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ANALYSIS OF FOREST CONSERVATION PERFORMANCE OF MAJOR FORESTED COUNTRIES: AN APPLICATION USING TOPSIS AND WASPAS

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ABSTRACT: Countries hosting extensive forest areas, particularly those encompassing a significant proportion of the world's forests, play a critical role in global biodiversity, environmental stability, and economic systems. Within this framework, the forest conservation performance of nine nations—Russia, Brazil, Canada, the USA, China, the Democratic Republic of Congo (DRC), Indonesia, India, and Peru—representing 65% of global forest cover, was evaluated using the 2024 Forest Environmental Performance Index (EPI-F) criteria through the WASPAS (Weighted Aggregated Sum Product Assessment) and TOPSIS (Technique for Order of Preference by Similarity to Ideal Solution) methodologies. Results indicated that rankings derived from WASPAS and TOPSIS diverged only for China and India. Furthermore, average forest conservation performance scores were computed using both approaches. According to WASPAS, India, China, and Peru exceeded the average, whereas TOPSIS identified India, China, Peru, and Indonesia as above-average performers. Consequently, a joint evaluation of both methods suggests that Russia, Brazil, Canada, the USA, the DRC, and Indonesia, whose forest conservation performances fall below the average, should reinforce their conservation policies to more effectively support global environmental integrity, biodiversity preservation, and economic sustainability. Moreover, sensitivity and comparative analyses confirmed the suitability of WASPAS and TOPSIS within the EPI-F framework for assessing these countries' forest conservation performance. Regarding limitations, the study exclusively employed data from 2024. Future research may benefit from longitudinal analyses spanning multiple years and incorporating additional multi-criteria decision-making (MCDM) techniques to broaden the methodological comparison.

Keywords: MCDM, WASPAS, TOPSIS, environmental performance index, forest conservation performance.

BAŞLICA ORMAN VARLIĞINA SAHIP ÜLKELERIN ORMAN KORUMA PERFORMANSININ ANALIZI: TOPSIS VE WASPAS YÖNTEMLERİYLE BİR DEĞERLENDİRME

ÖZET: Dünyadaki ormanların önemli bir bölümüne ev sahipliği yapan geniş orman alanlarına sahip ülkeler, küresel biyolojik çeşitliliğin korunması, çevresel denge ve ekonomik sistemler üzerinde belirleyici bir role sahiptir. Bu bağlamda, dünya ormanlarının %65'ini barındıran dokuz ülkenin—Rusya, Brezilya, Kanada, ABD, Çin, Kongo Demokratik Cumhuriyeti (KDC), Endonezya, Hindistan ve Peru—orman koruma performansları, 2024 yılı Orman Çevresel Performans Endeksi (EPI-F) kriterleri doğrultusunda, WASPAS (Ağırlıklı Toplam Çarpım Değerlendirme Yöntemi) ve TOPSIS (İdeal Çözüme Benzerliğe Göre Tercih Sıralaması Tekniği) çok kriterli karar verme yöntemleri kullanılarak değerlendirilmiştir. Bulgular, WASPAS ve TOPSIS yöntemlerinden elde edilen sıralamaların yalnızca Çin ve Hindistan açısından farklılık gösterdiğini ortaya koymuştur. Ayrıca, her iki yöntemle ülkelerin ortalama orman koruma performans değerleri hesaplanmıştır. WASPAS yöntemine göre Hindistan, Çin ve Peru ortalamanın üzerinde performans sergilerken; TOPSIS yöntemi Hindistan, Çin, Peru ve Endonezya'yı ortalamanın üzerinde değerlendirmiştir. Dolayısıyla, her iki yöntemin ortak değerlendirilmesi sonucunda, Rusya, Brezilya, Kanada, ABD, KDC ve Endonezya gibi ülkelerin orman koruma performanslarının ortalamanın altında kaldığı ve bu ülkelerin küresel çevre sağlığı, biyolojik çeşitlilik ve ekonomik sürdürülebilirliğe daha etkin katkı sağlayabilmeleri için orman koruma politikalarını güçlendirmeleri gerektiği sonucuna ulaşılmıştır. Ayrıca yapılan duyarlılık ve karşılaştırmalı analizler, WASPAS ve TOPSIS yöntemlerinin EPI-F çerçevesinde bu ülkelerin orman performanslarının değerlendirilmesinde uygun ve geçerli araçlar olduğunu ortaya koymuştur. Çalışmanın sınırlılıkları bağlamında, yalnızca 2024 yılına ait veriler kullanılmıştır. Gelecek araştırmalarda, çok yıllı verilerin dikkate alındığı daha kapsamlı analizlerin yapılması ve ilave çok kriterli karar verme (ÇKKV) yöntemlerinin dahil edilmesi, yöntemsel karşılaştırmaların genişletilmesine olanak sağlayabilir.

Anahtar Kelimeler: ÇKKV, WASPAS, TOPSIS, çevresel performans endeksi, orman koruma performansı.

INTRODUCTION

Forests are a critical component of ecosystem sustainability and play a vital role in preserving global environmental health (Dimitrakopoulos & Jones, 2021). Due to their contribution as carbon sinks in combating climate change and their crucial role in conserving biodiversity, the sustainable management of forests has gained increasing importance worldwide (FAO, 2024). Additionally, forests provide a range of ecosystem services, such as regulating the water cycle, preventing soil erosion, and supporting the livelihoods of local communities (Dåsnes, 2024). However, recent increases in deforestation rates, forest degradation, and biodiversity losses have underscored the need for more effective policies in forest management and conservation (Sarmiento et al., 2024).

Forest conservation performance refers to the extent to which forest ecosystems are preserved and maintained against anthropogenic threats, including deforestation, degradation, and habitat fragmentation (Babur et al. 2021). This concept is multidimensional and has been approached from various disciplinary perspectives in the scientific literature From an ecological standpoint, forest conservation performance reflects the ability to sustain native forest cover, preserve biodiversity, and maintain the ecological processes essential for ecosystem functionality (Lindenmayer & Laurance, 2016).

In particular, it encompasses actions and outcomes related to protecting primary forests and the ecological integrity of forest landscapes, the ability to maintain natural forest cover, protect habitats, and sustain ecosystem services (Matos et al., 2019). In terms of environmental governance, the term also denotes the effectiveness of institutional mechanisms, policy enforcement, and legal frameworks in curbing illegal logging, land-use change, and other anthropogenic pressures on forests (Kissinger et al., 2012). Geospatial indicators and remote sensing data have become increasingly important in quantifying such dimensions. Furthermore, within the framework of the Sustainable Development Goals (SDGs), forest conservation is explicitly addressed under Goal 15: “Life on Land”, which emphasizes the protection, restoration, and sustainable use of terrestrial ecosystems, particularly forests (United Nations, 2015). Performance in this area is thus essential to broader sustainability targets.

The sustainable management of forests is directly related not only to local or national environmental policies but also to global issues such as climate change, environmental justice, and sustainable development goals (Binsaeed et al., 2024). This is because the ongoing rapid deforestation increases carbon emissions, threatens water resources, and endangers biodiversity (Kalicka-Mikołajczyk, 2019). In this context, assessing and comparing countries' forest conservation performance can be seen as a critical step in combating deforestation and evaluating the effectiveness of sustainable forest management practices (FSC, 2024). Additionally, numerous studies in the literature have observed that forest conservation within the scope of sustainable development positively contributes to economic growth through forest products (Hao et al., 2019). In this regard, countries need to be aware of their forest protection performance and develop forest and environmental policies accordingly. To achieve this, there is a need for metrics that measure the forest protection performance of countries (Varzaru & Bocean, 2023).

