_2}| + |k_{C_3 \to C_4}| \dots + |k_{C_3 \to C_m}| = \left(\sum_{j=0, j\neq 2}^{m-1} |k_{C_3 \to C_{j+1}}|\right) = T_{C_3} \quad (14)$$

$$\vdots \quad \vdots \quad \vdots$$

$$(m)\ for\ C_m\ |k_{C_m \to C_1}| + |k_{C_m \to C_2}| + |k_{C_m \to C_3}| .. + |k_{C_m \to C_{m-1}}| = \left(\sum_{j=1}^{m-1} |k_{C_m \to C_j}|\right) = T_{C_m} \quad (15)$$

Step 6: Establishing Criterion Weight Values (w_j) (Altıntaş, 2023)

During this phase, the division of the cumulative cubic impact value of each criterion on the remaining criteria by the sum of the cumulative cubic impact values of all criteria takes place. This calculation enables the determination of the weight coefficient for each criterion.

$$w_j = \frac{T_{c_j}}{\sum_{j=1}^{m} T_{c_j}} \quad (16)$$

TOPSIS method

Step 1: Formation of the Decision Matrix (Kaya and Karaşan, 2020)

The matrix consisting of m decision alternatives and n criteria is defined in Equation 17.

$$A_{ij} = \begin{bmatrix} a_{11} & x_{12} & \cdots & k_{1n} \\ a_{21} & x_{22} & \cdots & k_{2n} \\ \vdots & \vdots & \vdots & \vdots \\ a_{m1} & x_{m2} & \cdots & k_{mn} \end{bmatrix} \quad (17)$$

Step 2: Attainment of the Standard Decision Matrix (Atan and Altan, 2020)

In the TOPSIS method, normalization is generally calculated through vector normalization. Accordingly, the normalized values (r_{ij}) are initially measured. The r_{ij} values are provided with Equation 18.

$$r_{ij} = \frac{a_{ij}}{\sqrt{\sum_{k=1}^{m} a_{kj}^2}} \quad i = 1,2,\dots,m \; ve \; j = 1,2,\dots,n) \quad (18)$$

After calculating the r_{ij} values, the standard decision matrix (R_{ij}) is obtained using Equation 19.

$$R_{ij} = \begin{bmatrix} r_{11} & r_{12} & \cdots & r_{1n} \\ r_{21} & r_{22} & \cdots & r_{2n} \\ \vdots & \vdots & \vdots & \vdots \\ r_{m1} & r_{m2} & \cdots & r_{mn} \end{bmatrix} \quad (19)$$

Step 3: Attainment of the Weighted Standard Decision Matrix (Özarı and Eran, 2019)

At this stage, the sum of the weights of the criteria (w_{ij}) must be equal to 1 $(\sum_{i=1}^{n} w_i)$. Accordingly, the obtained weighted standard decision matrix (V_{ij}) is shown in Equation 20.

$$V_{ij} = \begin{bmatrix} w_1 r_{11} & w_2 r_{12} & \cdots & w_n r_{1n} \\ w_1 r_{21} & w_2 r_{22} & \cdots & w_n r_{2n} \\ \vdots & \vdots & \vdots & \vdots \\ w_1 r_{m1} & w_2 r_{m2} & \cdots & w_n r_{mn} \end{bmatrix} \quad (20)$$

Step 4: Determination of the Positive Ideal (A^+) and Negative Ideal (A^-) Solution Values (Kaymaz et al., 2020)

For criteria oriented towards maximization, the positive ideal solution set is formed by selecting the column values in the weighted evaluation criteria matrix V_{ij} where the criteria are maximized, and for criteria oriented towards minimization, the smallest column values are preferred. In this context, the positive ideal solution values are calculated as shown in Equations 21 and 22.

$$A^+ = \{mak_i v_{ij} | \, j \in J), (min_i v_{ij} | \, j \in J'\} \quad (21)$$

$$A^+ = \{v_1^*, v_2^*, \dots, v_n^*\} \quad (22)$$

For criteria oriented towards maximization, the negative ideal solution set is formed by selecting the column values in the weighted evaluation criteria matrix V_{ij} where the criteria are minimized, and for criteria oriented towards maximization, the largest column values are preferred. In this context, the negative ideal solution values are calculated as shown in Equations 23 and 24.

