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EVALUATING CARBON AND ENERGY TAXATION PERFORMANCE IN BRICS-T COUNTRIES: AN INTEGRATED WENSLO–MCRAT APPROACH

BRICS-T Ülkelerinde Karbon ve Enerji Vergilendirme Performansının Değerlendirilmesi: Entegre Bir WENSLO–MCRAT Yaklaşım

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Abstract

As global climate mitigation efforts intensify, carbon taxation has become a crucial policy tool to curb emissions and enhance fiscal-environmental sustainability. This study assesses the carbon and energy taxation performance of BRICS-T countries (Brazil, Russia, India, China, South Africa, and Turkey) using an integrated multi-criteria decision-making (MCDM) model combining WENSLO (Weights by ENvelope and SLOpe) and MCRAT (Multiple Criteria Ranking by Alternative Trace). Five indicators—Net Effective Carbon Rates (NECR), Net Effective Energy Rates (NEER), Net Energy Tax Revenues and Reform Potential (NETRRP), Revenue Forgone with NECR (RF+NECR), and Shares of Emissions Priced (SEP)—were selected to capture both fiscal intensity and environmental scope. WENSLO was used to derive objective weights, while MCRAT provided performance rankings. Findings indicate South Africa leads in overall performance, followed by India and China, with Brazil and Russia trailing. Sensitivity analysis identifies NECR and SEP as the most influential indicators, significantly impacting rankings. Rank reversal analysis reveals that Turkey's relative position improves upon the removal of lower-performing countries. The study introduces a robust, data-driven framework for evaluating carbon taxation in emerging economies and offers strategic insights for enhancing climate-aligned fiscal policies.

Keywords: Carbon Taxation, WENSLO, MCRAT, BRICS-T, Environmental Taxation, Sensitivity Analysis.

JEL Codes: C61, H23, Q58

Öz

Küresel iklim değişikliğiyle mücadele çabalarının artmasıyla birlikte, karbon vergilendirmesi sera gazı emisyonlarını azaltmak ve mali-çevresel sürdürülebilirliği güçlendirmek adına önemli bir politika aracı hâline gelmiştir. Bu çalışma, BRICS-T ülkelerinin (Brezilya, Rusya, Hindistan, Çin, Güney Afrika ve Türkiye) karbon ve enerji vergilendirme performanslarını WENSLO (Weights by ENvelope and SLOpe) ve MCRAT (Multiple Criteria Ranking by Alternative Trace) yöntemlerinin bütünleştirildiği çok kriterli karar verme (ÇKKV) modeliyle değerlendirmektedir. Mali yoğunluk ve çevresel kapsamı yansıtan beş gösterge—Net Etkin Karbon Oranı (NECR), Net Etkin Enerji Oranı (NEER), Net Enerji Vergisi Gelirleri ve Reform Potansiyeli (NETRRP), Kayıp Gelir + NECR (RF+NECR) ve Fiyatlandırılan Emisyon Payı (SEP)—kullanılmıştır. WENSLO yöntemiyle nesnel ağırlıklar hesaplanmış, MCRAT ile ülkeler sıralanmıştır. Sonuçlara göre Güney Afrika en yüksek performansı gösterirken, onu Hindistan ve Çin izlemekte; Brezilya ve Rusya ise daha zayıf performans sergilemektedir. Duyarlılık analizi, NECR ve SEP kriterlerinin sıralamalar üzerindeki etkisinin yüksek olduğunu ortaya koyarken; sıra değişim analizi, düşük performanslı ülkelerin dışlanması durumunda Türkiye'nin göreli konumunun iyileştiğini göstermektedir. Bu çalışma, gelişmekte olan ekonomilerde karbon vergilendirme performansını nesnel ve veri temelli bir yaklaşımla değerlendiren özgün bir çerçeve sunmaktadır.

Anahtar Kelimeler: Karbon Vergilendirmesi, WENSLO, MCRAT, BRICS-T, Çevresel Vergilendirme, Duyarlılık Analizi

JEL Kodları: C61, H23, Q58

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1. Introduction

Various measures have been taken to reduce the negative environmental and economic impacts of global warming. The most important and first international step in this context was taken at the United Nations Conference on Environment and Development held in Rio de Janeiro in 1992 (Özsoy, 2022; Yolal, 2025). At the summit, two important agreements were adopted to reduce greenhouse gas emissions: the Kyoto Protocol and the Paris Agreement. The Paris Agreement was adopted as a legally binding agreement by 196 countries and entered into force in 201. The agreement included carbon taxation as a tool against climate change (Timilsina, 2022). Carbon taxes, one of the main tools of carbon pricing, were first implemented in the energy sector. This practice, which began in the 1990s in the Scandinavian countries and was later adopted by Switzerland in 2008, spread to developing countries such as South Africa, Mexico, Chile, and India in the 2010s (Khastar et al., 2020). In this context, the Pigouvian tax, a carbon tax, aims to reduce emissions by internalizing environmental externalities and promoting renewable energy (Meng and Yu, 2023). A well-designed carbon tax contributes to emission reductions and economic efficiency (Pomerleau and Asen, 2019) and provides a “double win” by reducing distortionary taxes (Fay et al., 2015). These early applications highlight the need to examine the policy objectives of carbon taxes and their cross-country variations.