The only quantitative measure of countries' forest conservation performance is the EPI-Forest (EPI-F) index, evaluated under the Environmental Performance Index (EPI). For the year 2023, this index assessed the forest conservation performance of 180 countries. The EPI-F index outlines performance criteria and their respective weight coefficients as follows: Primary Forest Loss (0.3), Intact Forest Landscape Loss (0.3), Tree Cover Loss Weighted by Permanency (0.25), Net Change in Tree Cover (0.1), and Forest Landscape Integrity (0.05). Moreover, the aforementioned index presents a comprehensive analysis of overall forest conservation performance rather than focusing on regional forest performance within countries (Block et al., 2024).

Consequently, studies on measuring countries' forest conservation performance appear to be highly limited in the literature. Various methodologies have thus been developed to evaluate forest conservation performance, typically focusing on forest and biodiversity protection (Bellamy et al., 2024), reforestation efforts (Bautista et al., 2024), and deforestation rates (Móstiga et al., 2024).

Methodologically, WASPAS (Weighted Aggregated Sum Product Assessment) provides more accurate rankings of alternatives than many other Multi-criteria decision-making (MCDM) methods (Demir et al., 2021). This is because the method allows for sensitivity analysis within itself, enabling verification of the ranking consistency of alternatives (Ecer, 2020). Furthermore, the WASPAS method yields highly reliable results in ranking decision alternatives, as it reflects a combination of the SAW (Simple Additive Weighting) and WPM (Weighted Product Method) techniques (Ayçin, 2019).

TOPSIS (Technique for Order Preference by Similarity to Ideal Solution), on the other hand, is a highly user-friendly technique due to its straightforward application and ease of interpreting results (Yıldırım, 2021). The method is based on logical reasoning, identifying the option closest to the positive ideal solution and furthest from the negative ideal solution as the most suitable outcome (Dinçer, 2019). Moreover, the method can be seamlessly integrated into the process of criteria weighting (Uludağ & Doğan, 2021). Additionally, TOPSIS offers a more comprehensive comparison than many other MCDM methods (Aktaş et al., 2015). Therefore, due to the advantages of these methods, the WASPAS and TOPSIS methods have been preferred for measuring the forest conservation performance of countries.

In this study, the forest conservation performance of nine countries (Russia, Brazil, Canada, USA, China, Democratic Republic of Congo-DRC, Indonesia, India, and Peru), covering 65% of the world's forests, was measured using the WASPAS and TOPSIS MCDM methods. Therefore, assessing the forest conservation performance of these countries is essential, as it has significant implications for global ecology and biodiversity (Rao, 2024). Furthermore, given these countries' vast forest resources, their forest conservation efforts likely to effect global economy, especially considering the relationship between forest conservation and economic growth. The primary motivation of this research is to identify which countries need to enhance their forest conservation efforts to contribute more substantially to global ecology, biodiversity, and the global economy. The secondary motivation is to examine whether the forest conservation performance of countries can be measured within the EPI-F framework using the WASPAS and TOPSIS methods. In other words, the measurability of countries' forest conservation performance based on their EPI-F criterion values will be assessed through sensitivity and comparative analyses.

This research, therefore, provides a valuable contribution to global environmental management and sustainability policies, as analyzing the forest conservation performance of the world's largest forest-holding countries using MCDM (WASPAS and TOPSIS) methods may enable policymakers to assess environmental conservation strategies on a more concrete and comparable basis. Additionally, establishing a comprehensive framework for assessing forest conservation performance through MCDM methods can serve as a guide in areas such as resource management, biodiversity, and combating climate change.

A comprehensive review of the literature on forest conservation performance reveals that, except for Block et al. (2024), there is a lack of studies employing quantitative indicators, numerical analysis, or mathematical approaches to evaluate countries' forest protection performance. In this context, the present study contributes not only to the forestry literature by addressing forest performance as a measurable concept, but also to the field of multi-criteria decision-making (MCDM) by applying robust decision-making methodologies. The originality of this research lies in its pioneering role as the first known study in the literature to assess the forest protection performance of countries through MCDM techniques. Accordingly, the methodology section of the research explains the data set, data analysis, and the WASPAS and TOPSIS methods. The discussion and conclusion section provides interpretations based on quantitative findings.

MATERIAL AND METHOD

Data Set and Data Analysis

The data obtained in this study are based on the most recent and updated 2024 values of the five criteria that comprise the EPI-F for each country. For convenience, abbreviations for these criteria are provided in Table 1. Furthermore, The geographical positions of the nine countries included in the study are presented in Figure 1

Table 1. Abbreviations of EPI-F Criteria

Criteria	Abbreviation
Primary Forest Loss (Benefit Criteria)	F1
Intact Forest Landscape Loss (Benefit Criteria)	F2
Tree cover loss weighted by permanency (Benefit Criteria)	F3
Net change in tree cover (Benefit Criteria)	F4
Forest Landscape Integrity (Benefit Criteria)	F5

Reference: Block et al., 2024

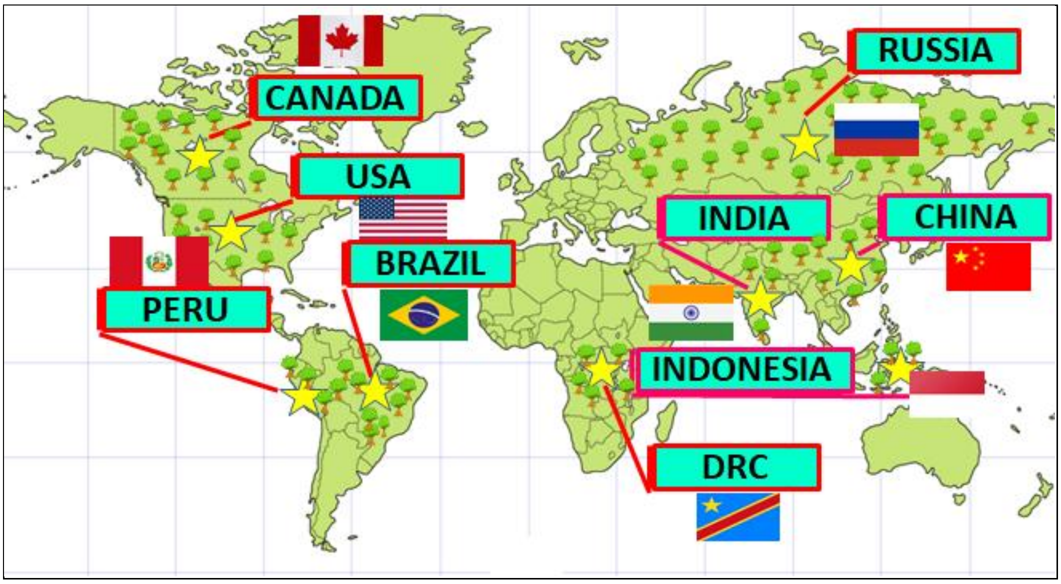

Figure 1. The Countries Included In The Study

The EPI-F criteria presented in Table 1 are elaborated below (Block et al., 2024).