$$A^- = \{min_i v_{ij} | \, j \in J), (min_i v_{ij} | \, j \in J'\} \quad (23)$$

$$A^- = \{v_1^-, v_2^-, \dots, v_n^-\} \quad (24)$$

Step 5: Measurement of Distance to Positive and Negative Points (Kaymaz et al., 2020)

Initially, to determine the deviations in the positive and negative ideal solution sets, Equation 25 is utilized for the detection of the distances of x and y values in the coordinate plane using the Euclidean Distance Approach.

$$d_{ij} = \sqrt{\sum_{k=1}^{n} (x_{ik} - x_{jk})^2} \quad (25)$$

In Equation 25 x_{ik} explains the kth variable value of the ith observation and x_{ik} explains the jth observation's kth variable value, along with the number of variables (criteria), denoted by n. Additionally, the number of measurements for the positive ideal distance (S_i^+) and negative ideal distance (S_i^-) metrics is equal to the number of decision alternatives. Thus, in the TOPSIS method, Equations 26 and 27 are utilized for calculating the distances to ideal and non-ideal points for each decision alternative.

$$Positive\ Ideal\ Distance: S_i^+ = \sqrt{\sum_{j=1}^{n} (v_{ij} - v_j^*)^2} \quad (26)$$

$$Negative\ İdeal\ Distance: S_i^- = \sqrt{\sum_{j=1}^{n} (v_{ij} - v_j^-)^2} \quad (27)$$

Step 6: Measurement of Relative Proximity to the Ideal Solution (Atan and Altan, 2020)

The proximity of each decision point to the positive ideal solution (C_i^*) is calculated utilizing measurements of positive and negative ideal distances. The main criterion here is the ratio of the negative distance measurement to the total distance measurement. Equation 28 is employed for measuring the proximity values to the positive ideal solution.

$$C_i^* = \frac{S_i^-}{S_i^- + S_i^+} \quad (28)$$

The value of C_i^* specified in Equation 18 should be within the range of $0 \leq C_i^* \leq 1$ when $C_i^* = 1$, it indicates the absolute proximity of the corresponding decision alternative to the positive ideal solution. On the other hand, if $C_i^* = 0$, it signifies the absolute proximity of the respective decision alternative to the negative ideal solution.

RESULTS

Computational analysis

In the study, initially, the weighting values of the OHI criteria were calculated using the relevant equations specified in the CEBM method, and then they were ranked. The weighting values (degrees of importance) of these OHI criteria and the rankings of the weighting values are described in Table 4.

Table 4. Weighting values of OHI criteria

Criteria	Total Effect	Weights	Ranking
OHI1	1.672	0.066	10
OHI2	3.013	0.119	3
OHI3	2.137	0.085	7
OHI4	3.299	0.131	2
OHI5	2.684	0.106	5
OHI6	2.26	0.090	6
OHI7	2.063	0.082	8
OHI8	1.711	0.068	9
OHI9	2.908	0.115	4
OHI10	3.49	0.138	1
Total	25.237	Mean: 0.100	

Upon examining Table 4, it can be observed that the weighting values of the criteria are ranked as follows: OHI10, OHI4, OHI2, OHI9, OHI5, OHI6, OHI3, OHI7, OHI8, and OHI1. Additionally, the average weight of the criteria was calculated according to countries, and it was observed that the OHI criteria with weights exceeding the calculated average weight are OHI10, OHI4, OHI2, OHI9, and OHI5. Therefore, based on this result, it has been evaluated that countries need to develop strategies for the improvement of OHI10, OHI4, OHI2, OHI9, and OHI5 criteria to enhance global ocean/marine health and thus contribute to the global economy. In the continuation of the study, the ocean/sea health performance of countries was calculated using the CEBM-based TOPSIS method and the equations described in the methodology section and presented in Table 5.

