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ORIGINAL ARTICLE

Comparative analysis of Brazil-Russia-India-China-SouthAfrica-Turkiye in terms of environmental pollution indicators using multi criteria decision making methods

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Abstract
This study aims to determine the ranking of criteria contributing to environmental pollution for Brazil-Russia-India-China-South Africa-Turkiye countries using multi-criteria decision-making methods based on average data for 2023. It also aims to rank the selected countries according to their performance. Environmental pollution criteria include carbon dioxide emissions, ecological footprint, per capita national income, renewable energy in primary energy consumption, trade, net foreign direct investment inflows, population, environmental policy stringency index and environmentally related technologies. The findings were determined according to the expert opinion-based method as follows: fossil energy use (0.123), carbon dioxide emissions (0.118), population (0.108), per capita national income (0.104), trade (0.099), environmental technologies (0.095), net foreign direct investment inflows (0.094), ecological footprint (0.093), environmental policy stringency index (0.090) and renewable energy in primary energy consumption (0.075). Accordingly, the ranking of the countries—from best to worst—was Turkiye, India, Brazil, South Africa, China and Russia. However, according to the objective method, the variable weights were determined as population (0.152), net foreign direct investment inflows (0.121), environmental technologies (0.118), national income per capita (0.108), fossil energy use (0.101), trade (0.095), ecological footprint (0.094), renewable energy in primary energy consumption (0.089), carbon dioxide emissions (0.062), environmental policy stringency index (0.055). Accordingly, the ranking of the countries—from best to worst—was Turkiye, India, South Africa, Brazil, China and Russia.

Keywords Main environmental indicators · Brazil-Russia-India-China-South Africa-Turkiye countries · Multi-Criteria Decision Making Methods

JEL Classification C40 · O21 · O32

Introduction

One of the fundamental goals of sustainable development (SDGs) is to "Take urgent action to combat climate change and its impacts" (UN, 2024). Global warming, resulting from climate changes, continues to affect all countries worldwide by creating extreme weather conditions. Despite numerous climate action plans being developed and implemented, these measures remain insufficient, leading to annual economic losses of hundreds of billions of dollars caused by climate-related disasters (UN, 2023). One of the major factors contributing to climate change is the release of harmful gases into the atmosphere, such as carbon dioxide (CO_2), nitrous oxide, methane, and chlorofluorocarbons. The spread of these gases, which are critical indicators of environmental pollution, accelerates global warming, further fueling climate change (Turrentine, 2022). In other words, production and consumption activities that disregard the rise in environmental pollution disrupt sustainable development and exacerbate global warming (EEA, 2024).

Environmental pollution can generally be defined as the contamination of water, soil, or air with harmful gases or

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energy, which adversely affects living organisms and their lives both quantitatively and qualitatively, causing short- or long-term damage to the atmosphere and ecosystem (Hussain, 1998). The environmental pollution problem faced today emerges as a complex result of interconnected forces influenced by various factors. There are clearly diverse and contradictory views regarding the underlying causes of environmental pollution. In other words, there is no consensus on which factors influence environmental pollution and how they impact it. No single cause can be identified as the primary reason for environmental degradation. Although the factors affecting environmental pollution are generally expressed, each of these factors can operate simultaneously and change the balances according to space and time (Appannagari, 2017). Therefore, the direction and extent to which the factors affecting environmental pollution affect is still a separate matter of debate (Liu & Lin, 2019).

In studies conducted on the factors affecting environmental pollution in terms of increase and decrease, many factors stand out. The most important of these is the amount of carbon emission, which is one of the gases emitted into the environment (Chen et al., 2023; Choudhury et al., 2023; Duan et al., 2022; Qiu et al., 2024). Carbon emission has been accepted as one of the main sources of air pollution, which causes serious concern due to its climatic effects as a greenhouse gas (GHG) (Hadipoor et al., 2021). In addition, carbon emission is one of the gases emitted most into nature as a result of many human production and consumption activities such as energy use, transportation, burning of fossil fuels, and changes in industrial use (EPA, 2024). For this reason, in studies conducted on carbon emission, it is stated that carbon emission significantly increases environmental pollution, and changes in carbon emission are taken as the basis as an indicator of environmental pollution (Gan et al., 2024; Wang et al., 2020; Yang et al., 2022). Another important indicator of environmental pollution is the ecological footprint. In addition to carbon emissions, the ecological footprint has recently been mentioned as an important determinant of environmental pollution, as it shows the anthropogenic pressure on the environment (Dogan et al., 2019). The ecological footprint is a science-based methodology that compares the ecosystem services used by humanity each year with the annual renewal capacity of the biosphere for these services (Network, 2019). In studies conducted on ecological footprint and environmental pollution, it is accepted that the increase in the ecological footprint significantly increases environmental pollution (Adebayo et al., 2024; Ozturk et al., 2024).

Rapid industrial growth and the ever-increasing trend in global population in recent centuries have increased the demand for energy resources, making it increasingly difficult to balance economic development and growth with environmental impacts (Dogan et al., 2019; Wang & Azam, 2024). Because this demand is met by energy production from non-renewable fuels that mostly cause GHG emissions. Despite concerns about the resulting effects of increasing GHG emissions, the inability to abandon economic growth and non-renewable energy use reveals the importance of the relationship between the environments; income and energy use (Dogan et al., 2019). In order to meet the consumption needs of the increasing population and ensure sustainable economic growth, countries have to produce more, host foreign direct investments and engage in foreign trade.[1] This situation leads to more energy use (Rahman, 2017, 2020). Since many countries still use non-renewable energy, this production and trade cycle is generally met by fossil energy sources (Rahman & Mamun, 2016). For this reason, increasing population, growth activities, greater openness to the outside world and foreign direct investment inflow are among the important indicators that increase environmental pollution by eliminating it with non-renewable energy sources (Martins et al., 2019).