Carbon taxes usually include the costs of CO_2 emissions; however, the goals of these levies can be different in different countries. These taxes mainly aim to cut down on greenhouse gas emissions, send signals to the market, and bring in money for the government (Sumner et al., 2011; Yolal, 2025). Their main strategies are to make tax changes that cut down on emissions while boosting growth, put money into low-carbon technologies, and help people who are hurt by high carbon costs. The four main ideas behind carbon taxes are: 1) the polluter pays, 2) prevention, 3) common but different responsibilities, and 4) fairness and appropriate punishment (United Nations, 2021). Carbon taxes are a significant method for generating revenue to tackle global emissions (Özbek, 2019). This situation has turned this subject into a major area of research. In this context, the current study aims to assess the effectiveness of carbon and energy taxation in BRICS-T economies, utilizing WENSLO and MCRAT for a comparative and data-driven policy analysis. However, despite these targets, quantitative evidence on the actual impact of carbon taxes is limited.

Despite increasing research on carbon taxation, most comparative studies use qualitative assessments or nominal tax rates. Therefore, we lack sufficient information about the effectiveness of carbon taxation for both the environment and the economy. Furthermore, modern research rarely uses objective weighting techniques to assess the importance of various criteria. To address these shortcomings, this study provides a comprehensive, data-based assessment of the effectiveness of energy and carbon pricing in BRICS-T economies through the integration of the WENSLO and MCRAT methodologies. It contributes to the academic literature by providing empirical data for practitioners and policymakers in developing economies seeking to establish carbon pricing frameworks. Therefore, our study combines objective weighting and multi-criteria evaluation methods to fill these gaps.

Two MCDM methods were used in this study: MCRAT (Multiple Criteria Ranking by Alternative Trace) and WENSLO (Weights by ENvelope and SLOpe). This study makes several significant contributions to the current body of research. The WENSLO-MCRAT model, which has never been used in this policy context before, offers a new and impartial way to measure how well carbon and energy levies work in the BRICS-T economies. Second, objective weighting (WENSLO) makes the evaluation of carbon policy more methodologically sound by removing any bias that might come from personal opinions about the value of criteria. Third, the study gives us a better idea of how well carbon taxes work by putting together economic and environmental data into a multi-criteria framework. A two-stage sensitivity analysis improves the reliability and robustness of the findings, making them more useful for policymakers looking for data-driven information about how to put the carbon price into effect.

2. Literature Review

Carbon dioxide, which accounts for approximately 80% of the world's ever-increasing greenhouse gas emissions, and the climate change it causes have become a significant problem. Carbon taxes, an important policy tool for reducing both the economic and environmental impacts of climate change, have gained considerable importance. The literature contains numerous studies supporting the critical functions of carbon taxes. Studies conducted in the ASEAN region by Solaymani (2017) and Yahoo and Othman (2017) have shown that well-structured, revenue-neutral carbon taxes can reduce emissions by limiting economic activity. This supports the idea of a "double win." Studies in Sweden and Indonesia (Shmelev and Speck, 2018) confirm the effectiveness of carbon taxes in reducing emissions. They are also influenced by macroeconomic influences, technological advances, and sectoral differences.

Empirical results from North America and Europe can be used to supplement the existing literature on carbon tax implementation. Çakmak (2018) found that British Columbia's carbon tax between 2008 and 2015 promoted both economic growth and emission reductions. Jin et al. (2018), using a Data Envelopment Analysis (DEA) model, showed that higher tax rates can promote environmentally friendly production processes. Fernando (2019) found a 52 tonne per capita reduction in CO2 emissions in the Nordic countries between 1990 and 2004. Sweden is a good example: Andersen (2019) discovered an 11% reduction in CO2 emissions from transportation between 1990 and 2005; Ercoşkun and Kovancılar (2023) also noted that channeling carbon tax revenues to environmental innovation provides both fiscal and ecological benefits. Martinsson et al. (2024) and Mideksa (2024) found that higher carbon tax rates and a shift to clean energy led to emissions reductions of up to 31% in Swedish manufacturing. Finland achieved the same reduction rate in 2005. Consistent with previous studies (Mideksa, 2024; Martinsson et al., 2024), Yolal (2025) emphasized the importance of optimal timing for the implementation of carbon taxes to prevent the erosion of competitiveness. These studies confirm that carbon taxes are effective in reducing emissions, but note that findings may vary depending on policy design, exemption strategies, and specific institutional frameworks.

In recent years, scholars have been examining the complex and multidimensional aspects of carbon taxes and climate policies using stakeholder-focused analytical frameworks and multi-criteria decision-making (MCDM) techniques. In a 2022 study, Chelly and colleagues evaluated different carbon tax scenarios, proposed four different multi-period technology selection models, and demonstrated that the timing of green investments depends more on targeted carbon prices than on the type of tax. Finally, Ratanakuakangwan and Morita (2022) integrated multiple evaluation criteria such as cost, emissions, social impacts, employment, and energy security in a sensitivity analysis-based model in Thailand and found that the most effective policies are those that prioritize environmental and social objectives rather than cost-driven approaches.

While the existing literature provides important insights into the environmental and economic impacts of carbon taxes, it suffers from several limitations. Many empirical studies are either confined to a single country context or rely on static econometric models to fully capture the multidimensional nature of the tax. Furthermore, research analyzing the relative importance of fiscal and environmental factors and applying objective weighting methods is quite limited. Another major problem is that there aren't many comparative assessments of rising economies, especially BRICS-T countries. This study seeks to rectify these deficiencies by amalgamating the WENSLO and MCRAT methodologies inside a data-driven framework. Aside from the new methods, the research's most important contribution is showing how an objective, multi-criteria assessment can lead to useful policy changes for developing countries. The analysis enhances the existing discourse regarding the formulation of a balanced carbon pricing system that reconciles environmental taxation, fiscal reform, economic growth, and decarbonization goals by pinpointing the structural and financial determinants that significantly impact tax performance.