Table 5. Countries' ocean/sea health performance values (Ci^*)

Countries	(Ci^*)	Rank	Countries	(Ci^*)	Rank
Argentina	0.519269	15	**Italy**	0.531301	14
Australia	0.610531	5	**Mexico**	0.608984	6
Brazil	0.673539	2	**Russia**	0.731705	1
Canada	0.564713	11	**S.Arabia**	0.566239	10
China	0.400724	18	**South Africa**	0.428932	16
France	0.621205	3	**South Korea**	0.590257	7
Germany	0.577571	9	**Türkiye**	0.562318	12
India	0.406321	17	**United Kingdom**	0.611918	4
Indonesia	0.537598	13	**USA**	0.589594	8
Mean: 0.562929					

Upon examining Table 5, it is noted that Russia, Brazil, and France rank as the top three countries with the highest ocean/sea health performance, while South Africa, India, and China rank at the bottom. Moreover, the countries surpassing the average ocean/sea health performance are ranked as follows: Russia, Brazil, France, the United Kingdom, Australia, Mexico, South Korea, the USA, Germany, Saudi Arabia, and Canada. Additionally, Türkiye's ocean/sea health performance closely aligns with the average value, as indicated in Table 5.

Sensibility analysis

This study explores the sensitivity of the CEBM-based TOPSIS approach in MCDM. We used various criteria weighting methods on the same dataset and compared the resulting values and rankings. We expect the rankings from our chosen sensitivity analysis to differ from those generated by other methods, confirming MCDM sensitivity in weight coefficient calculations (Gigovič et al., 2016).

Adhering to this methodology, we employed established objective weighting techniques to calculate and organize the weighting coefficients associated with the FIW components. These techniques, widely recognized in scholarly literature, included ENTROPY, CRITIC, SD, SVP, MEREC, and LOPCOW. The corresponding numerical results are meticulously presented in Table 6.

Table 6. Values of Objective Criterion Weighting Methods

Criteria	ENTROPY		CRITIC		SD		SVP		MEREC	
	Value	Rank	Value	Rank	Value	Rank	Value	Rank	Value	Rank
OHI1	0.1032	2	0.1512	2	0.1201	1	0.1488	3	0.1380	3
OHI2	0.0996	5	0.1140	4	0.0917	7	0.1079	4	0.1429	2
OHI3	0.0985	7	0.0796	7	0.1045	5	0.0701	6	0.0617	4
OHI4	0.0979	8	0.0568	9	0.0897	8	0.0334	9	0.0237	9
OHI5	0.0996	4	0.0873	5	0.1011	6	0.0756	5	0.0266	8
OHI6	0.0977	9	0.0824	6	0.1127	2	0.0466	8	0.0284	7
OHI7	0.1047	1	0.1727	1	0.1116	3	0.2465	1	0.0295	6
OHI8	0.1019	3	0.1509	3	0.1104	4	0.2026	2	-0.0115	10
OHI9	0.0992	6	0.0782	8	0.0775	10	0.0620	7	0.0327	5
OHI10	0.0976	10	0.0269	10	0.0808	9	0.0064	10	0.5279	1

Upon examining Table 6, it is observed that the rankings of OHI criteria under the CEBM method differ from the rankings of OHI criteria determined under other methods. Furthermore, in the continuation of sensitivity analysis, countries' ocean/sea health performances were measured using the ENTROPY, CRITIC, SD, SVP, and MEREC-based TOPSIS methods and presented in Table 7.

Upon examination of Table 7, it has been observed that the rankings of countries' ocean/sea health performance values determined using the CEBM-based TOPSIS method differ from the rankings of countries' ocean/sea health performance values obtained using ENTROPY, CRITIC, SD, SVP, and MEREC-based TOPSIS methods. Based on this finding, it is evaluated that the CEBM-based TOPSIS method is sensitive in measuring ocean/sea health performance within the scope of OHI.

Table 7. Countries' Ocean/Sea Health Performance Values and Rankings using ENTROPY, CRITIC, SD, SVP, and MEREC-based TOPSIS