The increasing interest in environmental pollution also seeks an answer to the question of what steps should be taken to reduce environmental pollution. Environmental pollution, which increases due to the increase in economic growth, causes an increase in environmental awareness throughout the country after a certain threshold level. This situation requires that the environmental policies implemented in the country be addressed within a certain framework. An important indicator of the environmental policies implemented by countries is the environmental stringency index (EPS). This index provides the opportunity to compare countries and is defined as the degree to which the implemented environmental policies explicitly or implicitly set a price for polluting and environmentally harmful behaviors. The higher the pricing tariff implemented against polluting activities, the more deterrent sanctions are considered to be applied in this area, and therefore, the increase in EPS can be interpreted as the increase in environmental quality to that extent (Xie et al., 2023). This situation forces environmental polluters to

[1] There are disagreements on the relationship between FDI inflow and environmental pollution. There are two views in this context. According to Wang et al. (2023), these can be defined as the "pollution haven hypothesis" and the "pollution halo hypothesis". The pollution haven hypothesis states that in countries where pricing related to environmental regulations is low or absent, the manufacture of harmful products that cause high levels of environmental damage by enterprises increases environmental pollution in these countries. According to the pollution halo hypothesis, clean technology is transferred to host countries through FDI by investing companies. As a result, multinational companies are more likely to operate in accordance with environmental legislation and use environmentally friendly technology and production methods, thereby reducing environmental pollution in the countries receiving investment (Kisswani and Zaitouni, 2023).

take corrective measures and encourages countries to make environmentally friendly technological advances (Cheng et al., 2019; Huo et al., 2023; Zhu et al., 2024) with a focus on renewable energy use (Dilanchiev, et al., 2024; Lu et al., 2024; Shen et al., 2024). As a result of these developments, environmental quality gradually begins to improve (Destek & Sinha, 2020).

The wide variety of factors affecting environmental pollution causes various difficulties in policy making in this area. For this reason, it is seen that policy strategies that include factors affecting environmental pollution should be addressed with a holistic analysis (Grening and Bernow, 2004). At this point, it is crucial to express the factors affecting environmental pollution in a specific order based on their impact levels on a country-by-country basis. In this context, the present study employs Multi-Criteria Decision-Making Methods (MCDM), specifically SWARA, CRITIC, and ARAS, to rank BRICS-T countries based on factors affecting environmental pollution. First, the importance weights of the criteria were determined using SWARA, a subjective weighting method, and CRITIC, an objective weighting method. Subsequently, the countries were ranked according to environmental pollution indicators by integrating the weights obtained through the SWARA and CRITIC methods into the ARAS method. Finally, a comparison was made between the ranking results of the countries estimated using the SWARA-ARAS and CRITIC-ARAS methods. All data were taken from the World Bank, Global Footprint Network, Our World in Data, and OECD databases, based on 2023.

The aim of the current study is to conduct research on BRICS-T countries. One of the main reasons for this is that BRICS-T countries are still the largest consumers of fossil energy worldwide (Wang et. al. 2022). These countries represent the world's largest emerging markets. In 2022, they accounted for approximately 26% of the world's total GDP. Over the past decade, these economies have grown at an average annual rate of approximately 2.87%, exceeding the global average of 2.73%. However, this rapid economic growth has also increased energy demand, and these countries accounted for approximately 46% of the world's total primary energy consumption in 2022. Since these economies are expected to continue to grow rapidly, their energy consumption is likely to increase further in the coming decades. In this context, the BRICS-T's transition away from the current fossil fuel-dominated energy system will be crucial to achieving the Paris Agreement's goal of limiting global temperature rise to 1.5 ℃ (Eurekalert, 2025).

BRICS-T countries have begun to realize the negative effects of fossil fuel consumption and are trying to contribute some of their increased wealth to expanding renewable energy capacity. While renewable energy consumption has increased, fossil fuel energy consumption has decreased in most BRICS countries. However, regional emissions have not been supported by increasing income or economic progress. Therefore, it is recommended that climate policies be implemented more aggressively to support investment in clean and green energy technology (Dalei & Gupta, 2024). At this point, effective policies need to be developed for BRICS-T countries. For this reason, comparing these countries in terms of environmental quality indicators, which are important determinants of sustainable development, is very important for effective policy development.

In this context, the present study, based on the average values for 2023, aims to:

i. Conduct a performance measurement for BRICS-T countries using indicators that reflect environmental quality,
ii. Create a weighted ranking for the selected indicators,
iii. Determine the relative importance values of the criteria, and
iv. Provide general insights into the policies followed by countries that demonstrate successful environmental quality performance.

The study compares the selected countries in terms of environmental pollution and aims to propose policy recommendations based on the success of countries with better environmental quality performance. However, the study has certain limitations. It does not distinguish which sectors in these countries contribute more to environmental pollution or where environmental quality improvements are specifically required to achieve sustainable development.

This research was conducted at the state university in Erzincan between January and March 2025.

Literature review

Some studies on environmental pollution utilize Multi-Criteria Decision-Making (MCDM) methods to identify more effective policies for reducing pollution. Among these studies, Greening and Bernow (2204) used MCDM methods to find the ideal choice in energy and environmental policies. In the application, a wide range of characteristics and various stakeholder preferences related to multiple pollutant reduction and energy system development strategies were analyzed. Huang et al. (2011) used Multi-Criteria Decision Making Methods to examine 300 articles published in WOS between 2000 and 2009 in the field of environmental applications. As a result of the examination, it was found that this method was frequently used in environmental applications. With a similar goal, 196 published articles between 1995 and 2015 were selected and examined in Mardani et al. (2017) study. All published articles were categorized and analyzed in 13 different areas. According to the findings obtained as a result of the study, decision-making

approaches can help decision makers and stakeholders solve some problems in situations of uncertainty in the environmental decision-making process, and these approaches have seen an increasing interest among previous researchers to use these approaches in various steps of the environmental decision-making process. In the study of Tian et al. (2023), where the MCDM method was used for article review, the method choice between green logistics and low-carbon transportation systems was analyzed by examining 190 articles between 2010 and 2022.

In the study of Gok Kısa (2022), which is one of these methods used to make optimal choices for environmental practices, the environmental performances in OECD countries are evaluated, current problems are identified and effective solutions are found by using the Entropy and WASPAS methodologies from the Multi-Criteria Decision Making Methods. According to the results of the Entropy-WASPAS method applied in the study; Denmark, Germany, France, Sweden and Japan are the countries with the best performance in terms of environmental health and vitality. In addition, pollution emissions, biodiversity and habitat and waste management criteria were found to be the most important factors in maintaining environmental performance.