3. Methodology

This research evaluates the efficacy of energy and carbon taxes in the BRICS-T economies through an MCDM technique. The WENSLO method was used to make sure that the assessment criteria weighing process was fair. This method only uses the inherent features and distributions of the data to set the criterion weights, not expert opinion or subjective inputs. After the goal weights were set, MCRAT was used to rank the countries depending on how well they did overall on the given criteria.

A two-stage sensitivity analysis was conducted to assess the robustness and reliability of the findings. The weights of each criterion were systematically varied in the first stage to assess the impact of changes in individual importance on the final rankings. In the second stage, rank reversal analysis was used to determine how well the model performed under different conditions where items were removed. This meant eliminating the worst-performing option and restarting the rankings.

The next section discusses the dataset and the initial decision matrix created for the study. The WENSLO and MCRAT techniques are also described in detail.

3.1. WENSLO Method

The basic methods used by the WENSLO method to calculate the criteria weights will be discussed in the next section (Pamucar et al., 2024).

Step 1. Construct the decision matrix.

$$[x_{ij}]_{m\times n} = \begin{bmatrix} A/C & C_1 & C_2 & \dots & C_n \\ A_1 & x_{11} & x_{12} & \dots & x_{1n} \\ A_2 & x_{21} & x_{22} & \dots & x_{2n} \\ \dots & \dots & \dots & \dots & \dots \\ A_m & x_{m1} & x_{m2} & \dots & x_{mn} \end{bmatrix} \quad (1)$$

where:

x_{ij} denotes the performance of the i. alternative concerning the j. criterion.

$A_1, A_2, \dots, A_m$ denotes an option vector space.

m denotes the number of options.

$C_1, C_2, \dots, Cn$ represents a vector space of criteria.

n denotes the quantity of criteria.

Step 2. The input data are normalized to obtain a dimensionless decision matrix. The following equation is used for linear normalization:

$$z_{ij} = \frac{x_{ij}}{\sum_{i=1}^{m} x_{ij}}, \forall j \in [1,2,\dots,n] \quad (2)$$

The normalized decision matrix is presented as follows:

$$Z(A,C) = \left[z_{ij}\right]_{m\times n} = \begin{bmatrix} A/C & C_1 & C_2 & \dots & C_n \\ A_1 & z_{11} & z_{12} & \dots & z_{1n} \\ A_2 & z_{21} & z_{22} & \dots & z_{2n} \\ \dots & \dots & \dots & \dots & \dots \\ A_m & z_{m1} & z_{m2} & \dots & z_{mn} \end{bmatrix} \quad (3)$$

In the normalized decision matrix Z, each element z_{ij} satisfies the condition $0 < z_{ij} < 1$.

Step 3. In this step, class intervals for each criterion are determined using Sturges' rule to support objective weight calculation.

$$\Delta z_j = \frac{\max_{1\le i\le m} z_{ij} - \min_{1\le i\le m} z_{ij}}{1 + 3.322 \times \log(m)}, \qquad \forall j \in [1,2,\dots,n] \quad (4)$$

Step 4. The slope of each criterion is calculated using the following equation:

$$\tan\varphi_j = \frac{\sum_{i=1}^{m} z_{ij}}{(m-1)\times \Delta z_j}, \qquad \forall j \in [1,2,\dots,n] \quad (5)$$

Step 5. The envelope of each criterion is determined by calculating the total Euclidean distance between its initial and final normalized values, as shown in Equation (6).

$$E_j = \sum_{i=1}^{m-1} \sqrt{\left(z_{i+1,j} - z_{ij}\right)^2 + \Delta z_j^2}, \qquad \forall j \in [1,2,\dots,n] \quad (6)$$

Step 6. In this step, the envelope–slope ratio is calculated by dividing the total Euclidean distance by the criterion slope, as defined in Equation (7).

$$q_j = \frac{E_j}{\tan\varphi_j}, \qquad \forall j \in [1,2,,\dots n] \quad (7)$$

Step 7. In this step, the final criterion weights are determined using the following equation.

$$w_j = \frac{q_j}{\sum_{i=1}^{n} q_j}, \qquad \forall j \in [1,2,\dots,n] \quad (8)$$

3.2. MCRAT Method

Urošević et al. (2021) introduced MCRAT, a new method for evaluating alternatives based on a matrix trace ranking system. It has many benefits, such as being clear, logical, applicable in many situations, and capable of handling stress. MCRAT is an MCDM method that compares options according to various criteria. It provides reliable, widely available, and proven results (Ulutaş et al., 2023). MCRAT facilitates the decision-making process by ranking options according to a number of variables. The recently developed MCRAT method has many advantages. The most important ones are that it is simple to use, has a logical structure, is well-supported, methodologically sound, and can be used in many different situations (Abdulaal and Bafail, 2022). The following illustrates how the method is implemented (Urošević et al., 2021):

Step 1. The decision matrix (B) is constructed using Equation (9).

$$B = \left[b_{ij}\right]_{m\times n} \tag{9}$$

Step 2. The decision matrix is normalized using Equations (10) for beneficial criteria and (11) for non-beneficial criteria.

$$b_{ij}^{*} = \frac{b_{ij}}{max\ (b_{ij})} \tag{10}$$

$$b_{ij}^{*} = \frac{min\ (b_{ij})}{b_{ij}} \tag{11}$$

Step 3. The weighted normalization values are calculated using Equation (12), and the weighted normalized matrix is presented in Equation (13).