Countries	ENTROPY TOPSIS		CRITIC TOPSIS		SD TOPSIS		SVP TOPSIS		MEREC TOPSIS	
	Value	Rank	Value	Rank	Value	Rank	Value	Rank	Value	Rank
Argentina	0.5193	15	0.5994	9	0.5567	11	0.6058	9	0.5067	8
Australia	0.6105	5	0.5915	10	0.5668	9	0.6612	6	0.4091	16
Brazil	0.6735	2	0.6432	4	0.6272	3	0.7034	4	0.5029	9
Canada	0.5647	11	0.5021	15	0.5059	13	0.5272	13	0.4221	15
China	0.4007	18	0.4277	17	0.4631	17	0.3545	18	0.6142	4
France	0.6212	3	0.6020	8	0.6224	4	0.5735	10	0.6845	2
Germany	0.5776	9	0.6146	6	0.5792	8	0.6892	5	0.3993	17
India	0.4063	17	0.3805	18	0.3633	18	0.4074	17	0.4528	14
Indonesia	0.5376	13	0.5091	13	0.4675	16	0.5668	11	0.4859	12
Italy	0.5313	14	0.6204	5	0.5804	7	0.6572	7	0.3903	18
Mexico	0.6090	6	0.4883	16	0.5026	14	0.5080	14	0.5387	7
Russia	0.7317	1	0.8354	1	0.8056	1	0.8480	1	0.8011	1
Saudi Arabia	0.5662	10	0.5213	12	0.5018	15	0.5617	12	0.4604	13
South Africa	0.4289	16	0.6054	7	0.5594	10	0.6380	8	0.4969	11
South Korea	0.5903	7	0.7551	2	0.6922	2	0.7965	2	0.5645	5
Türkiye	0.5623	12	0.5044	14	0.5189	12	0.4837	15	0.5486	6
United Kingdom	0.6119	4	0.6475	3	0.5982	5	0.7133	3	0.5010	10
USA	0.5896	8	0.5418	11	0.5805	6	0.4797	16	0.6561	3

Comparative analysis

In the comparative analysis, the proposed model is evaluated alongside other MCDM calculation methods to assess similarities and differences. The objective is to ensure the credibility and reliability of the proposed model by establishing positive and significant relationships with various MCDM methods (Keshavarz-Ghorabaee et al., 2021). To this end, the ocean/sea health performances of countries were initially assessed using commonly employed methods such as CEBM-based SWA, ARAS, EDAS, WASPAS, GRA (Grey Relation Analysis), MAUT, ROV, and COCOSO. These assessments are summarized in Table 8.

In the second part of the comparative analysis, correlation values between the ocean/sea performance values of countries calculated under the OHI and CEBM-based SWA, ARAS, EDAS, WASPAS, GRA, MAUT, ROV, and COCOSO methods were computed. These correlation values are presented in Table 9, and a visual representation of the correlation values is depicted in Figure 1.

Drawing from Walters (2009) research, Keshavarz-Ghorabaee (2021) suggests that a correlation value falling within the range of 0.400-0.600, as evaluated between the MEREC method and others (SD, ENTROPY, and CRITIC), indicates a moderate association between the variables. Notably, correlations surpassing 0.600 signify a strong and significant relationship. Upon examining Table 9 and Figure 1 concurrently, it is evident that the CEBM-based TOPSIS method demonstrates a positive, significant, and high correlation with other methods except for COCOSO. These findings lead to the conclusion that the proposed model (CEBM-based TOPSIS) for assessing countries' OHI criteria values is both credible and reliable.

Simulation analysis

Simulations explore the proposed method's behavior under diverse scenarios by varying decision matrix values. We expect its behavior to increasingly diverge from other methods as scenarios multiply. Ideally, its average variance across scenarios should surpass others, demonstrating its strength in differentiating weightings based on context. ADM (ANOM for variances with Levene) analysis further delves into this, visually assessing the consistency of variances across scenarios. Deviations from established limits suggest heterogeneity, while consistency within them affirms uniformity (Keshavarz-Ghorabaee et al., 2021).

Table 8. Country rankings of ocean/marine health performance values using CEBM-based SWA, ARAS, EDAS, WASPAS, GRA, MAUT, ROV, and COCOSO methods