Primary forest loss: Primary forest loss refers to the irreversible degradation of natural forest ecosystems that have remained largely intact and minimally affected by human activities. This indicator holds critical significance in monitoring the disappearance of carbon-dense tropical forests and assessing global progress in combating climate change.

Intact forest landscape loss: Intact forest landscape loss refers to the fragmentation, structural disruption, or irreversible degradation of large-scale forested ecosystems that have largely preserved their ecological functionality, natural composition, and habitat integrity. Ecological functionality refers to the capacity of an ecosystem to maintain its natural processes, components, and dynamics. This term encompasses an ecosystem's ability to conserve biodiversity, facilitate energy flow, sustain nutrient cycles, and provide ecosystem services. Natural composition, on the other hand, refers to the distinctive distribution and proportions of the natural components (plants, animals, microorganisms, soil, water, etc.) within an ecosystem or habitat at a given point in time. Habitat integrity denotes the state of a habitat in which its natural structure, functions, and components remain intact and undisturbed. In other words, if the ecological processes (e.g., nutrient cycling, energy flow, species interactions), biodiversity, and physical structure of a habitat are preserved in their natural state, then habitat integrity is maintained. Therefore, since forest conservation also signifies the preservation of the broader ecosystem, activities aimed at ensuring healthy forests are of critical importance. These landscapes, minimally impacted by human activity, represent some of the most vital biomes for maintaining planetary ecological stability.

Tree cover loss weighted by permanency: Tree cover loss weighted by permanency is a comprehensive environmental indicator that captures not only the quantitative extent of deforestation within a given geographic area but also the ecological significance of such loss based on its nature and long-term permanence. This metric distinguishes between temporary, potentially reversible disturbances and permanent deforestation, thereby providing a more accurate reflection of the enduring consequences of environmental degradation.

The net change in tree cover: The net change in tree cover represents a comprehensive indicator based on the balance between total gains and losses in forested areas over a defined time period. This metric not only captures trends in deforestation but also enables a quantitative assessment of the environmental impacts of reforestation and natural regeneration processes. As such, it provides critical insight into broader land-use dynamics and serves as a robust proxy for evaluating ecosystem resilience, carbon sequestration potential, and the effectiveness of national forest governance and environmental sustainability policies.

Forest landscape integrity: Forest landscape integrity is a comprehensive, spatially explicit indicator that reflects the extent to which forest ecosystems are affected by anthropogenic disturbances. This concept serves as a critical parameter in evaluating the structural continuity of forested areas, the preservation of biodiversity, the connectivity of habitats, and the sustainability of ecosystem services. Within the framework of the Environmental Performance Index 2024, forest landscape integrity not only captures the physical intactness of forest environments but also provides essential insights into the ecological resilience of landscapes and the effectiveness of national forest conservation strategies. As such, it plays a pivotal role in assessing long-term environmental stability and guiding evidence-based policy interventions for sustainable land management.

WASPAS Method

WASPAS is a method provided by combining the SAW and WPM techniques (Chakraborty, et al., 2015). In this method, the combined optimality coefficient and total relative importance quantity are calculated. The total relative importance value explains the performance of decision alternatives or the preferred alternative in decision problems (Demir et al., 2021).

In addition, a review of the literature reveals that the WASPAS method has been widely utilized in measuring the performance of decision alternatives and in solving selection problems (Ecer, 2020). Within this context, Kökyıldırım and Atmen (2024) conducted an assessment of the financial capacity of electric power enterprises. Ramadani et al. (2024) performed an analysis of the head of an academic program. Arisantoso et al. (2023) carried out studies on webcam selection. Handayani et al. (2023) conducted evaluations regarding the selection of English courses. Ghadai et al. (2024) analyzed the end milling process for machining Al 1070 alloy. Dağıstanlı and Kurtay (2024) focused on facility location evaluation. Lastly, Brodny et al. (2024) investigated the determination of quality of life in cities.

The application steps of the WASPAS method are explained below (Ayçin, 2019).

m: Number of decision alternatives ($j = 1,2, \dots \dots, m$).
n: Number of criteria ($j = 1,2, \dots \dots, n$).
x_{ij}: The value of the $i-th$ alternative according to the $j-th$ evaluation criterion ($j = 1,2, \dots \dots, n$).
x_{ij}^{*}: The normalized value of the $i-th$ alternative according to the $j-th$ evaluation criterion ($j = 1,2, \dots \dots, n$).
w_j: Weight of the $j-th$ criterion *(j=1,2,……,n).*
C: Criteria

Step 1: Obtaining Decision Matrix (X)

In this step, the decision matrix (X) is constructed. The decision matrix contains the values assigned to each alternative (e.g., countries) based on each criterion (e.g., forest conservation performance criteria). Eqs. (1).

$$X = \begin{bmatrix} C_1 & C_2 & \dots & C_m \\ x_{11} & x_{12} & & x_{1n} \\ x_{21} & x_{22} & \cdots & x_{2n} \\ \vdots & \vdots & \vdots & \vdots \\ x_{m1} & x_{m2} & \cdots & x_{mn} \end{bmatrix} \tag{1}$$

Step 2: Normalisation of Decision Matrix (x_{ij}^{*})

In this step, the decision matrix values are normalized to a range between 0 and 1 based on benefit and cost-oriented criteria.

For benefit-oriented criteria: Eqs. (2).

$$x_{ij}^{*} = \frac{x_{ij}}{\max(x_{ij})} \quad i = 1,2, \dots m; \; j = 1,2, \dots . n \tag{2}$$

For cost-oriented criteria: Eqs. (3).

$$x_{ij}^{*} = \frac{\min(x_{ij})}{x_{ij}} \quad i = 1,2, \dots m; \; j = 1,2, \dots . n \tag{3}$$

Step 3: Calculation of the Total Relative Importance of Alternative i According to the Weighted Sum Method (WSM) ($Q_i^{(1)}$)

In this step, the total relative importance of each alternative i is calculated using the Weighted Sum Method (WSM). This method involves multiplying the normalized values of each criterion by their respective weights and then summing these weighted values. The resulting $Q_i^{(1)}$ value represents the overall performance score of alternative i based on the WSM approach. Eqs. (4).

$$Q_i^{(1)} = \sum_{j=1}^{n} x_{ij}^{*} \, . \, w_j \tag{4}$$

Step 4: Calculation of the Total Relative Importance of Alternative i According to the Weighted Product Method (WPM) ($Q_i^{(2)}$)

In this step, the total relative importance of each alternative i is calculated using the Weighted Product Method (WPM). In this method, the normalized values of each criterion are raised to the power of their respective weights and then multiplied. The resulting $Q_i^{(2)}$ alue represents the overall performance score of alternative i based on the multiplicative aggregation of weighted criteria. Eqs. (5).

$$Q_i^{(2)} = \prod_{j=1}^{n} (x_{ij}^{*})^{w_j} \tag{5}$$

Step 5: Calculation of the Weighted Aggregate General Criterion Value for WSM and WPM Models (Q_i)