$$v_{ij} = w_{jcomb} \times b_{j}^{*} \tag{12}$$

$$V = \left[v_{ij}\right]_{m\times n} \tag{13}$$

Step 4. The ideal alternative is identified using Equation (14).

$$y_j = max\left(v_{ij} \mid 1 \le j \le n\right) \tag{14}$$

The ideal alternatives are presented in the following set formulation:

$$Y = \left\{y_1, y_2, \dots, y_j\right\} \tag{15}$$

Step 5. This step involves dividing the ideal alternative into two subgroups using Equation (16), while Equation (17) defines the structure of the ideal alternative.

$$Y = \mathrm{Y}^{max} \cup Y^{min} \tag{16}$$

$$Y = \{y_1, y_2, \dots, y_k\} \cup \{y_1, y_2, \dots, y_h\}; k + h = j, \tag{17}$$

where k denotes the number of criteria, and $h = n - k$ represents the number of remaining alternatives.

Step 6. This step involves decomposing the remaining alternatives using Equations (18) and (19).

$$K = \mathrm{K}_{\mathrm{i}}^{max} \cup K_{\mathrm{i}}^{min} \tag{18}$$

$$K = \{k_1, k_2, \dots, k_{ik}\} \cup \{k_1, k_2, \dots, k_{ih}\} \tag{19}$$

Step 7. Equations (20) and (21) are employed to calculate each component of the magnitude of the ideal alternative.

$$Y_k = \sqrt{y_1^2 + y_2^2 + \cdots y_k^2} \tag{20}$$

$$Y_h = \sqrt{y_1^2 + y_2^2 + \cdots y_h^2} \tag{21}$$

The magnitude of each alternative is similarly calculated using the approach defined in Equations (22) and (23).

$$E_k = \sqrt{e_{i1}^2 + e_{i2}^2 + \cdots e_{ik}^2} \tag{22}$$

$$E_h = \sqrt{e_{i1}^2 + e_{i2}^2 + \cdots e_{ih}^2} \tag{23}$$

Step 8. Matrix T, which represents the components of the best possible alternative, is constructed using Equation (24).

$$T = \begin{bmatrix} Y_k & 0 \\ 0 & Y_h \end{bmatrix} \tag{24}$$

Step 9. Matrix S_i, representing the component of each alternative, is constructed using Equation (25).

$$S_i = \begin{bmatrix} E_{ik} & 0 \\ 0 & E_{ih} \end{bmatrix} \tag{25}$$

Step 10. Matrix ZiZ_iZi is formulated using Equation (26).

$$Z_i = T \times S_i = \begin{bmatrix} z_{11;i} & 0 \\ 0 & z_{22;i} \end{bmatrix} \tag{26}$$

Step 11. The trace of matrix Z_i is calculated using Equation (27).

$$tr(Z_i) = z_{11;i} + z_{22;i} \tag{27}$$

3.3. Dataset

This study evaluates the performance of the BRICS-T economies concerning energy and carbon taxes using a structured framework of five variables. We carefully picked these criteria to show how well fiscal environmental programs work and how well they cover all the bases. The dataset includes Priced Emission Shares (SEP), which show the full range of carbon pricing, including market-based methods; Forgotten Revenue and Net Effective Carbon Rates (RF + NECR), which indicate issues such as simultaneous taxation and subsidies; Net Effective Carbon Rates (NECR), which measure how effectively carbon taxation operates; and Net Effective Energy Rates (NEER), which capture the overall tax burden on energy products. The WENSLO-MCRAT study is based on these criteria, which are based on both economic and environmental importance. This lets us make objective comparisons between countries in many different ways. All of the data used in this study came from the "Taxes and Environment" component of the OECD Data Explorer portal (OECD, 2023). Table 1 shows the criteria and their properties.

Table 1. Overview of the Criteria

Code	Criteria	Unit	Max/Min	Year
C1	Net Effective Carbon Rates	Euros per tonne of CO2-equivalent	Max	2023
C2	Net Effective Energy Rates	Euros per gigajoule	Max	2023
C3	Net Energy Tax Revenues and Reform Potential	Total reform potential (Percentage of GDP)	Max	2023
C4	Revenue Forgone and Net Effective Carbon Rates	EUR 120 per tonne of CO2e benchmark	Min	2023
C5	Shares of Emissions Priced	Above EUR 0 per tonne of CO2e	Max	2023

Table 2 presents the initial decision matrix, which consists of the alternatives and their performance values with respect to each evaluation criterion.

Table 2. Rank Evolution of Alternatives Across Iterative Elimination Steps

Country	C1	C2	C3	C4	C5
Brazil	0.30	0.51	1.8	2.85	5.6
Russia	3.83	0.33	5.7	8.70	9.7
India	7.23	0.68	4.7	7.66	53.9
China	6.77	0.66	5.0	7.89	44.7
South Africa	13.78	1.36	6.3	10.34	34.9
Türkiye	7.57	0.75	2.1	3.46	31.4

Following the creation of the initial decision matrix, the weights of the criteria were determined using the WENSLO method. Then, the alternatives are ranked according to the MCRAT method. The next section presents the results of these methods and their related interpretations, respectively.

4. Analysis

The results of the integrated decision-making model that combines the MCRAT and WENSLO approaches are shown in this section. First, we go over the outcomes of using these techniques to evaluate the BRICS-T nations' performance in terms of energy and carbon taxes. The resilience and stability of the model outputs under various parameter settings and structural changes in the decision matrix are next evaluated using a two-stage sensitivity analysis.