Countries	SWA		ARAS		EDAS		WASPAS	
	Value	Rank	Value	Rank	Value	Rank	Value	Rank
Argentina	0.3190	7	0.7511	15	0.3709	15	0.7706	15
Australia	0.2953	14	0.8275	3	0.6957	3	0.8474	3
Brazil	0.3457	2	0.8597	2	0.8269	2	0.8848	2
Canada	0.2805	17	0.7955	10	0.5591	10	0.8139	9
China	0.3031	13	0.7115	17	0.2210	17	0.7132	17
France	0.3343	5	0.8233	4	0.6728	4	0.8434	4
Germany	0.3080	11	0.8086	7	0.6101	8	0.8307	7
India	0.3031	12	0.6885	18	0.1078	18	0.7017	18
Indonesia	0.2928	15	0.7584	14	0.4052	13	0.7775	14
Italy	0.2829	16	0.7592	13	0.3939	14	0.781	13
Mexico	0.3309	6	0.8190	5	0.6614	5	0.8405	5
Russia	0.3758	1	0.8933	1	0.9746	1	0.9178	1
Saudi Arabia	0.3168	8	0.7905	11	0.5383	11	0.8125	10
South Africa	0.2488	18	0.7164	16	0.2367	16	0.725	16
South Korea	0.3138	9	0.8081	8	0.6104	7	0.8261	8
Türkiye	0.3427	3	0.7904	12	0.5283	12	0.8083	12
United Kingdom	0.3105	10	0.8113	6	0.6152	6	0.8358	6
USA	0.3412	4	0.8009	9	0.5857	9	0.8112	11
Countries	**GRA**		**MAUT**		**ROV**		**COCOSO**	
	Value	**Rank**	**Value**	**Rank**	**Value**	**Rank**	**Value**	**Rank**
Argentina	0.5019	16	0.2036	16	0.2090	15	2.7895	18
Australia	0.6481	4	0.4340	4	0.3058	5	256.27	7
Brazil	0.6880	2	0.4846	2	0.3547	2	319.98	5
Canada	0.5967	8	0.3344	9	0.2975	6	160.87	16
China	0.5285	14	0.2375	14	0.2321	14	190.9	15
France	0.6109	6	0.3551	6	0.3119	4	304.07	6
Germany	0.6006	7	0.3425	7	0.2969	7	248.76	10
India	0.4795	18	0.1697	18	0.1914	18	248.05	11
Indonesia	0.5557	13	0.2887	13	0.2385	13	204.12	13
Italy	0.4929	17	0.1857	17	0.2058	16	199.89	14
Mexico	0.6660	3	0.4570	3	0.3349	3	249.58	9
Russia	0.7031	1	0.5059	1	0.3710	1	427.21	1
Saudi Arabia	0.6175	5	0.3846	5	0.2752	10	394.58	2
South Africa	0.5111	15	0.2302	15	0.1925	17	57.701	17
South Korea	0.5715	11	0.3024	11	0.2635	12	240.6	12
Türkiye	0.5957	9	0.3392	8	0.2842	9	371.43	3
United Kingdom	0.5786	10	0.3057	10	0.2866	8	254.2	8
USA	0.5684	12	0.2981	12	0.2729	11	358.44	4

Table 9. Correlation values of CEBM-based TOPSIS method with other methods

Methods	SWA	ARAS	EDAS	WASPAS	GRA	MAUT	ROV	COCOSO	OHI
TOPSIS	0.678*	0.985**	0.982**	0.991**	0.850**	0.831**	0.884**	0.589*	0.965**

p*<.05, p**<.01

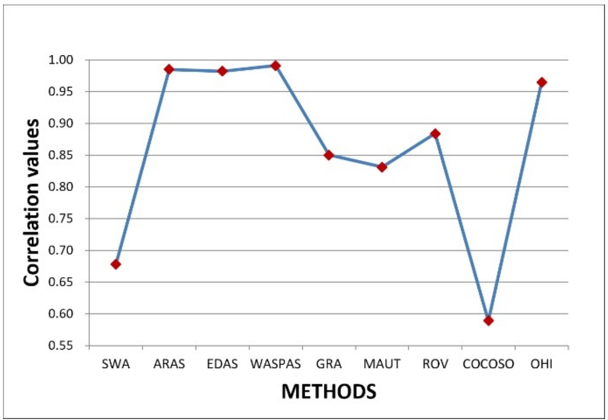

Figure 1. Correlation values of methods

ADM offers a visual representation to assess variance evenness, incorporating parameters such as the overall average ADM, upper decision limits (UDL), and lower decision limits (LDL). Deviation of a group's standard deviation from the decision limits suggests heterogeneity in variances, while consistency within the LDL and UDL affirms uniformity (Keshavarz-Ghorabaee et al., 2021). In this regard, in the simulation analysis, initially, a total of 10 scenarios (decision matrices) were created, with 3 in the first group and 7 in the second group. Subsequently, correlation values between the CEBM-based TOPSIS method and the CEBM-based SWA, ARAS, EDAS, WASPAS, GRA, MAUT, and COCOSO methods were measured for each created scenario. The correlation values measured for these scenarios are described in Table 10.