In this step, the weighted aggregate general criterion value $Q_i$for the WSM and WPM models is calculated. This value is obtained by combining the performance scores derived from both the Weighted Sum Method $Q_i^{(1)}$ and the Weighted Product Method $Q_i^{(2)}$. The aggregation is performed using a predefined weighting factor (0.5) allowing for a balanced evaluation that integrates both additive and multiplicative perspectives. The resulting Q_i value provides the overall assessment score for each alternative. Eqs. (6).

$$Q_i = 0{,}5. Q_i^{(1)} + 0{,}5. Q_i^{(2)} = 0{,}5. \sum_{j=1}^{n} x_{ij}^{*} \, . w_j + 0{,}5. \prod_{j=1}^{n} (x_{ij}^{*})^{w_j} \tag{6}$$

Step 6: Calculation of the Relative Importance Value of Decision Alternatives (Q_i). Eqs. (7).

$$Q_i = \boldsymbol{\lambda} \, . \, Q_i^{(1)} + (1 - \boldsymbol{\lambda}). Q_i^{(2)} = \boldsymbol{\lambda}. \sum_{j=1}^{n} x_{ij}^{*} \, . \, w_j + \boldsymbol{\lambda}. \prod_{j=1}^{n} (x_{ij}^{*})^{w_j} \tag{7}$$

The Q value shown in Equation 7 represents the total relative importance of the $i - th$ decision alternative according to the WASPAS method. Decision alternatives are ranked in descending order based on these Q values calculated using the WASPAS method. The alternative with the highest Q value is selected as the best alternative. The parameter λ, used in the WASPAS method, takes a value between 0 and 1. When $\lambda = 0$, the WASPAS method becomes equivalent to the WPM, and when $\lambda = 1$, it becomes equivalent to the WSM. To calculate the optimal λ value, the operation shown in Equation 8 is performed.

$$\lambda = \frac{\sigma^2.(Q_i^{(2)})}{\sigma^2.\left(Q_i^{(1)}\right) + \sigma^2.(Q_i^{(2)})} \tag{8}$$

TOPSIS Method

TOPSIS was introduced to the MCDM literature by Hwang and Yoon in 1980 (Hwang & Yoon, 1981). In TOPSIS, alternatives are evaluated based on two key points: the positive ideal solution, which maximizes benefits and minimizes costs, and the negative ideal solution, which minimizes benefits and maximizes costs (Demirci, 2020). A decision point moves closer to the positive ideal solution as it moves away from the negative ideal solution, giving it a ranking advantage (Uludağ & Doğan, 2021).

A review of the literature reveals that many researchers have utilized the TOPSIS method to evaluate the performance of alternatives. Within this scope, Korkmaz and Gürer (2018) conducted a financial performance assessment of forest village cooperatives. Sari (2021) focused on forest fire susceptibility mapping. Laktuka et al. (2023) evaluated bioeconomy development opportunities within the forestry sector. Wang et al. (2023) concentrated on estimating forest carbon sequestration capacity. Naskar et al. (2024) performed forest fire susceptibility mapping for the West Sikkim District. Peng et al. (2024) addressed the determination of a forest ecological environment assessment system. Additionally, Francy and Rao (2024) analyzed the cold extrusion parameters of AA 2024 alloy. Amiri et al. (2024) worked on the evaluation of renewable energy sources. Otay et al. (2024) focused on the assessment of sustainable energy systems. Alsanousi et al. (2024) conducted financial performance analyses. Tran et al. (2024) carried out studies on the determination of optimal robots. Almomani et al. (2024) investigated the selection of thermal barrier coating materials. Finally, Khichad et al. (2024) analyzed highway performance and safety.

The application steps of the TOPSIS method are explained below (Atan and Altan, 2020).

p: Number of decision alternatives $(j = 1,2, \dots \dots, p)$.
n: Number of criteria $(j = 1,2, \dots \dots, r)$.
x_{ij}: The value of the $i - th$ alternative according to the $j - th$ evaluation criterion $(j = 1,2, \dots \dots, r)$.
x_{ij}^*: The normalized value of the $i - th$ alternative according to the $j - th$ evaluation criterion $(j = 1,2, \dots \dots, r)$.
w_j: Weight of the $j - th$ criterion *(j=1,2,……,r).*
C: Criteria

Step 1: Attainment of the Decision Matrix (T)

In this step, the decision matrix is constructed based on the alternative and criterion values, as previously indicated in Equation 1. Eqs. (9).

$$T = \begin{bmatrix} C_1 & C_2 & \dots & C_p \\ t_{11} & t_{12} & & t_{1r} \\ t_{21} & t_{22} & \cdots & t_{2r} \\ \vdots & \vdots & \vdots & \vdots \\ t_{P1} & t_{P2} & \cdots & t_{pr} \end{bmatrix} \tag{9}$$

Step 2: Formulation of Standard Decision Matrix (U_{ij})

In this step, independently from the WASPAS method, the normalized values for cost and benefit criteria are calculated using a single formula based on Equation 10. Subsequently, the normalized decision matrix is constructed using Equation 11.

$$u_{ij} = \frac{t_{ij}}{\sqrt{\sum_{k=1}^{p} t_{kj}^2}} \tag{10}$$

$$U_{ij} = \begin{bmatrix} u_{11} & u_{12} & \cdots & u_{1n} \\ u_{21} & u_{22} & \cdots & u_{2n} \\ \vdots & \vdots & \vdots & \vdots \\ u_{m1} & u_{m2} & \cdots & u_{mn} \end{bmatrix} \tag{11}$$

Step 3: Obtaining the Weighted Standard Decision Matrix (Z_{ij})

In this step, the weighted standardized decision matrix (Z_{ij}) is obtained by multiplying each normalized criterion value by its corresponding weight. This process adjusts the normalized decision matrix to reflect the relative importance of each criterion, ensuring that the influence of each criterion on the final decision is proportionate to its assigned weight. Eqs. (12).

$$Z_{ij} = \begin{bmatrix} w_1 u_{11} & w_2 u_{12} & \cdots & w_r u_{1r} \\ w_1 u_{21} & w_2 u_{22} & \cdots & w_r u_{2n} \\ \vdots & \vdots & \vdots & \vdots \\ w_1 u_{p1} & w_2 u_{p2} & \cdots & w_r u_{pr} \end{bmatrix} \tag{12}$$

Step 4: Measurement of the Positive (A^+) and Negative Ideal Solution (A^-) Values

In this step, the Positive Ideal Solution (A^+) and Negative Ideal Solution (A^-) values are determined. The Positive Ideal Solution represents the best performance values for benefit criteria and the worst for cost criteria, while the Negative Ideal Solution represents the opposite. These reference points are used to evaluate and compare alternatives. Eqs. (13-16).