In Demircioglu and Ulukan (2020), MCDM methods were used to determine the methods of combating environmental pollution, from the least polluted to the most polluted. In the study of Sahin et al (2020), analytical hierarchy process (AHP), which is one of the multi-criteria decision-making methods used in the investigation of air pollution in Iğdır city center and four districts (Tuzluca, Iğdır Center, Karakoyunlu and Aralık), and geographic information systems (GIS) methods were used in order to develop solution techniques for air pollution. In the study where spatial analyzes of pollutant parameters were made, pollution distribution maps were created by determining the pollutant parameters and dynamic mapping and station-based statistics were evaluated. According to the findings, Iğdır center is the place with the lowest quality in the air pollution problem for the GIS-AHP method.

Muhammad et al. (2021) used MCDM methods to find the ideal technique for solid waste management in Nigeria to reduce environmental pollution. In the study, seven different criteria related to environment, society and cost were used, and it was found that the cost criterion was the most important criterion. In addition, four waste treatment methods were evaluated in the study, namely incineration, composting, sanitary landfills and anaerobic digestion, and it was concluded that composting was the most effective method. Similarly, Bilgilioglu et al. (2022), who conducted research for the Mersin province in Turkiye on the selection of solid waste management, conducted an analysis with eleven different criteria, including height, slope, permeability, distance from linearity, groundwater level, distance from rivers and water surfaces, distance from roads, distance from settlements, distance from protected areas and land cover. The most suitable solid waste storage areas in the province were determined in accordance with the determined criteria. Paul et al. (2023) study, it was stated that MCDM-EDAS methods should be used in the selection of the most suitable solid waste storage areas for India,

In Etfatpanah et al. (2022), which presented a comparative analysis of renewable energy methods for reducing environmental pollution in Jiangsu Province, China, five important multi-criteria decision-making methods were used in the field of energy technology selection, including SAW, TOPSIS, ELECTRE, VIKOR and COPRAS. The decision problem in the study was evaluated according to twelve basic and important criteria to rank clean energy options. The choices consist of four clean energy options, including solar photovoltaic, wind, nuclear and biomass. According to the results of the five MCDM methods, the most suitable renewable energy options were solar photovoltaic and wind energy. When reviewing studies focusing on environmental pollution and utilizing MCDM methods, it is evident that these methods are applied to the decision-making process to implement the most ideal policies for reducing pollution. Notably, the studies primarily conduct country-specific analyses, with no cross-country comparisons observed.

Literature gap

One of the primary goals of sustainable development is undoubtedly to address climate change, and one of the crucial steps in this process is controlling environmental pollution. Therefore, it is essential to analyze the factors that influence environmental pollution in terms of both its increase and decrease, and to determine the extent to which these factors impact pollution levels. A review of the existing literature reveals that most studies tend to focus on the energy type to be used and the region selection for the implementation of energy systems within countries. Furthermore, there is a limited amount of research on the BRICS-T countries, which have recently garnered more political and economic attention.

In this context, this study aims to address the gaps identified in the literature by focusing on the following objectives:

(i) Identifying the factors that influence environmental pollution in BRICS-T countries.
(ii) Determining which factors have the greatest impact on environmental pollution in these countries.
(iii) Comparing countries to assess which ones are most successful or unsuccessful in terms of environmental pollution indicators.

(iv) Investigating the policies adopted by the high-performing countries in terms of environmental pollution indicators.
(v) Assessing the applicability of these policies to other countries.

Materials and methods

For this purpose, the definitions and details of the variables obtained from the BRICS-T database are provided in Table 1. All the data has been calculated based on the average values for 2023, and detailed information regarding the criteria is presented.

The indicators in Table 1 represent some of the parameters that reflect the environmental pollution indicators of countries. Many factors contribute to the sustainable development of nations. The main reason for selecting these variables is that they are the most fundamental environmental pollution indicators. Using these indicators, the trends of the BRICS-T countries in terms of environmental pollution can be easily observed, and changes in their performance can be compared. Furthermore, in the existing literature on environmental pollution analyzed within the context of countries and country groups, the selection of the criteria listed in Table 1 has significantly influenced the choice of criteria in this study.

Determining which factor performs better in showing the development of environmental pollution is particularly important for policy making. In this context, MCDM methods were used in the analytical part of the study. This method takes into account different qualitative and quantitative criteria that need to be corrected to find the best solution. In addition, since each criterion is weighted differently according to its importance in certain situations during the application of the method, it can be effectively used as the most accurate decision-making method (Taherdoost and Madanchian, 2023). With this method, the relative importance of technological indicators is determined and the evaluation process of countries in terms of various indicators is facilitated with less complex but reliable calculation methods (Torkayesh and Torkayesh, 2021). In the context of indicators, which is the main purpose of the study, the methods applied in the context of MCDM are shown in Fig. 1, focusing on the environmental pollution development indicators of BRICS-T countries.

Table 1 Criteria, attributes and codes

Order	Criteria	Database	Codes
1	CO2 emissions (metric tons per capita)	World Bank	CO2
2	Ecological footprint	Global Footprint Network	EFP
3	GDP per capita (constant 2015 US$)	World Bank	GDP
4	Renewables (% equivalent primary energy)	Our World in Data	RENuse
5	Primary energy consumption (TWh)	Our World in Data	Euse
6	Trade (% of GDP)	World Bank	Trade
7	Foreign direct investment, net inflows (% of GDP)	World Bank	FDI
8	Population (total)	World Bank	POP
9	Environmental Policy Stringency Index (EPS)	OECD	EPS
10	Environment-related technologies	OECD	ETECN