When Table 10 and Figure 2 are examined together, it is observed that especially the CEBM-based TOPSIS method shows positive, significant, and high relationships with CEBM-based SWA, ARAS, EDAS, WASPAS, GRA, MAUT, and ROV methods across scenarios, while it exhibits a moderate level of relationship with the CEBM-based COCOSO method. Furthermore, upon evaluation of Table 10, it is noted that as the number of scenarios increases, the correlation values of the CEBM-based TOPSIS method with other CEBM-based methods decrease. Additionally, within the scope of the simulation analysis, the variance values of the methods were calculated according to the created scenarios. The variance values of these methods are presented in Table 11.

Table 10. Correlation values of the CEBM-based TOPSIS method with other methods across scenarios

Scenarios		SWA	ARAS	EDAS	WASPAS	GRA	MAUT	ROV	COCOSO
First Group	1	0.680*	0.991**	0.990**	0.995**	0.875**	0.845**	0.890**	0.610*
	2	0.700**	0.983**	0.989**	0.990**	0.848**	0.839**	0.881**	0.575*
	3	0.725**	0.978**	0.980**	0.996**	0.870**	0.850**	0.884**	0.569*
Second Group	4	0.635*	0.962**	0.965**	0.988**	0.820**	0.800**	0.870**	0.577*
	5	0.641*	0.955**	0.950**	0.900**	0.845**	0.821**	0.879**	0.546*
	6	0.663*	0.956**	0.954**	0.984**	0.833**	0.811**	0.872**	0.539*
	7	0.635*	0.978**	0.967**	0.980**	0.835**	0.815**	0.863**	0.548*
	8	0.618*	0.948**	0.942**	0.991**	0.822**	0.803**	0.855**	0.532*
	9	0.594*	0.961**	0.955**	0.973**	0.801**	0.795**	0.833**	0.527*
	10	0.644*	0.937**	0.948**	0.969**	0.812**	0.803**	0.812**	0.542*

p*<.05, p**<.01

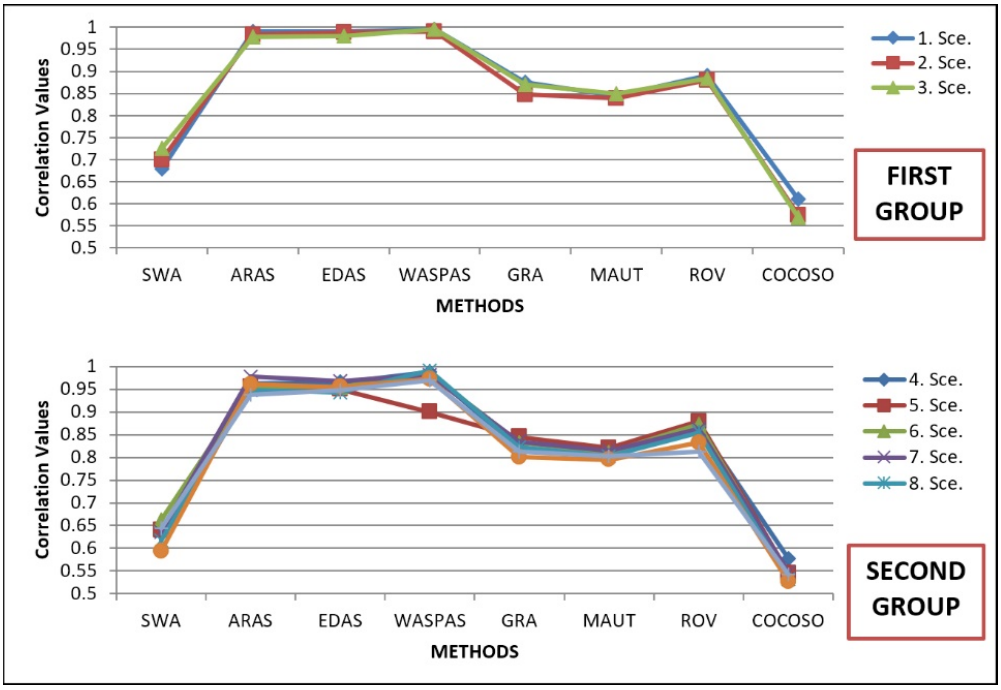

Figure 2. Position of correlation values of the CEBM-based TOPSIS method with other CEBM-based methods (Sce.: Scenario)

Upon reviewing Table 11, it's evident that the CEBM-based TOPSIS method exhibits higher variance compared to other CEBM-based MCDM methods. This suggests its superior ability to differentiate decision alternatives within the OHI criteria context. In the subsequent simulation analysis, an ADM evaluation of countries' ocean/sea health performance values was conducted specifically for the CEBM-based TOPSIS method across various scenarios. Relevant data for each scenario are detailed in Figure 3.