For Positive İdeal Solution:

$$A^+ = \{mak_i z_{ij} |\, j \in J), (min_i z_{ij} |\, j \in J'\} \tag{13}$$

$$A^+ = \{z_1^*, z_2^*, \dots, z_r^*\} \tag{14}$$

For Negative İdeal Solution:

$$A^{-} = \{min_i z_{ij} | \ j \ \in J), (min_i z_{ij} | \ j \ \in J'\} \tag{15}$$

$$A^{-} = \{z_1^{-}, z_2^{-}, \dots, z_r^{-}\} \tag{16}$$

Step 5: Calculation of Distance to Positive $(PID - K_i^{+})$ and Negative Ideal Distance $(NID - K_i^{-})$

In this step, the distances of each alternative to the Positive Ideal Solution $(PID - K_i^{+})$ and nd the Negative Ideal Solution $(PID - K_i^{+})$ are calculated using Euclidean distance formulas. These distances quantify how close each alternative is to the best and worst possible criterion values, serving as a basis for ranking the alternatives. Eqs. (17,18).

$$PID: K_i^{+} = \sqrt{\sum_{j=1}^{r} (z_{ij} - z_j^{*})^2} \tag{17}$$

$$NID: K_i^{-} = \sqrt{\sum_{j=1}^{r} (z_{ij} - z_j^{-})^2} \tag{18}$$

Step 6: Measurement of Relative Proximity to the Ideal Solution (S_i^{*})

In this step, the relative closeness (S_i^{*}) of each alternative to the Ideal Solution is calculated. It is computed as the ratio of the Negative Ideal Distance to the sum of both Negative and Positive Ideal Distances, indicating how close an alternative is to the optimal solution. Eqs. (19).

$$S_i^{*} = \frac{K_i^{-}}{K_i^{-} + K_i^{+}} \tag{19}$$

RESULTS

Computational Analysis

In the study, the decision matrix for the EPI-F criteria values of the 10 countries in question was initially calculated using Equation 1, followed by the normalized values computed with Equation 2, as the criteria are benefit-oriented. The decision matrix and normalized decision matrix values are presented in Table 2.

Table 2. Decision And Normalized Decision Matrix

Decision Matrix					
Countries	**F1**	**F2**	**F3**	**F4**	**F5**
w	**0,3**	**0,3**	**0,25**	**0,1**	**0,05**
Russia	43,87	18,2	63,1	49,9	90,2
Brazil	56,3	40,2	37	20,3	75,1
Canada	47,5	29,2	65,9	36,2	89,9
US	87,6	18,1	49,9	43,9	66,5

China	85,3	73,2	66	54,8	71,4
DRC	55,4	45,8	39	32,2	75,6
Indonesia	65	60,9	31,8	36,9	66,1
India	71,9	90,4	63,6	56,6	70,9
Peru	69,1	53,9	57	45,1	88,6
Normalized Decision Matrix					
Countries	**F1**	**F2**	**F3**	**F4**	**F5**
Russia	0,501	0,249	0,956	0,911	1,000
Brazil	0,643	0,549	0,561	0,370	0,833
Canada	0,542	0,399	0,998	0,661	0,997
US	1,000	0,247	0,756	0,801	0,737
China	0,974	1,000	1,000	1,000	0,792
DRC	0,632	0,626	0,591	0,588	0,838
Indonesia	0,742	0,832	0,482	0,673	0,733
India	0,821	1,235	0,964	1,033	0,786
Peru	0,789	0,736	0,864	0,823	0,982

In the third step of the method, the total relative importance values of the decision alternatives are calculated based on the Weighted Sum Model (WSM) using Equation 4, and in the fourth step, based on the Weighted Product Model (WPM) using Equation 5. The relative importance values of the decision alternatives, calculated according to the WSM and WPM models, are presented in Table 3.

Table 3. $WSM - Q_1$ and $WPM - Q_2$ Scores

Countries	$\boldsymbol{WSM - Q_1}$	$\boldsymbol{WPM - Q_2}$
Russia	0,464	0,529
Brazil	0,498	0,633
Canada	0,532	0,631
US	0,563	0,613
China	0,842	0,992
Australia	0,525	0,664
DRC	0,593	0,721
Indonesia	0,858	0,995
India	0,673	0,819
Peru	0,464	0,529

In the final step of the WASPAS method, Equations 7 and 8 were used to calculate the total relative importance values of the alternatives (countries) in order to rank them correctly and effectively. Therefore, the weighted aggregate general criterion values explained in Equation 4 were not taken into consideration.

Table 4. Alternative Scores

Countries	$\boldsymbol{\lambda}$	Score	Rank
Russia	0,533	0,494	9
Brazil	0,560	0,557	8
Canada	0,543	0,577	7
USA	0,521	0,587	5
China	0,541	0,911	2
DRC	0,558	0,586	6
Indonesia	0,549	0,651	4
India	0,537	0,921	1
Peru	0,549	0,739	3
Mean	---	0,669	

Upon examining Table 6, the ranking of countries based on their forest conservation performance is as follows: India, China, Peru, Indonesia, USA, DRC, Canada, Brazil, and

Russia. Additionally, the average forest conservation performance value of the countries was calculated, and it was determined that the countries with performance values above this average are India, China, and Peru.

Furthermore, the forest conservation performances of the countries were measured using the TOPSIS method. In the first step of the TOPSIS method, the decision matrix is created using Equation 8. This decision matrix was previously presented in Table 1. In the second step of the method, the standardized decision matrix is created using Equation 10 and Equation 11, and the resulting standardized decision matrix is shown in Table 5.

Table 5. Standardized Values

Countries	F1	F2	F3	F4	F5
Russia	0,221	0,092	0,317	0,251	0,454
Brazil	0,283	0,202	0,186	0,102	0,378
Canada	0,239	0,147	0,331	0,182	0,452
US	0,441	0,091	0,251	0,221	0,334
China	0,429	0,368	0,332	0,276	0,359
DRC	0,279	0,230	0,196	0,162	0,380
Indonesia	0,327	0,306	0,160	0,186	0,332
India	0,362	0,455	0,320	0,285	0,357
Peru	0,348	0,271	0,287	0,227	0,446

In the third step of the method, the standardized values are weighted using Equation 12. The weighted standardized values are explained in Table 6.

Table 6. Weighted Standardized Values

Criteria	F1	F2	F3	F4	F5
w	**0,300**	**0,300**	**0,250**	**0,100**	**0,050**
Russia	0,066	0,027	0,079	0,025	0,023
Brazil	0,085	0,061	0,047	0,010	0,019
Canada	0,072	0,044	0,083	0,018	0,023
US	0,132	0,027	0,063	0,022	0,017
China	0,129	0,110	0,083	0,028	0,018
DRC	0,084	0,069	0,049	0,016	0,019
Indonesia	0,098	0,092	0,040	0,019	0,017
India	0,108	0,136	0,080	0,028	0,018
Peru	0,104	0,081	0,072	0,023	0,022

In the fourth step, the positive ideal solution values are calculated using Equation 13 and Equation 14, while the negative ideal solution values are calculated using Equation 15 and Equation 16. The calculated values are presented in Table 7.

Table 7. Positive And Negative Ideal Scores

Solutions	F1	F2	F3	F4	F5
A^{+}	0,132	0,110	0,083	0,028	0,023
A^{-}	0,066	0,027	0,040	0,010	0,017

In the fifth step of the method, the distances to the positive ideal solutions are measured using Equation 17. Accordingly, the positive distance values of the alternatives (countries) are presented in Table 8.