4.1. Results of the Integrated WENSLO-MCRAT Model

The WENSLO approach was used to objectively ascertain each criterion's relative value in the evaluation process. Regardless of personal preferences, this method determines criteria weights by using the dataset's geometric and distributional properties. Specifically, the primary weighting element that reflected each criterion's sensitivity and discriminative capacity was the envelope-slope ratio. Table 3 displays the specific outcomes of the weight computation based on WENSLO.

Table 3. WENSLO-Based Results for Criterion Weight Determination

Criterion	Δz_j	Slope values	Envelope values	Envelope-slope ratio
C1	0.0974	2.0535	0.7478	0.3642
C2	0.0685	2.9202	0.5903	0.2021
C3	0.0501	3.9886	0.5184	0.1300
C4	0.0522	3.8286	0.5185	0.1354
C5	0.0765	2.6158	0.6013	0.2299

Figure 1 illustrates the normalized weights of the five evaluation criteria as determined by the WENSLO method. Among these, NECR emerges as the most influential criterion with a weight of 0.3431, indicating its dominant role in the overall assessment. This is followed by SEP (Shares of Emissions Priced) with a weight of 0.2165, and NEER (Net Effective Energy Rates) with 0.1904. The remaining two criteria, RF+NECR and NETRRP, have comparatively lower weights of 0.1276 and 0.1224, respectively. The distribution of weights suggests that carbon-specific fiscal measures (NECR) and comprehensive pricing mechanisms (SEP) are considered the most critical dimensions in evaluating carbon and energy taxation performance across the BRICS-T countries.

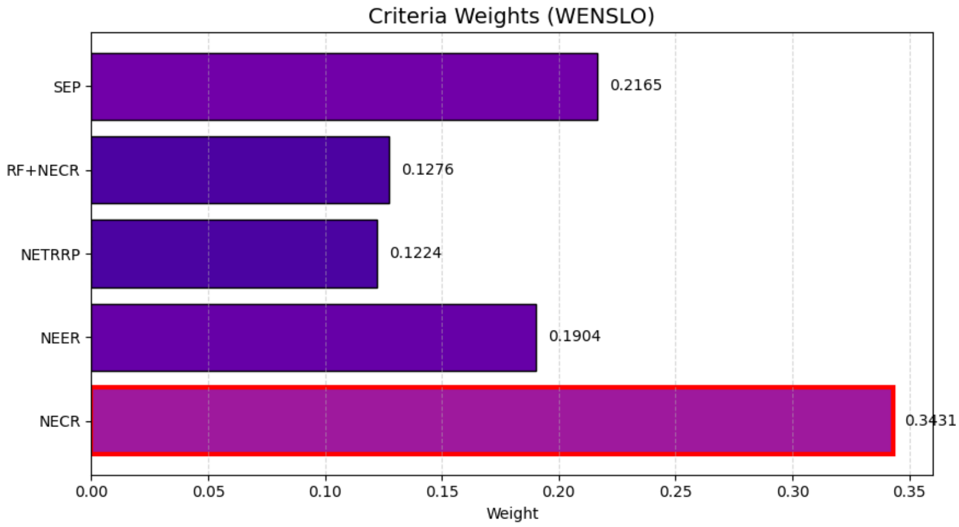

Figure 1. Final Criteria Weight Values

Following the determination of criterion weights using the WENSLO method, the MCRAT technique was employed to rank the BRICS-T countries based on their aggregated performance across all evaluation criteria.

Figure 2 presents the MCRAT scores for each country. As illustrated, South Africa ranks first with the highest composite score of 0.2062, indicating its relatively strong performance across the evaluated indicators. India follows with a score of 0.1505, slightly ahead of China (0.1362) and Turkey (0.1310). Russia and Brazil are positioned at the lower end of the ranking, with scores of 0.0788 and 0.0548, respectively. These results reflect notable disparities among the BRICS-T countries in terms of carbon and energy taxation performance, with South Africa emerging as the most robust performer in the current assessment framework.

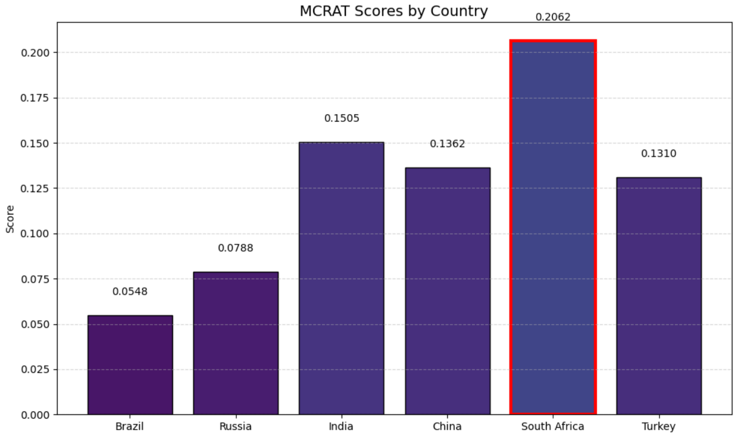

Figure 2. MCRAT-Based Performance Scores of BRICS-T Countries

4.2. Sensitivity Analysis

A comprehensive sensitivity analysis was carried out to evaluate the robustness of the final alternative rankings produced by MCRAT. In this analysis, the criterion weights initially calculated using WENSLO were systematically altered to observe how changes in individual criterion importance affect the overall decision outcome. Specifically, the weight of each criterion was incrementally varied from 0% to 100% in steps of 10%, while the remaining weights were proportionally adjusted to ensure the total weight sum remained normalized to 1. For each new weighting scenario, the MCRAT method was reapplied to the decision matrix to recalculate the scores and derive the updated rankings of all six alternatives. This process was repeated for all five criteria, resulting in a total of 330 unique ranking scenarios (11 weight levels × 5 criteria × 6 alternatives), allowing for a detailed examination of how sensitive each alternative's rank is to variations in the relative importance of the criteria, namely NECR, NEER, NETRRP, RF+NECR, and SEP. The results are visualized in Figure 3.