As illustrated in Figure 3, the computed ADM values for each scenario are positioned below the upper decision limit (UDL) values and above the lower decision limit (LDL) values. Consequently, the variances in the identified weights for each scenario demonstrate uniformity. This verification was further validated through the implementation of the Levene Test. The essential statistics for the Levene Test are presented in Table 12.

Derived from the data in Table 12, the observed p-value (p=0.328) exceeds the critical threshold of 0.05, confirming the uniformity of variances in criterion weights across scenarios. In summary, the results obtained from the simulation analysis suggest the robustness and stability of the CEBM based TOPSIS method.

Table 11. Variance values of CEBM-based MCDM methods across scenarios

Scenarios	SWA	ARAS	EDAS	WASPAS	GRA
1	0.000025546	0.000012265	0.000477377	1.4212E-05	3,7235E-05
2	0.000025435	0.000012756	0.000477461	1.4567E-05	3,7278E-05
3	0.000025237	0.000012476	0.000477487	1.4287E-05	3,7451E-05
4	0.000025678	0.000012876	0.000477167	1.4483E-05	3,7535E-05
5	0.000025568	0.000012686	0.000477781	1.4496E-05	3,7812E-05
6	0.000025789	0.000012365	0.000477387	1.4461E-05	3,7665E-05
7	0.000025276	0.000012851	0.000477218	1.4764E-05	3,7496E-05
8	0.000025349	0.000012199	0.000477569	1.4512E-05	3,7571E-05
9	0.000025587	0.000012571	0.000477435	1.4645E-05	3,7768E-05
10	0.000025836	0.000012941	0.000477476	1.4328E-05	3,7223E-05
Mean	2.55301E-05	1.25986E-05	0.000477436	1.4476E-05	3,7503E-05
Scenarios	**MAUT**	**ROV**	**COCOSO**	**TOPSIS**	
1	0.000275666	0.000111882	0.000553709	0.000067812	
2	0.000275712	0.000111768	0.000553634	0.000067749	
3	0.000275756	0.000111671	0.000553671	0.000067843	
4	0.000275812	0.000111596	0.000553471	0.000067666	
5	0.000275561	0.000111682	0.000553575	0.000067705	
6	0.000275468	0.000111699	0.000553684	0.000067645	
7	0.000275669	0.000111866	0.000553901	0.000067712	
8	0.000275802	0.000111878	0.000553875	0.000067684	
9	0.000275799	0.000112101	0.000553913	0.000067688	
10	0.000275682	0.000121411	0.000554015	0.000067586	
Mean	0.000275693	0.000112755	0.000553745	0.000067709	

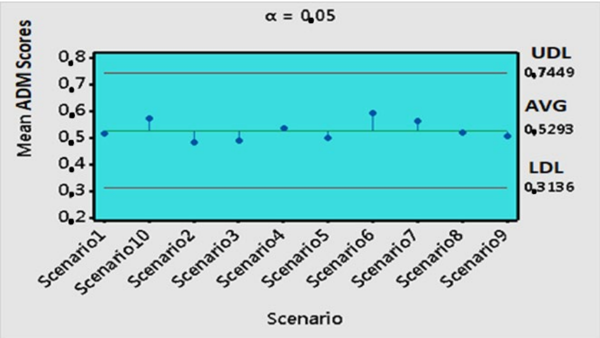

Figure 3. ADM visual

Table 12. Levene test

Levene Statistic	df1	df2	Sig.
0,345	2	16	0,388

p**<.05

DISCUSSION

Due to the intensification of inter-country relations and the direct and indirect activities it brings, the health levels of oceans and seas worldwide have become a significant contemporary and global issue (Gilmour et al., 2021). This is because countries can benefit more efficiently from oceans and seas through the policies and strategies they develop for the sustainability of ocean/sea health (Halpern et al., 2012). Therefore, the awareness of countries regarding their performance in ocean/sea health is of great importance (Frid and Caswell, 2017). Particularly, acknowledging the correlation between economic growth and ocean pollution (Chen et al., 2017), G20 nations require precise assessments of sea health. This is because the activities and methodologies of G20 countries regarding ocean/sea health can influence the global economy and other dimensions associated with the economy (OECD, 2019). In this context, this study evaluates the ocean/marine health of 18 countries in the G20 group using the CEBM-based TOPSIS method, aiming to inform policy-making, environmental sustainability, and global marine ecosystem protection.