Table 8. Scores of Distance to Positive Points

Countries	F1	F2	F3
Russia	0,00435	0,00689	0,00001

Brazil	0,00223	0,00248	0,00133
Canada	0,00366	0,00441	0,00000
US	0,00000	0,00691	0,00041
China	0,00001	0,00000	0,00000
DRC	0,00236	0,00171	0,00115
Indonesia	0,00116	0,00034	0,00185
India	0,00056	0,00067	0,00001
Peru	0,00078	0,00085	0,00013
Countries	**F4**	**F5**	Si^{+}
Russia	0,000006	0,000000	0,464
Brazil	0,000301	0,000014	0,498
Canada	0,000087	0,000000	0,532
US	0,000030	0,000036	0,563
China	0,000000	0,000022	0,842
DRC	0,000129	0,000013	0,525
Indonesia	0,000081	0,000037	0,593
India	0,000001	0,000024	0,858
Peru	0,000024	0,000000	0,673

Continuing from the fifth step of the method, the distances to the negative ideal solutions are calculated using Equation 18, and the calculated values are explained in Table 9.

Table 9. Scores of Distance to Negative Points

Countries	**F1**	**F2**	**F3**
Russia	0,0000	0,0000	0,0015
Brazil	0,0004	0,0011	0,0000
Canada	0,0000	0,0003	0,0018
US	0,0044	0,0000	0,0005
China	0,0039	0,0069	0,0018
DRC	0,0003	0,0017	0,0001
Indonesia	0,0010	0,0042	0,0000
India	0,0018	0,0119	0,0016
Peru	0,0014	0,0029	0,0010
Countries	**F4**	**F5**	Si^{-}
Russia	0,0002	0,0000	0,529
Brazil	0,0000	0,0000	0,633
Canada	0,0001	0,0000	0,631
US	0,0001	0,0000	0,613
China	0,0003	0,0000	0,992
DRC	0,0000	0,0000	0,664
Indonesia	0,0001	0,0000	0,721
India	0,0003	0,0000	0,995
Peru	0,0002	0,0000	0,819

In the final step of the method, the performances of the decision alternatives (their relative distances to the ideal solution) are measured using Equation 19, and the measured values are ranked and presented in Table 10.

Table 10. Measurement of Relative Proximity to The Ideal Solution (Alternative Scores)

Countries	Q	**Rank**
Russia	0,286	9
Brazil	0,328	8
Canada	0,344	7
US	0,452	5
China	0,951	1
DRC	0,389	6
Indonesia	0,552	4

India	0,778	2
Peru	0,639	3
Mean	0,524	

Considering Table 4 and Table 10, which present the performance rankings of countries based on the WASPAS and TOPSIS methods, the rankings for Peru, Indonesia, USA, DRC, Canada, Brazil, and Russia have shown consistency. In terms of countries with performance values above the average (high performance), the results of both methods are similar for China, India, and Peru. Consequently, China, India, and Peru stand out compared to other countries, particularly in criteria F1 (Primary Forest Loss) and F2 (Intact Forest Landscape Loss).

The data presented in Table 4 and Table 10 assess countries' forest conservation performance by comparing them based on different criteria and methods. In this context, both tables reflect the rankings of the countries according to the WASPAS and TOPSIS methods. The consistency in rankings for countries such as Peru, Indonesia, USA, DRC, Canada, Brazil, and Russia across both methods indicates that the overall performance of these countries remains at a relatively stable level, signaling compatibility between the methods. Nevertheless, it can be evaluated that the forest conservation policies and practices of countries performing above the average are more effective compared to those of other nations.

The high performance of countries appears to stem from their strategic approaches specifically targeting the F1 (Primary Forest Loss) and F2 (Intact Forest Landscape Loss) criteria. These criteria play a significant role in forest ecosystem conservation. Primary forests are crucial for carbon storage, biodiversity, and ecosystem balance, while intact forest landscapes refer to areas largely preserved from human impact. In particular, the high forest conservation performance of this countries underscores their commitment to sustainable forest management. Additionally, the overall performance consistency of Peru, Indonesia, the USA, DRC, Canada, Brazil, and Russia indicates that these countries maintain a certain level of balance in forest conservation.

The high forest conservation performance of countries is not solely based on technical criteria but is also closely related to the comprehensive policies, governance structures, and geographical characteristics developed by these countries. In China, robust legal regulations have been established to ensure the sustainability of forest resources, and these regulations are effectively enforced (Fu et al., 2024)). Coordination between central government and local authorities facilitates the monitoring and control of forestry activities, thereby enhancing forest conservation success (Lei, 2008). Consequently, the country's extensive forest areas and biodiversity form the fundamental basis for its natural conservation efforts. In India, forest conservation success is achieved through various national and regional conservation programs and policies, as well as the active involvement of local communities in forest management (Manikandan & Prabhu, 2012). This participatory approach, combined with India's geographical diversity and climatic conditions, enables the protection of diverse forest ecosystems and is considered to have positively contributed to the country's conservation performance. Peru's forest conservation performance stems from its hosting of ecologically critical forest areas such as the Amazon Rainforest. The country not only implements national policies aimed at preserving forest ecosystems effectively but has also developed collaborative governance models between local communities and the state (Granados, 2024). Consequently, Peru supports the conservation of different forest types, thereby contributing to the overall success of its forest protection efforts.

Sensitivity Analysis

One approach to assessing the robustness of MCDM methods is by introducing new alternatives to the original set or eliminating weaker alternatives from it. In such instances, the MCDM method is expected not to exhibit significant shifts in the ranking of alternatives. This issue is known as the 'rank reversal problem' and has received substantial attention in the literature (Demir & Arslan, 2022). In this context, a rank reversal application was conducted for sensitivity analysis, starting with the lowest-performing alternative according to the WASPAS and TOPSIS methods. The resulting country rankings are presented in Table 11 and Table 12.

Table 11. Reversal Ranking for WASPAS

Countries	S0	S1	S2	S3
Russia	9	---	---	---
Brazil	8	8	---	---
Canada	7	7	7	---
US	5	5	5	5
China	2	2	2	2
DRC	6	6	6	6
Indonesia	4	4	4	4
India	1	1	1	1
Peru	3	3	3	3
Countries	**S4**	**S5**	**S6**	**S7**
Russia	---	---	---	---
Brazil	---	---	---	---
Canada	---	---	---	---
US	5	---	---	---
China	2	2	2	2
DRC	---	---	---	---
Indonesia	4	4	---	---
India	1	1	1	1
Peru	3	3	3	---

Table 12. Reversal Ranking for TOPSIS

Countries	S0	S1	S2	S3
Russia	9	---	---	---
Brazil	8	8	---	---
Canada	7	7	7	---
US	5	5	5	5
China	1	1	1	1
DRC	6	6	6	6
Indonesia	4	4	4	4
India	2	2	2	2
Peru	3	3	3	3
Countries	**S4**	**S5**	**S6**	**S7**
Russia	---	---	---	---
Brazil	---	---	---	---
Canada	---	---	---	---
US	5	---	---	---
China	1	1	1	1
DRC	---	---	---	---
Indonesia	4	4	---	---
India	2	2	2	2
Peru	3	3	3	---

An examination of Tables 11 and 12 reveals that, according to the reversal ranking method, the rankings of countries remain unchanged across scenarios within both the WASPAS and TOPSIS methods. The visual representations of Tables 11 and 12 are illustrated in Figure 2.

Consequently, these findings indicate that the forest conservation performance of countries, within the scope of EPI-F, demonstrates sensitivity when measured by the WASPAS and TOPSIS methods.