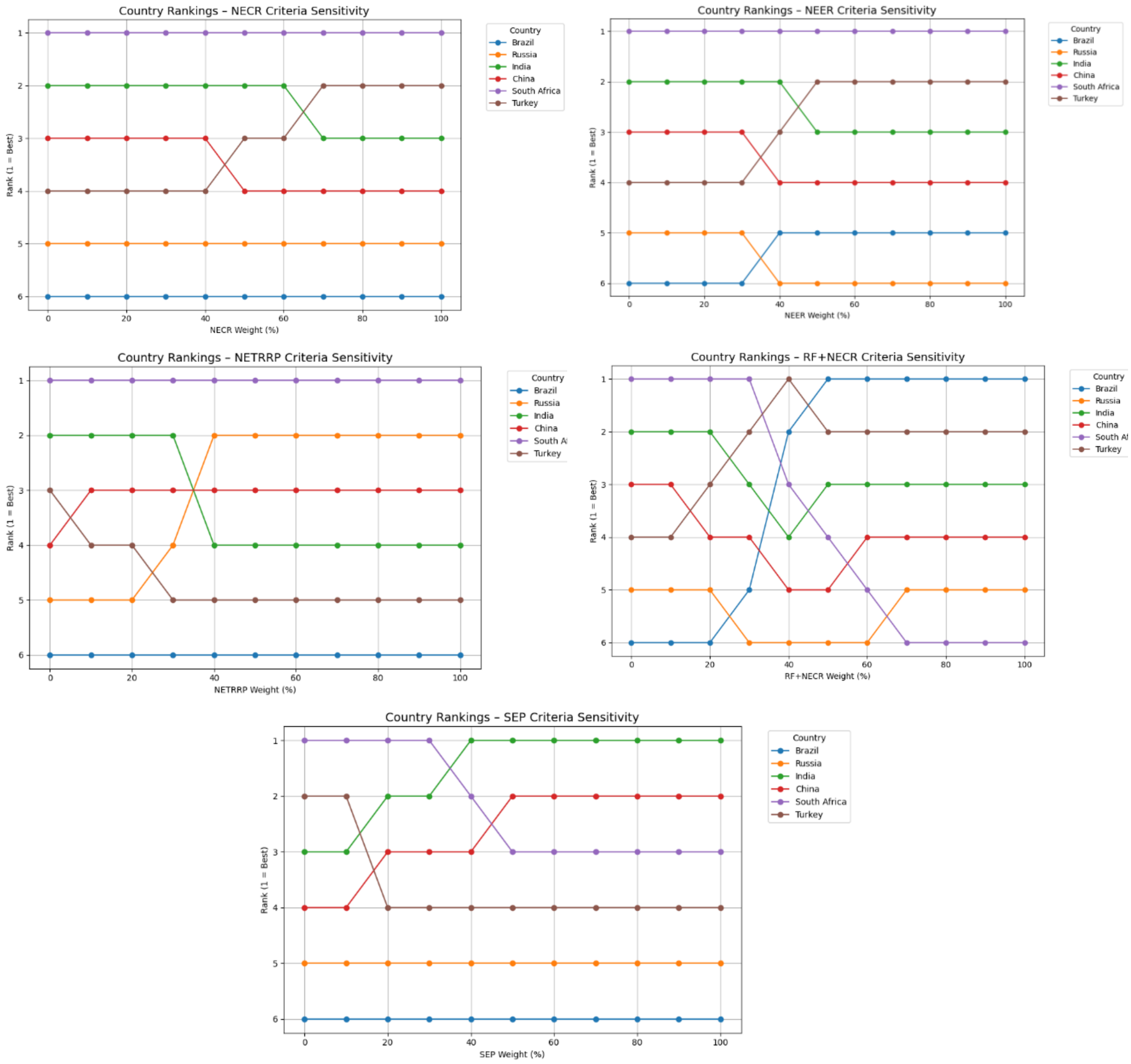

Figure 3. **Ranking Variability Under Systematic Weight Adjustments for Each Criterion**

The results indicate that the final rankings are highly sensitive to changes in the weights of certain criteria. In particular, NECR and SEP exhibit relatively high sensitivity, with significant fluctuations observed in the rankings of India, China, and South Africa. This highlights the strong influence of these two criteria on the overall evaluation. Similarly, NEER and RF+NECR show noticeable rank reversals, especially between China, India, and Turkey, reflecting how shifts in criterion importance can alter the relative positioning of these countries. In contrast, Brazil and Russia consistently maintain lower rankings across all weighting scenarios, indicating that their performance is comparatively weak and less responsive to individual criterion changes.

As a second stage of the sensitivity analysis, a rank reversal analysis was performed to evaluate the robustness and stability of the decision-making model, based on the initial rankings obtained through the MCRAT method and the criterion weights derived from the WENSLO technique.