Upon reviewing the literature, no research examining the ocean/marine health performance of G20 countries through any numerical method other than the Ocean Health Index (2023) has been encountered. In this context, it has been determined that within the scope of the Ocean Health Index (2023), the top three countries exhibiting the highest marine/ocean health performance are Russia, Brazil, and Australia. However, in the current research, this ranking has been observed as Russia, Brazil, and France. Therefore, based on this finding, it is assessed that Russia and Brazil demonstrate a notable performance in ensuring ocean/sea health compared to other countries. Additionally, according to the Ocean Health Index (2023), countries that surpass the average marine health performance include Russia, Brazil, Australia, Germany, South Korea, France, Italy, Mexico, and Saudi Arabia. In the present study, however, this ranking has been realized as Russia, Brazil, Australia, the United Kingdom, Mexico, South Korea, the United States, Germany, Saudi Arabia, and Canada. Thus, based on the results of the Ocean Health Index (2023) and the current research, consistency is observed in terms of surpassing the average marine/ocean health performance value for Russia, Brazil, France, Germany, South Korea, the United Kingdom, Mexico, and Saudi Arabia.

CONCLUSION

Especially the major economies prioritize activities related to ocean/sea health primarily because they affect ocean/sea health, the global economy, and other economic dimensions. Therefore, the efforts of G20 countries in the field of ocean/sea health are of vital importance. Because the activities of especially large economies regarding ocean/sea health affect global ocean/sea health and the global economy, it is important to determine which ocean/sea health criteria large economies should prioritize and which large economies need to improve their ocean/sea health performance for the global ocean/sea health to reach better levels and for the global economy to thrive. In this context, in the study, the ocean/sea health performances of 18 countries in the G20 group for the year 2023 were measured using the latest Ocean Health Index (OHI) data and the CEBM-based TOPSIS Multi-Criteria Decision Making (MCDM) method. According to the findings, using the CEBM method, the most important OHI criteria for countries were determined to be biodiversity, carbon capacity, fishing opportunities, clean water, and coastal protection. According to this, it has been evaluated that countries need to place more importance on the biodiversity criterion in order to contribute more to global ocean/sea health and the economy. Subsequently, based on the CEBM-based TOPSIS method, the top three countries with the highest ocean/sea health performance were determined to be Russia, Brazil, and France, while the bottom three countries were ranked as China, India, and South Africa. In addition, the average of the performance values calculated using the CEBM-based TOPSIS method showed that the countries with performance values above the average were Russia, Brazil, France, the United Kingdom, Australia, Mexico, South Korea, the United States, Germany, Saudi Arabia, and Canada. Based on this result, it is considered that G20 countries whose ocean/sea health performance values are below the average need to improve their performance to contribute more to the global marine/ocean health in the global economy and other relevant dimensions. Finally, sensitivity, comparison, and simulation analysis of the method show that the CEBM-based TOPSIS method can be used to measure countries' ocean/sea health performances. Recommendations suggest G20 countries focus on biodiversity (OHI10), carbon storage (OHI4), artisanal fishing opportunities (OHI2), clean waters (OHI9), and coastal protection (OHI5) for global ocean/marine health. Countries with lower-than-average performance according to this study, like United States, Türkiye, Indonesia, Italy, Argentina, South Africa, India, and China, are encouraged to enhance their marine health to contribute global economy. Methodologically, comparing CEBM-based other MCDM methods ensures a comprehensive examination of marine health performance measurement. In addition, the ocean/sea health performances of other international economic organizations (G20, OECD, European Union, E7, etc.) can be measured, allowing for a comparison of the ocean/sea health performances of these organizations and their member countries.

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AUTHOR CONTRIBUTIONS

The data collected and findings obtained for this article were provided by Furkan Fahri Altıntaş.

CONFLICTS OF INTEREST

The authors declare that there are no conflicts of interest or competing interests.

ETHICS APPROVAL

No specific ethical approval was necessary for the study.

DATA AVAILABILITY

For any questions, the corresponding author should be contacted.

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