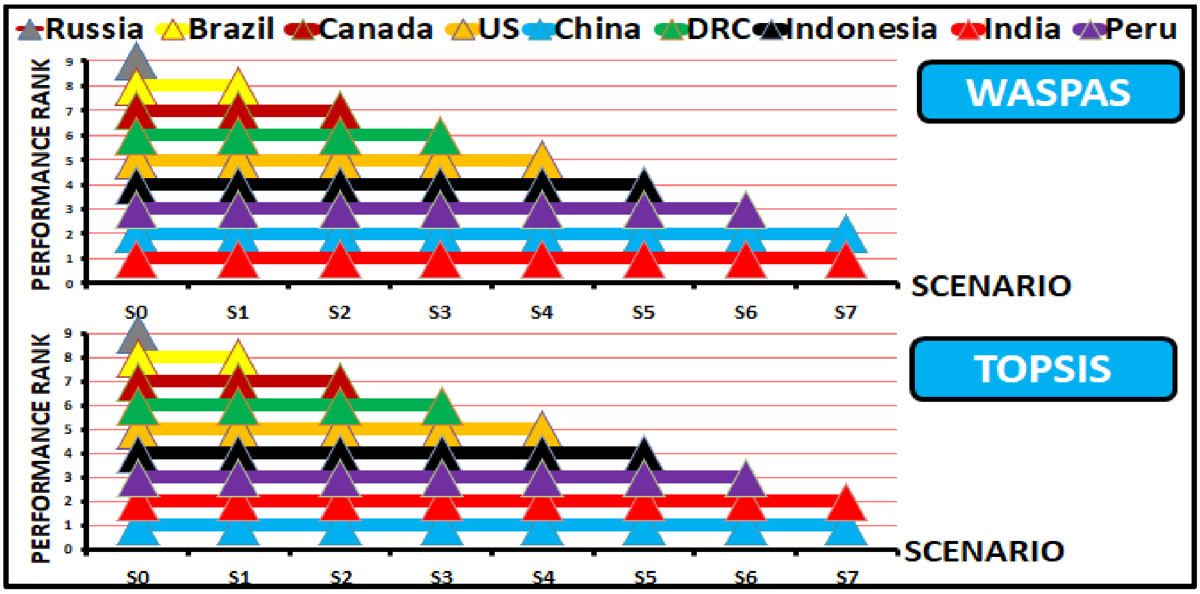

Figure 2. Reversal Ranking Visual in Scope of Sensitivity Analysis

Comparative Analysis

The comparative analysis evaluates the relationships and relative positions of the proposed method in comparison to other methodologies used in calculating MCDM methods. The proposed approach should establish its credibility, reliability, and consistency with other methods, while also showing a positive and statistically significant correlation with various MCDM techniques (Keshavarz-Ghorabaee et al., 2021). A review of the literature reveals that methods such as ARAS (The Additive Ratio Assessment), SAW, WPA, EDAS (Evaluation Based on Distance from Average Solution), MARCOS (The Measurement of Alternatives and Ranking according to Compromise Solution), and MAUT (The Multiple Attribute Utility Theory) are frequently used in selection problems or in measuring the performance of decision alternatives (Demir et al., 2021; Uludağ & Doğan, 2021). Additionally, these methods exhibit technically distinct features when applied to measure the performance of decision alternatives (Ecer, 2020; Demir et al., 2021; Uludağ & Doğan, 2021). In this context, ARAS, SAW, WPA, EDAS, MARCOS, and MAUT methods were chosen to compare the forest protection performance values of countries, as well as the rankings of these values, as identified using the WASPAS and TOPSIS methods. The forest protection performance values and their rankings calculated using these MCDM methods are presented in Table 13.

Table 13. Performance Score of Countries by The Other MCDM Models

Methods	**ARAS**		**SAW**		**WPA**	
Countries	**S.**	**R.**	**S.**	**R.**	**S.**	**R.**
Russia	0,487	9	0,588	8	0,491	9
Brazil	0,537	8	0,544	9	0,531	8
Canada	0,563	7	0,623	6	0,567	6
US	0,597	5	0,664	4	0,553	7
China	0,910	2	0,921	2	0,917	2
DRC	0,568	6	0,588	7	0,584	5
Indonesia	0,648	4	0,647	5	0,638	4

India	0,933	1	0,926	1	0,923	1
Peru	0,725	3	0,760	3	0,751	3
Methods	**EDAS**		**MARCOS**		**MAUT**	
Countries	**S.**	**R.**	**S**	**R**	**S.**	**R.**
Russia	0,100	9	0,982	6	0,297	6
Brazil	0,122	8	0,848	9	0,040	9
Canada	0,221	7	0,995	4	0,315	4
US	0,278	5	0,985	5	0,379	3
China	0,944	2	1,299	2	0,732	1
DRC	0,245	6	0,918	8	0,059	8
Indonesia	0,400	4	0,965	7	0,133	7
India	0,993	1	1,309	1	0,693	2
Peru	0,623	3	1,162	3	0,299	5

S.=Score, **R.**=Rank

As part of the comparative analysis, the correlation values between the forest conservation performance scores of countries, as calculated by the WASPAS and TOPSIS methods, and the performance scores determined by other MCDM methods were calculated. The correlation values are presented in Table 14.

Table 14. Pearson Correlation Scores

Methods	**TOPSIS**	**ARAS**	**SAW**	**WPA**
WASPAS	0,967**	0,966**	0,950**	0,963**
Methods	**WASPAS**	**ARAS**	**SAW**	**WPA**
TOPSIS	0,967**	0,998**	0,972**	0,997**
Methods	**EDAS**	**MARCOS**	**MAUT**	
WASPAS	0,967**	0,902**	0,787**	
Methods	**EDAS**	**MARCOS**	**MAUT**	
TOPSIS	0,995**	0,929**	0,804**	
p*<.05, p**<.01				

Upon reviewing Table 14, it is observed that the correlations between the countries' forest conservation performance scores calculated by the WASPAS and TOPSIS methods and those determined by other MCDM methods are all significant, positive, and high. Therefore, based on these quantitative values, it can be concluded that measuring countries' forest conservation performance within the EPI-F framework using the WASPAS and TOPSIS methods is both credible and reliable.

DISCUSSION

Evaluating countries' forest conservation performance is of great importance for assessing the effectiveness of environmental sustainability strategies (Schenck, 2023). Forests play a critical role as carbon sinks in the fight against global climate change (Khanna, 2015). Furthermore, forests provide essential ecosystem services such as biodiversity conservation, water cycle regulation, and soil erosion prevention (Parthiban et al., 2019; Dindaroğlu et al., 2021). Thus, the effectiveness of forest conservation policies has become a decisive factor in achieving both local and global environmental goals (Block et al., 2024). The assessment of countries' forest conservation performance using various MCDM methods, such as WASPAS and TOPSIS, is thought to offer valuable contributions from both scientific and policy perspectives, as these methods are highly advantageous in evaluating the performance of decision alternatives (Ecer, 2020).

The WASPAS and TOPSIS methods allow for comparative analyses by evaluating countries' performance across multiple criteria. Analyses based on critical criteria, such as F1 (Primary Forest Loss) and F2 (Intact Forest Landscape Loss), as in this study, reveal the effectiveness of countries' forest management policies. The high performance of China, India, and Peru with both methods is thought to reflect these countries' committed approaches and the effectiveness of their long-term strategies in reducing forest loss. This demonstrates the potential effectiveness of sustainable forest management policies, particularly in developing countries, when implemented correctly.