Source: Authors' own elaboration

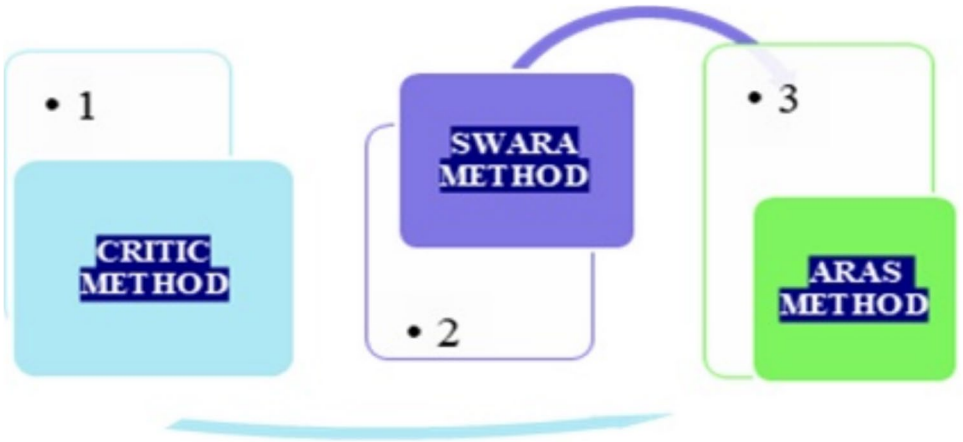


Fig. 1 Conceptual framework flow chart. Source: Authors' own elaboration

SWARA method

The SWARA method (Step-Wise Weight Assessment Ratio Analysis) is a technique used to determine the weights of criteria by collecting expert opinions and evaluating these opinions collectively (Aghdaie et al., 2013). The most critical aspect of this method is ensuring that the individuals identified as experts have sufficient experience and knowledge in the relevant field. The method is implemented in six steps. These steps are outlined as follows (Bardakçı, 2020):

Step 1: Ranking and assigning importance levels

In this step, the individuals identified as experts are asked to rank the criteria from the most important to the least important based on their experience and knowledge. Then, the criteria ranked from the most important to the least important are assigned values between 1 and 0 in multiples of five. The assigned values are presented as $p_j^k; where j = 1, \ldots, n and k = 1, \ldots, l and 0 \leq p_j^k \leq 1.$

Step 2: Calculating the relative average importance score

The relative average importance $(\overline{p_j})$ for all criteria is calculated using Eq. (1):

$$\left(\overline{p_j}\right) = \frac{\sum_{k=1}^{l} p_j^k}{l} \; j = 1, \ldots, n \, and \, l = \text{number of experts} \tag{1}$$

Step 3: Calculating the comparative importance values

After the criteria are ranked from highest to lowest based on their relative average importance scores, the sequential differences (s_j) are calculated. This value is referred to as the comparative importance value of the average score.

Step 4: Calculating the coefficient values

For each criterion, the coefficient value (c_j) is calculated using equation:

$$c_j = \begin{cases} 1, j = 1 \\ s_j + 1, j > 1 \end{cases}, j = 1, 2, \ldots \tag{2}$$

Step 5: Calculating the adjusted weights

Adjusted weights $(s_j\prime)$ are calculated for all criteria. The adjusted weight for each criterion is calculated using Eq. (3):

$$s_j\prime = \begin{cases} 1, j = 1 \\ \frac{s_{j-1}\prime}{c_j}, j > 1 \end{cases}, j = 1, 2, \ldots \tag{3}$$

Step 6: Calculating the final weights

Final weight values are calculated by Eq. (4). The sum of all weights will equal 1:

$$w_j = \frac{s_j\prime}{\sum_{j=1}^{n} s_j\prime}, \; j = 1, 2, \ldots, n \tag{4}$$

CRITIC method

The CRITIC method was used for weighting the criteria. The most important feature of this method is that it provides an objective weighting approach based on the correlation between criteria and their standard deviation (Diakoulaki et al., 1995). It also takes into account the conflicts between criteria. Considering all these features, the CRITIC method was applied to calculate the weights of the criteria. After defining the problem and creating the initial matrix, the solution steps of the method proceed as follows (Arslan, 2020):

Step 1: Creating the normalization matrix

Equations (5) and (6) are used to create the normalization matrix,

$$\mathrm{r_{ij}} = \frac{\mathrm{x_{ij}} - \mathrm{f_i^{min}}}{\mathrm{f_i^{max}} - \mathrm{f_i^{min}}}, \text{(for benefit criteria)} \tag{5}$$

$$\mathrm{r_{ij}} = \frac{\mathrm{f_i^{max}} - \mathrm{x_{ij}}}{\mathrm{f_i^{max}} - \mathrm{f_i^{min}}}, \text{(for cost criteria)} \tag{6}$$

Step 2: Calculating the correlation between criteria

The correlation between the considered criteria is calculated.

Step 3: Calculating the information content

The calculation of information content (c_j) for each criterion is done using Eq. (7)

$$c_j = \sigma_j * \sum_{k=1}^{n} (1 - l_{kj}), \quad \sigma_j : standartdeviationandl_{kj} : correlationcoefficient \tag{7}$$

Step 4: Calculating the criteria weights

The criteria weights are (w_j) calculated using Eq. (8). The sum of all weights will equal 1.

$$w_j = \frac{C_j}{\sum_{k=1}^{n} C_k} \tag{8}$$

ARAS Method

The ARAS (Additive Ratio Assessment) method was developed in 2010 by Zvasdaskas and Turkis. This method is used to rank alternatives based on their performance. The evaluation is carried out using a suitability function, and the performance of the alternatives is assessed by comparing the proportional similarity to the optimal alternative (Zvasdaskas and Turkis, 2010). The steps involved in the ARAS method are as follows (Adem & Dağdeviren, 2020):

Step 1: Constructing the decision matrix

The decision matrix is constructed to represent m (rows) as alternatives and n (columns) as criteria, as shown in Eq. (9).

$$X = \begin{bmatrix} x_{01} & \cdot & x_{0j} & \cdot & x_{0n} \\ \cdot & \cdot & \cdot & \cdot & \cdot \\ x_{i1} & \cdot & x_{ij} & \cdot & x_{in} \\ \cdot & \cdot & \cdot & \cdot & \cdot \\ x_{m1} & \cdot & x_{mj} & \cdot & x_{mn} \end{bmatrix}, \; i = 0, \ldots, m; j = 1, \ldots, n \tag{9}$$

Here, x_{ij} represents the performance value of the i-th alternative with respect to the j-th criterion, and x_{0j} represents the optimal value of the j-th criterion. If the values of x_{0j} are unknown, they can be determined using Eq. (10):

$x_{0j} = \max_i x_{ij}$ if the j-th criterion is a maximization criterion.