In this analysis, the process began with all six alternatives (Brazil, Russia, India, China, South Africa, and Turkey). At each iteration, the alternative with the lowest performance score (i.e., the lowest MCRAT score) was systematically eliminated from the decision matrix. The WENSLO method was then reapplied to the reduced matrix to recalculate the criterion weights for the remaining alternatives, thereby simulating the impact of alternative removal on the weighting scheme. Subsequently, MCRAT was applied again using the updated weights to produce new scores and ranks.

This iterative elimination continued until only two alternatives remained. At each step, the performance scores and ranks of the remaining countries were recorded, allowing for a detailed examination of how the ranking of alternatives changed dynamically as weaker options were excluded. The results are presented in Table 4.

Table 4. Rank Evolution of Alternatives Across Iterative Elimination Steps

Country	Step 1		Step 2		Step 3		Step 4	
	Rank	Score	Rank	Score	Rank	Score	Rank	Score
Brazil	–	–	–	–	–	–	–	–
Russia	5	0.074092	–	–	–	–	–	–
India	2	0.149784	3	0.128222	3	0.133432	–	–
China	3	0.134884	4	0.127802	–	–	–	–
South Africa	1	0.196155	1	0.181371	1	0.174667	1	0.217114
Turkey	4	0.128623	2	0.140011	2	0.143934	2	0.203285

The results in Table 4 show how the rankings of the remaining countries change during the rank reversal analysis, which is performed by successively eliminating the lowest performing alternatives. In Step 0, Brazil was eliminated as it had the lowest performance score, followed by Russia as the second weakest alternative. From Step 1 onwards, five countries remained, and their rankings were recalculated at each iteration using updated WENSLO weights and MCRAT scoring.

South Africa has performed strongly and consistently in every situation during the elimination process, maintaining its top ranking and even raising its score in the final phase. By going from fourth in Step 1 to second in Step 4, Turkey demonstrates a notable improvement, suggesting that when poorer options are removed, its relative performance improves. China's performance, on the other hand, suffered, going from third in Step 1 to elimination in Step 3. India ranked second and third across the steps, maintaining a competitive but rather erratic performance.

According to the ranking development, South Africa performs the best overall under the iterative elimination approach, whereas Turkey does better under the reduced scenarios but looks pretty bad with the entire set. The stability and sensitivity of nation rankings based on alternative composition are better understood thanks to this dynamic approach.

The findings are also displayed in Figure 4, along with the corresponding heatmap visualization and the ranking progress through the elimination phases. A crucial component in confirming the stability and equity of the multi-criteria decision-making model was the explicit identification of alternatives whose rankings are affected by the existence or lack of other possibilities.

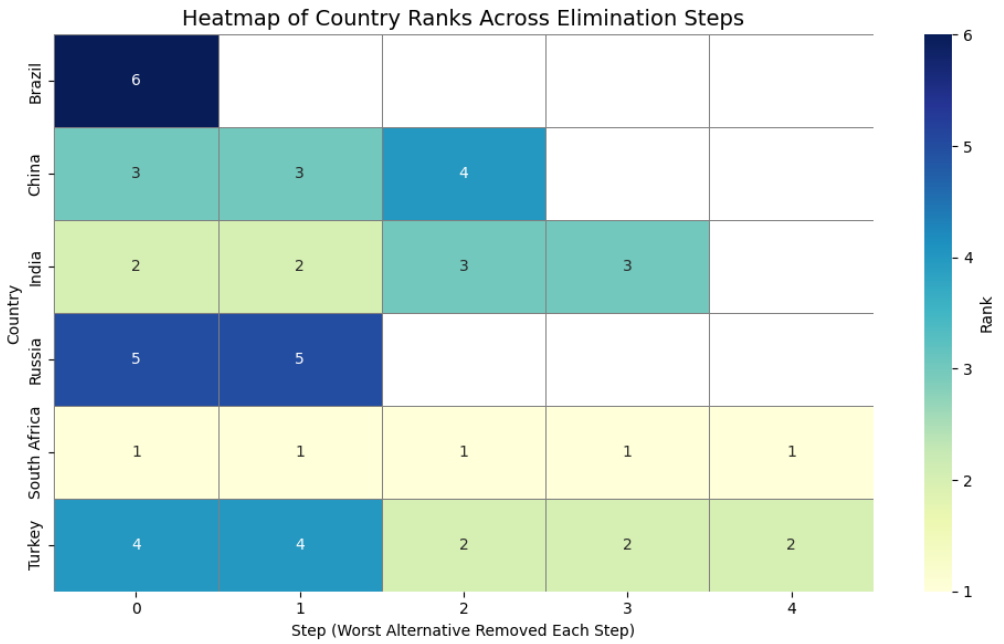

Figure 4. Ranking Variability Under Systematic Weight Adjustments for Each Criterion

5. Discussion

This study evaluates the BRICS-T nations' performance in terms of energy and carbon taxes using an integrated WENSLO-MCRAT multi-criteria decision-making framework. The WENSLO technique, which finds that SEP and Net Effective Carbon Ratios (NECR) are the most important criteria, was used to first determine the objective criteria weights. The MCRAT investigation found that Brazil and Russia had the lowest overall performance scores. South Africa usually had the greatest scores, followed by India. A comprehensive sensitivity analysis validated the rankings, underscoring the vulnerability of India, China, and Turkey to variations in the relative importance of various categories. The second-stage rank reversal study also proved that the model was stable. This showed that Turkey did much better as worse options were taken away, while South Africa stayed at the top of the rankings through all of the elimination rounds. These results show both the good and bad sides of the BRICS-T economies. They also show how useful and reliable the suggested way of making decisions is for looking at complicated policy areas like carbon taxes.