$x_{0j} = \min_i x_{ij}^*$ if the j - th criterion is a minimizastion criterion (10)

Step 2: Creating the normalization matrix

In the decision matrix, a transformation is applied to make the criteria with different optimization directions align in the same direction. After this transformation, the normalization matrix is created. When constructing this matrix, Eq. (11) is used if all criteria are maximization-type, and Eq. (12) is used if they are minimization-type. The resulting matrix will be as shown in Eq. (13).

$$\overline{x}_{ij} = \frac{x_{ij}}{\sum_{i=0}^{m} x_{ij}} \tag{11}$$

$$\overline{x}_{ij} = \frac{\frac{1}{x_{ij}^*}}{\sum_{i=0}^{m} x_{ij}} \tag{12}$$

$$\overline{X} = \begin{bmatrix} \overline{x_{01}} & \cdot & \overline{x_{0j}} & \cdot & \overline{x_{0n}} \\ \cdot & \cdot & \cdot & \cdot & \cdot \\ \overline{x_{i1}} & \cdot & \overline{x_{ij}} & \cdot & \overline{x_{in}} \\ \cdot & \cdot & \cdot & \cdot & \cdot \\ \overline{x_{m1}} & \cdot & \overline{x_{mj}} & \cdot & \overline{x_{mn}} \end{bmatrix}, i = 0, \ldots, \overline{m} \; and j = 1, \ldots, \overline{n} \tag{13}$$

Step 3: Creating the weighted normalization matrix

The criterion weights range between 0 and 1, with the sum of all criterion weights equal to 1. In this way, the weighted normalization matrix is created using Eq. (14), as shown in Eq. (15).

$$\hat{x}_{ij} = \overline{x}_{ij} w_j; i = 0, \ldots, \overline{m} \tag{14}$$

$$\hat{X} = \begin{bmatrix} \widehat{x_{01}} & \cdot & \widehat{x_{0j}} & \cdot & \widehat{x_{0n}} \\ \cdot & \cdot & \cdot & \cdot & \cdot \\ \widehat{x_{i1}} & \cdot & \widehat{x_{ij}} & \cdot & \widehat{x_{in}} \\ \cdot & \cdot & \cdot & \cdot & \cdot \\ \widehat{x_{m1}} & \cdot & \widehat{x_{mj}} & \cdot & \widehat{x_{mn}} \end{bmatrix}, i = \overline{0, \ldots, m}; j = \overline{1, \ldots, n} \tag{15}$$

Step 4: Calculating the optimality function value

The optimality function value is calculated for each alternative. The alternative with a higher function value can be interpreted as the more efficient alternative. S_i, the optimality function, is calculated using Eq. (16).

$$S_i = \sum_{j=1}^{n} \hat{x}_{ij}; i = 0, \ldots, \overline{m} \tag{16}$$

Step 5: Calculating the degree of benefit and obtaining the ranking

For each alternative, the degree of benefit (K_i) is calculated using the optimality function value S_i as shown in Eq. (17). The calculated degree of benefit will be in the range of 0 to 1. Then, by ranking these values from largest to smallest, the alternatives will be ranked according to their importance.

$$K_i = \frac{S_i}{S_0}, i = 0, \ldots, m \quad (17)$$

Findings

The criterion weights calculated using the SWARA method are shown step by step.

Step 1: Ranking of importance degrees and their values

In this step, the values obtained from the opinions of 6 experts in the field are presented in Table 2, which reflects the ranking and assigned values for each criterion.

Step 2: Calculating the relative average importance score

The relative average importance scores of the criteria are calculated according to Eq. (1) and are presented in Table 3.

Table 3 Calculated values and criterion weights for obtaining criterion weights

Criteria	$\overline{p_j}$	s_j	c_j	s_j'	w_j
Euse	0,87	0	1	1	**0,123**
CO2	0,83	0,04	1,04	0,961,538,462	**0,118**
POP	0,74	0,09	1,09	0,882,145,378	**0,108**
GDP	0,7	0,04	1,04	0,848,216,709	**0,104**
Trade	0,65	0,05	1,05	0,807,825,437	**0,099**
ETECN	0,61	0,04	1,04	0,776,755,228	**0,095**
FDI	0,59	0,02	1,02	0,761,524,734	**0,094**
EFP	0,58	0,01	1,01	0,753,984,885	**0,093**
EPS	0,55	0,03	1,03	0,73,202,416	**0,090**
RENuse	0,35	0,20	1,20	0,610,020,133	**0,075**

Source: Authors' own calculations

The bold text in Tables 3 and 6 indicates the weights of the criteria

Step 3: Calculating the comparative importance values

The comparative importance value of each criterion relative to the average importance score is calculated as described in Step 3 of the method, and these values are presented in Table 3.

Step 4: Calculating the coefficient values

The coefficient values are calculated according to Eq. (2) and are presented in Table 3.

Step 5: Calculating the adjusted weights

The adjusted weights for all criteria are calculated according to Eq. (3) and are presented in Table 3.

Table 2 Importance Degrees of the Criteria

Criteria	DM1	DM2	DM3	DM4	DM5	DM6
CO2	0.95	0.9	0.35	1	0.95	0.95
EFP	0	1	0.25	0.95	0.7	0
GDP	0.1	0.4	0.3	0.9	0.05	0.1
RENuse	0.85	0.95	0.75	0.8	1	0.85
Euse	0.7	0.75	0.55	0.85	0.65	0.7
Trade	0.55	0.3	0.6	0.75	0.75	0.55
FDI	0.6	0.7	0.85	0.7	0.85	0.6
POP	0.5	0.6	0.95	0.6	0.6	0.5
EPS	0.35	0.8	0.45	0.55	0.9	0.35
ETECN	0.2	0.85	0.4	0.5	0.8	0.2

Source: Authors' own calculations

Table 4 Initial Decision Matrix

	Countries/criteria	Brazil	Russia	India	China	South Africa	Turkiye
Min	*CO2*	1,55	22,598	1,174	4,685	8,324	1,341
Min	*EFP*	1,624	3,268	0,501	1,465	1,883	1,73
Max	*RENuse*	43,193	6,258	7,238	7,55	0,781	12,963
Min	*Euse*	2733,286	7842,802	5410,419	22,970,486	1304,488	1146,348
Min	*GDP*	7620,304	7445,547	1099,533	4677,756	5415,94	8225,128
Min	*FDI*	2,822	1,745	1,337	3,466	1,189	1,252
Min	*POP*	187,201,543	145,330,129	1,164,275,714	1,304,407,069	50,050,173	69,677,450
Min	*Trade*	23,969	55,325	36,728	43,372	49,507	48,618
Max	*ETECN*	0,303	0,744	0,204	1,315	0,186	0,579
Max	*EPS*	0,395	0,59	1,358	0,982	0,561	1,363

Source: Authors' own calculations

Table 5 Normalization Matrix

	Countries/criteria	Brazil	Russia	India	China	South Africa	Turkiye
Min	*CO2*	0,982	0	1	0,836	0,666	0,992
Min	*EFP*	0,594	0	1	0,651	0,5	0,555
Max	*RENuse*	1	0,129	0,152	0,159	0	0,287
Min	*Euse*	0,927	0,693	0,804	0	0,992	1
Min	*GDP*	0,084	0,109	1	0,497	0,394	0
Min	*FDI*	0,282	0,755	0,935	0	1	0,972
Min	*POP*	0,89	0,924	0,111	0	1	0,984
Min	*Trade*	1	0	0,593	0,381	0,185	0,213
Max	*ETECN*	0,104	0,494	0,016	1	0	0,348
Max	*EPS*	0	0,201	0,995	0,606	0,171	1

Source: Authors' own calculations

Step 6: Calculating the final weights

The final weight values are calculated using Eq. (4) and are presented in Table 3.

As seen in Table 3, according to the SWARA Method, the most important criterion among the environmental pollution indicators is Euse, with a weight of 0.123. The other criteria are ranked as follows: CO2 with a weight of 0.118, POP with a weight of 0.108, GDP with a weight of 0.104, Trade with a weight of 0.099, ETECN with a weight of 0.095, FDI with a weight of 0.094, EFP with a weight of 0.093, EPS with a weight of 0.090, and RENuse with a weight of 0.075.

The criteria weights calculated using the CRITIC method are shown step by step. The initial decision matrix is presented in Table 4.

In the next step, the calculated criteria weights are determined as follows.

Table 6 Information Content of the Criteria and Criteria Weights

Criteria	c_j	w_j
POP	6,708	**0,152**
FDI	5,367	**0,121**
ETECN	5,196	**0,118**
GDP	4,782	**0,108**
Euse	4,482	**0,101**
Trade	4,213	**0,095**
EFP	4,167	**0,094**
RENuse	3,949	**0,089**
CO2	2,730	**0,062**
EPS	2,422	**0,055**

Source: Authors' own calculations

The bold text in Tables 3 and 6 indicates the weights of the criteria

Step 1: Creating the normalization matrix

The values in the initial decision matrix are normalized

using Eq. (5) and Eq. (6), and the normalization matrix is created as shown in Table 5.

As seen in Table 5, all criterion values are within the range of 0 to 1.

Step 2: Calculation of correlation between criteria

The Spearman's rank correlation between the criteria has been calculated using statistical software packages.

Step 3: Calculation of information content

The information content has been calculated using Eq. (7), and the results are presented in Table 6.

Step 3: Calculation of criteria weights

The criteria weights have been calculated using Eq. (8), and the results are shown in Table 6.

As seen in Table 6, according to the CRITIC Method, the most important criterion among the environmental pollution indicators is POP, with a weight of 0.152. The other criteria are ranked as follows: FDI with a weight of 0.121, ETECN with a weight of 0.118, GDP with a weight of 0.108, Euse with a weight of 0.101, Trade with a weight of 0.095, EFP with a weight of 0.094, RENuse with a weight of 0.089, CO2 with a weight of 0.062, and EPS with a weight of 0.055.

The alternative ranking calculated using the ARAS method is shown step by step.

Step 1: Creation of the decision matrix

The decision matrix is presented in Table 7.

Table 7 Decision matrix

	Countries/criteria	Optimal Values	Brazil	Russia	India	China	South Africa	Turkiye
Min	*CO2*	**1,174**	1,55	22,598	1,174	4,685	8,324	1,341
Min	*EFP*	**0,501**	1,624	3,268	0,501	1,465	1,883	1,73
Max	*RENuse*	**43,193**	43,193	6,258	7,238	7,55	0,781	12,963
Min	*Euse*	**1146,348**	2733,28	7842,80	5410,41	22,970,48	1304,48	1146,34
Min	*GDP*	**1099,533**	7620,30	7445,54	1099,53	4677,75	5415,94	8225,12
Min	*FDI*	**1,189**	2,822	1,745	1,337	3,466	1,189	1,252
Min	*POP*	**50,050,173**	187,201,543	145,330,129	1,164,275,714	1,304,407,069	50,050,173	69,677,450
Min	*Trade*	**23,969**	23,96	55,32	36,72	43,37	49,50	48,61
Max	*ETECN*	**1,315**	0,303	0,744	0,204	1,315	0,186	0,579
Max	*EPS*	**1,363**	0,395	0,59	1,358	0,982	0,561	1,363

Source: It has been obtained from the databases specified in Table 1

The bold text in Table 7 indicates the optimal values. In other words, it shows the most suitable values for the alternatives

Table 8 Normalization Matrix

	Countries/criteria	Optimal Values	Brazil	Russia	India	China	South Africa	Turkiye
Max	*CO2*	0,245	0,185	0,012	0,245	0,061	0,034	0,214
Max	*EFP*	0,297	0,091	0,045	0,297	0,101	0,079	0,086
Max	*RENuse*	0,356	0,356	0,051	0,059	0,062	0,006	0,106
Max	*Euse*	0,269	0,113	0,039	0,057	0,013	0,237	0,269
Max	*GDP*	0,349	0,05	0,051	0,349	0,082	0,07	0,046
Max	*FDI*	0,189	0,079	0,128	0,168	0,064	0,189	0,179
Max	*POP*	0,293	0,078	0,1	0,012	0,011	0,293	0,21
Max	*Trade*	0,216	0,216	0,093	0,141	0,119	0,104	0,106
Max	*ETECN*	0,282	0,065	0,16	0,043	0,282	0,04	0,124
Max	*EPS*	0,206	0,059	0,089	0,205	0,148	0,084	0,206

Source: Authors' own calculations

Table 9 Optimality function value, degree of benefit, and ranking of alternatives

	SWARA-ARAS			CRITIC-ARAS		
	S_i	K_i	Ranking	S_i	K_i	Ranking
Optimal Values	0,269	1		0,273	1	
Brazil	0,125	0,465	**3**	0,122	0,447	**4**
Russia	0,075	0,280	**6**	0,083	0,303	**6**
India	0,158	0,587	**2**	0,144	0,529	**2**
China	0,091	0,338	**5**	0,092	0,335	**5**
South Africa	0,119	0,444	**4**	0,129	0,471	**3**
Turkiye	0,160	0,594	**1**	0,153	0,561	**1**

Source: Authors' own calculations

The bold textindicates the ranking of thealternatives. It is bolded toattract readers' attention

Step 2: Creation of the normalization matrix

A transformation was applied to align the criteria with different optimization directions in the same direction. Since the type of criterion does not matter in terms of importance, all criteria were converted to maximization type. Subsequently, Eq. (11) was used, and the normalization matrix shown in Table 8 was created.