This study highlights the importance of the work by using a WENSLO-based analysis to prove the weights and examine the carbon taxation methods applied in the BRICS-T economies by NECR. NECR, which shows the actual cost of CO_2 emissions through both carbon taxes and emissions trading indicators, is a good option for policy measurement because it is a composite indicator. In a study by Boute (2024), it was stated that NECR is necessary for evaluating whether policies adopted by third countries are compatible with the climate targets set by the EU and, in particular, with practical tools such as the Carbon Border Adjustment Mechanism (CBAM). This situation has demonstrated that it is crucial to re-evaluate both climate governance and global trade rules, as well as national policies. Vesala (2023) noted that the historical development of NECR has gradually given it more leverage in reducing carbon emissions in Finland. The study found that countries with stricter carbon pricing strategies performed better in carbon price assessments. Countries that performed well under high NECR conditions were India and South Africa in particular.

Sensitivity analysis results indicate that PKP and NECR have an impact on the rankings of South Africa, China, and India. This shows that performance rankings can change significantly when policymakers assign different weights to the components that influence them. Therefore, countries with medium-level performance may be stronger or weaker depending on the evaluation framework, and priority should be given to policy formulation.

Reversing the ranking in the study has helped to obtain more information about the structure of the decision model. This situation revealed how Turkey's ranking concealed comparisons with countries performing poorly and improved after weak preferences were removed. This demonstrated that using more than simple rankings affects the context and competitiveness assessment results and is quite essential.

From a policy perspective, the WENSLO-MCRAT model examined in this study is recognized as providing a solid foundation for the fair and impartial evaluation of carbon taxation solutions. The analysis used in this study has served as a guide for countries in developing carbon pricing strategies based on weight distributions and comparative effectiveness. Countries such as Turkey and India, in particular, can achieve successful performance by using and further developing their fiscal instruments using robust criteria such as PKP and NECR.

Comparing the progress of South Africa, India, and Turkey in establishing clear rules for developing country economies offers essential insights. South Africa's continued leadership demonstrates that successfully integrated carbon pricing can provide various environmental and financial benefits to other countries and serve as a model for them. India's performance is generally strong but has a fragile structure. This situation demonstrates that it will contribute both to the stability of policies aimed at providing more incentives within the scope of renewable energy and to increasing effective carbon rates. Turkey's gradual recovery is ensuring greater clarity in emissions-based tax structures, making fiscal and climate goals more aligned. Countries that are not performing well in this regard need to improve their effective carbon rates and broaden their tax base. The experience of all BRICS-T countries shows that consistent, transparent, and flexible carbon tax regimes are crucial for establishing long-term economic and environmental policies.

6. Conclusion and Suggestions for Future Research

The aim of this study was to evaluate the effectiveness of energy and carbon taxation in BRICS-T countries using a hybrid multi-criteria decision-making framework combining the WENSLO and MCRAT methodologies. The WENSLO method was used to weight objective criteria, and countries were ranked based on their performance across five different criteria. The analysis revealed that the economies of BRICS-T countries are very different. India and China outperformed South Africa, while Brazil and Russia performed the worst. These results were confirmed through sensitivity analysis and ranking reversal assessments. Furthermore, the NECR and SEP components were shown to have a significant impact on the final rankings.

From a policy point of view, the results clearly show that we need unified, clear, and complete carbon pricing systems. South Africa's great performance shows how important it is to work together on energy and fiscal reforms. India's results are less impressive but still good, which shows how important it is to set good carbon rates and improve policy coordination. Türkiye's changing circumstances show how much can be gained from targeted fiscal restructuring and more specialized emissions-based tax systems. Brazil and Russia could do better, though, if they broadened the tax base, improved institutional processes, and made fiscal tools more in line with environmental goals.

These findings suggest that the effectiveness of carbon taxation depends not only on tax rates but also on the policies, governance framework, and institutional context in which it is implemented. The study demonstrates that data-driven, multi-criteria frameworks such as WENSLO-MCRAT can assist developing nations aiming for low-carbon expansion by effectively linking empirical assessments to policy formulation.

This study has some problems, even though the WENSLO–MCRAT framework is strong. To begin with, the analysis is based on static, cross-sectional data, which means that these data can't show how the effectiveness of a policy changes over time or when the economy changes. Second, even though the criteria for the evaluation were based on research and relevance, they don't cover everything that needs to be looked at to see how well the carbon price works. For example, important factors like how easy it is to implement, how likely it is to get political support, or how well institutions can handle it are not looked at closely enough. The model also assumes that policymakers in each country are fair and consistent. However, this assumption may not always be true in real life, especially in developing countries where the government is not always working well together. Finally, the WENSLO method provides an impartial means of distributing weight; however, its lack of expert involvement may result in the exclusion of significant nuances that a hybrid approach could offer.

Subsequent research may expand the scope of this study by incorporating dynamic variables, including the progression of the carbon market, the structure of subsidy systems, and technological readiness into the analysis. Longitudinal studies evaluating the effectiveness of carbon pricing over time could significantly enhance the literature by providing in-depth insights into the consequences of policy. Moreover, integrating qualitative indicators such as institutional capacity, public acceptance, and governance quality into the analytical framework could enhance the methodological rigor of the study and support the development of more comprehensive and effective policy recommendations.

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