Step 3: Creation of the weighted normalization matrix

Using Eq. (14), the weighted normalization matrices are created by applying both the weights from the SWARA method and the weights from the CRITIC method.

Step 4: Calculation of the optimality function value

The optimality function value for each alternative was calculated using Eq. (16). The calculated values are presented in Table 9.

Step 5: Calculation of the degree of benefit and obtaining the ranking

For each alternative, the degree of benefit (K_i) was calculated using the optimality function value S_i with Eq. (17). These calculated values, along with the ranking from largest to smallest, are used to rank the alternatives based on their importance. The ranking is shown in Table 9.

As seen in Table 9, according to the SWARA-ARAS Method, the ranking of alternatives from best to worst is as follows: Turkiye, India, Brazil, South Africa, China, and Russia. According to the CRITIC-ARAS Method, the ranking of the alternatives—from best to worst—is Turkiye, India, South Africa, Brazil, China and Russia. Thus, it is seen that the first two and last two places do not change in both methods.

Results and discussion

In this study, it was aimed to determine ten different criteria from environmental pollution indicators for BRICS-T countries by using SWARA, CRITIC and ARAS methods from MCDM methods based on the average values of 2023 and to determine which of these criteria are at the forefront in terms of importance. In addition, the ranking of countries that follow successful strategies according to the determined criteria was addressed specifically for BRICS-T countries. With these findings, which are important in presenting effective policy recommendations for national economies, it was aimed to address the strategies for reducing environmental pollution in the mentioned countries in detail.

The study results revealed that the factors causing environmental pollution have different weights among countries and that each method provides important outputs from different aspects. In the analysis part of the study, firstly, the criteria among the environmental pollution indicators were ranked from the most important to the least important according to the SWARA method. Accordingly, the ranking among the criteria was determined as Euse, CO2, POP, GDP, Trade, ETECN, FDI, EFP, EPS and RENuse. Accordingly, it was seen that the criterion that affects environmental pollution the most in BRICS-T countries is primary energy consumption. This finding is very important especially for BRICS-T countries that increased their primary energy consumption after 2021. These countries present primary energy consumption structures where fossil energy use, especially coal, is still dominant. Coal consumption constitutes 71% of the world total. Coal consumption in these countries is still seen as the biggest driver of carbon emission growth and the consumed fossil energy resources are at a much higher point than the global level (Wen et al., 2024). Renewable energy use in BRICS-T members accounts for only 16% of total energy use (Samour et. al. 2023). This situation can be attributed to the fact that the environmental pollution indicator, which is considered the least important according to the

weight share, is renewable energy use. In this direction, it can be said that sustainable energy use is still at a minimum level in BRICS-T countries (Wahyudi, 2024).

According to the CRITIC method based on objective assessment principles, it has been determined that the environmental pollution criteria in BRICS-T countries are ranked from the most important to the least important as POP, FDI, ETECN, GDP, Euse, Trade, EFP, RENuse, CO2 and EPS. This finding shows that the most effective factor affecting environmental pollution in BRICS-T countries is population. The large population sizes in these countries support this result. It is estimated that the total population of BRICS countries will reach 3.25 billion in 2023, accounting for more than 40% of the global population. Most of these people reside in China and India, each with a population exceeding 1.4 billion, while the total population of the other three countries is just under 420 million (Statista, 2024). The criterion with the lowest weight is EPS, which expresses the stringency of environmental protection strategies. This can be attributed to the low levels of the EPS index in BRICS countries. This finding is consistent with the study by Wolde-Rufael and Weldemeskelb (2020), who stated that the EPS index is low in BRICS-T countries and is not yet at the threshold value that will contribute to sustainable development.

Following the integration of the SWARA method, the ARAS method ranked the alternatives as Turkiye, India, Brazil, South Africa, China, and Russia. After integrating the CRITIC method, the ARAS method ranked the alternatives as Turkiye, India, South Africa, Brazil, China, and Russia. It was observed that the criteria importance ranking and weights of environmental pollution indicators calculated by both methods differ. This is because the SWARA method relies on expert opinions, while the CRITIC method is based on actual values. This result is expected. However, it was found that the rankings of the alternatives obtained by integrating both methods with the ARAS method were almost the same. Specifically, the countries in the first two and last two positions were the same, which indicates that despite differences in the methods, the results provided consistent outcomes. To summarize, although some differences are observed in the criteria weights of SWARA (subjective) and CRITIC (objective) methods, the country rankings made with ARAS are largely consistent. In particular, the first two (Turkey, India) and the last two (China, Russia) country rankings are determined similarly in both methods. This shows that the methods provide robust and reliable outputs.

According to both methods, Turkey is ranked as the most successful country in terms of environmental pollution indicators. This can be explained by Turkey's recent increase in renewable energy investments, diversification in the energy system, and reforms in environmental policies. Green tax transformations and energy efficiency policies in public transportation in particular play a role in this success. Turkey's renewable energy capacity has increased by 50% in the last five years. In 2019, Turkey became the country that added the 5th highest new capacity in Europe and the 15th highest in the world. According to the IEA report, it is also a point that should not be overlooked that Turkey has greater growth potential in solar, wind, and geothermal fields (IEA, 2021). On the other hand, it is striking that Russia ranks last in both methods. The main reason for this is Russia's inadequate environmental policies, heavy dependence on fossil fuels, and deficiencies in waste management. In addition, the fact that the wastewater treatment infrastructure is out of date and carbon emissions are at high levels weakens Russia's environmental report card (Ackermann et. al. 2024). Following Russia, China has not achieved the desired success in the transition to renewable energy use due to its high population and fossil fuel use. On the other hand, other BRICS countries, especially India and South Africa, have partially adapted to the transformation process in terms of environmental quality, but it is seen that investments and incentives have not yet reached a sufficient level.

Conclusion

Based on the average data for 2023, the MCDM methods applied to the BRICS-T countries resulted in the ranking of the criteria influencing environmental pollution according to their importance. It was found that the most influential criteria are fossil energy use and population. The BRICS-T countries continue to meet the increasing demand and need for economic growth through fossil energy consumption. Notably, the Chinese economy ranks first in primary energy consumption with 170.74 EJ, followed by India in third place with 39.02 EJ, and Russia in fourth place with 31.29 EJ. In China, fossil fuel use accounts for 81.6% of primary energy, while this proportion rises to 89% in India (Şahin, 2024). This situation indicates that the first intervention required to combat environmental pollution in these countries is reducing fossil energy use. A key alternative in this regard is focusing on the shift towards renewable energy use (Raffat, 2021).

The analysis indicates that the population in these countries is significantly high, and projections suggest that this trend will continue in the future. This highlights the need for measures targeting population growth in order to reduce environmental pollution. Policies aimed at controlling the level of population growth could be effective in this regard. However, rather than aiming for a sudden reduction in population, it is crucial to focus on changing the consumption habits of the current population, raising awareness about reducing environmental pollution, and increasing social awareness (Baus, 2017).

One of the main objectives of the study was to rank the countries based on their success in addressing environmental pollution criteria. It is necessary to closely examine the steps taken by Turkiye to reduce environmental pollution. Turkiye is a country that has had to increase its energy use in many periods in line with its increasing demand, economic growth targets and economic requirements. In other words, the rapid economic and population growth experienced in Turkiye in the last twenty years has not only led to a strong growth in energy demand but also increased import dependency. However, accordingly, Turkiye has restructured its energy system to rationalize energy demand growth, reduce energy prices and slow down the rate of import growth. These reforms include measures targeting modernization, liberalization and increased domestic production capacity. In particular, Turkiye has undergone a significant diversification in its energy mix in the last decade. Renewable electricity production has tripled in the last decade, and the commissioning of Turkiye's first nuclear energy facility has further diversified the country's fuel mix (IEA, 2024). In addition to the growth in renewable energy usage in Turkiye (IEA, 2024), the country has made positive strides in addressing environmental pollution through developments such as the green transformation of the tax system (Dursun & Tutcu, 2024), increased use of public transportation and electric energy, and stricter environmental inspections. These initiatives demonstrate that Turkiye has taken meaningful steps toward reducing environmental pollution.

The analysis shows that Russia is the least successful country among the selected countries. The main reason for this is Russia's heavy reliance on fossil energy (IEA, 2023). Additionally, today, household waste recycling and environmental pollution are among Russia's biggest problems. In Russia, approximately 400 kg of household solid waste is produced per capita, and effective methods for the disposal of inorganic waste have not yet been developed. Furthermore, human waste also has a significant impact on water body pollution. The water used for sewage systems in cities often directly mixes with open water bodies, and the presence of low-quality treatment plants, many of which are outdated and have unusable equipment, prevents them from effectively managing their functions. Due to these and similar effects, Russia has not yet implemented effective actions regarding environmental pollution indicators (Semenova, 2020). Recently, efforts have been made to expand sustainable development-supported activities supported by technology, particularly in Russia, and the issue of soil protection and combating desertification is important for both Russia and the BRICS countries (Vasilev, 2025). In addition, the 9th BRICS Industry Ministers Meeting was held on May 21, 2025 in the BRICS-T countries with the aim of establishing more inclusive and sustainable global cities supported by smart digital technology. In this context, it was stated that an economic transformation should take place in the focus of technological developments that prioritize climate change reduction, and it was proposed to establish the BRICS Part-NIR Innovation Center (BPIC) (Molina, 2025).

India and South Africa have received clean technology funds within the BRICS-T country group, and these are not sufficient to significantly estimate fossil fuel consumption and regional emissions. Therefore, although climate change is a global problem, clean technology funds should not be limited to a few countries. The remaining countries of the BRICS group should also receive sufficient clean technology funds to help them transition to low-carbon economies by reducing fossil fuel energy consumption. Therefore, current policies need to be reformed and new climate policies introduced will encourage investment in clean technology and reduce fossil fuel dependency to reduce regional emission to effectively achieve a low-carbon economy (Dalei & Gupta, 2024).

Based on the findings from the analysis and the examination of policy implementations in the country samples, it is clear that combating environmental pollution is a comprehensive process and requires action across broad areas rather than partial interventions. Therefore, it is evident that steps such as moving away from fossil energy use, shifting towards renewable energy sources, implementing green transformation in tax policies, raising awareness in society about consumption and environmental pollution, and prioritizing environmental quality in production and consumption processes are crucial.

This study focused only on general environmental pollution indicators in the selection of criteria and did not include sector-based distinctions. For this reason, the study has certain limitations. Future studies can analyze the relative effects of, for example, industry, agriculture and transportation sectors on pollution in more detail. In addition, dynamic analyses can be conducted by examining trends over time using longer-term data.

Appendix

- This study aims to determine the ranking of criteria contributing to environmental pollution for BRICS-T countries using MCDM based on average data for 2023.
- It also aims to rank the selected countries according to their performance.
- The findings were determined according to the expert opinion-based method as follows: Euse, CO2, POP, GDP, Trade, ETECN, FDI, EFP, EPS, and RENuse.
- The ranking of the countries- from best to worst- was Turkiye, India, Brazil, South Africa, China and Russia.

- According to the objective method, the variable weights were determined as POP, FDI, ETECN, GDP, Euse, Trade, EFP, RENuse, CO2, and EPS.
- Accordingly, the ranking of the countries—from best to worst—was Turkiye, India, South Africa, Brazil, China and Russia.

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Data Availability The databases for the datasets generated and analyzed during the current study are listed in Table 1. However, they are available from the corresponding author upon reasonable request.

Declarations

Conflict of interest The authors hereby declare that this article was not submitted or published elsewhere. potentially influence the objectivity or interpretation of the research findings. No conflict of interest.

Ethical approval This article does not contain any studies with human participants performed by any of the authors.

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