According to the research findings, the consistency in the rankings of countries such as Peru, Indonesia, the USA, DRC, Canada, Brazil, and Russia indicates that these countries' forest conservation policies have achieved a certain level of stability. However, the high performance of countries like China and India, particularly in the F1 and F2 criteria, highlights their leading role in global forest conservation efforts.

It has been observed that studies measuring countries' forest performance are quite limited in the literature. In this context, Block et al. (2024) primarily use comprehensive indicators such as the EPI and present results through multi-criteria evaluation methods. The findings of this study, consistent with those of Block et al. (2024), show that China, India, and Peru have performed above average. The key reason for the higher performance of these countries compared to others is their strategic approaches to preventing deforestation. Block et al. (2024) measured the forest conservation performance of countries within the framework of the EPI methodology, ranking the countries as India, China, Peru, Indonesia, USA, Canada, DRC, Brazil, and Russia. The study also calculated the average forest conservation performance of these countries, observing that India, China, and Peru had performances above this average.

When examining the findings of both this study (WASPAS and TOPSIS) and those of Block et al. (2024), it is evident that the rankings of Peru, Indonesia, USA, Canada, Brazil, and Russia in terms of forest conservation performance are consistent. Consequently, these results suggest that Peru, Indonesia, the USA, Canada, Brazil, and Russia exhibit a notable level of forest conservation performance. Additionally, when comparing the findings of the current study and those of Block et al. (2024), the consistency is further underscored by the fact that the countries with performances above the average forest conservation level, as measured by the WASPAS method, are China, India, and Peru. Therefore, within the scope of this research (WASPAS and TOPSIS), China, India, and Peru have been identified as countries performing above the average in terms of forest conservation. From an alternative perspective, the forest conservation performances of Indonesia, the United States, the Democratic Republic of Congo, Canada, Brazil, and Russia are considerably higher compared to many other countries (Block et al., 2024). Conversely, it can be argued that China, India, and Peru face pressing challenges in enhancing their forest protection efforts. The fact that China and India are the two most populous countries globally necessitates the implementation of stronger policies to safeguard forests despite growing population pressures. This situation compels these nations to adopt more cautious and resolute approaches towards sustainable forest management. Meanwhile, Peru's case is distinct due to the critical role its tropical forests play in maintaining global climate balance. The significance of tropical forest health not only at the local but also at the global environmental sustainability level has driven Peru to develop more effective forest conservation policies, supported by international collaboration. Accordingly, the forest protection strategies of these countries bear strategic importance not only nationally but also for the future sustainability of global ecosystems.

Since 1998, China has developed strategies to control the excessive consumption of forest resources and to increase forest area and stocks (Lei, 2008; Aguilar, 2021). In particular, the policy of coordination between state and central government in forest conservation under forest laws can be considered a key factor in China's success in forest protection (Fu et al., 2024). On the other hand, Zhao et al. (2023) found that central and local authorities have developed a common mission to shift forest development from an economic focus to an ecological one. Moreover, it has been observed that China works in favor of ecological balance in its commercial relations, particularly in the trade of non-deforested products (Vasconcelos et al., 2024). In India, significant policies for the protection of forest areas were initiated by the Indian Forest Act in 1894 (Saxena, 1999). In particular, the Indian Forest Act of 1952 developed strategies for protecting forests, national forests, village forests, and tree lands (Rawat, 2002). Additionally, Joshi et al. (2010) evaluated that, at the state level, there is a high likelihood of achieving ecological policy goals in the context of forest cover trends and current land-use practices. Therefore, India's strategies for afforestation and forest protection have successfully raised awareness about the importance of forest conservation across all relevant sectors (Manikandan & Prabhu, 2012). In Peru, a wide forest conservation management regime has been established due to the vast Amazon Basin. Particularly in the production of forest products, ecological balance and forest protection trends are carefully considered under the forest law (Schleicher et al., 2017). Furthermore, Salo et al. (2023) observed that Peru has adopted a forest management structure based on the economically sustainable use of resources with a focus on forest economy for forest conservation. Additionally, due to its important biodiversity basin, Peru contributes significant global financial resources to reduce emissions resulting from deforestation and forest degradation (Granados, 2024). As a result, the high forest conservation performance of China, India, and Peru compared to other countries is believed to be attributed to the reasons outlined in the literature. Additionally, based on the findings, it is assessed that the USA, DRC, Canada, Brazil, and Russia need to improve their forest conservation performance to support global ecosystem health. In this context, Brazil, which demonstrates relatively lower performance compared to Peru, India, and China, must implement more effective, sustainable, and traceable forest governance policies to improve its performance in the indicators of Intact Forest Landscape Loss, Tree Cover Loss Weighted by Permanency, and Net Change in Tree Cover. Similarly, Canada (in terms of Intact Forest Landscape Loss), the United States (Intact Forest Landscape Loss), the Democratic Republic of the Congo (DRC, Net Change in Tree Cover), and Indonesia (Net Change in Tree Cover) also require policy-driven structural reforms. In this regard, Canada should enhance its preventive measures to protect vast forest landscapes; Brazil needs to establish monitoring systems that can minimize the persistence of forest degradation; and both DRC and Indonesia must prioritize reforestation strategies aimed at balancing net tree cover change. These actions are critically important for achieving long-term environmental sustainability.

In terms of the study's limitations, the forest conservation performance data for the countries are restricted solely to the year 2024. Incorporating data from multiple years would broaden the scope of the study and enhance the generalizability of the findings. This approach would enable a more comprehensive and holistic analysis by evaluating the forest conservation performance of countries over specific periods rather than a single year.

From a methodological perspective, the measurement of forest conservation performance of countries under the EPI-F framework using the WASPAS and TOPSIS methods has been evaluated as sensitive, reliable and credible. In this context, it has been concluded that the forest conservation performance of countries under the EPI-F framework can be measured using the WASPAS and TOPSIS methods. In terms of recommendations, it has been assessed that countries such as the USA, DRC, Canada, Brazil, and Russia, which exhibit lower performance than the average forest protection performance according to both methods, should improve their forest protection performance in order to contribute more to global protection bio-diversity, environmental ecology, and the global economy.

From a methodological standpoint, the forest protection performance of countries can be measured using different MCDM methods (ARAS, COPRAS (The Complex Proportional Assessment), EDAS, MABAC (The Multi-Attributive Border Approximation Area Comparison), MARCOS, MAIRCA (The Multi Attributive Ideal-Real Comparative Analysis), COCOSO (The Combined Compromise Solution), DNMA (A Double Normalization-Based Multiple Aggregation), RAFSI (The Ranking Of Alternatives Through Functional Mapping of Criterion Sub-Intervals into a Single Interval), WEDBA (Weighted Euclidean Distance Based Approximation), EAMR (The Evaluation by Area-Based Method of Ranking), TODIM (An Acronym in Portuguese for Interative Multi-criteria Decision Making), GRA (Grey Relation Analysis), etc.), allowing for a comparison of the results. Furthermore, not only in general terms but also on a continental basis, the forest protection performance of countries can be compared.

CONCLUSION

This study aims to evaluate the forest protection performance of 10 countries using the WASPAS and TOPSIS multi-criteria decision-making methods. The analyses show that there are significant differences in the forest protection performance of the countries. Both the WASPAS and TOPSIS methods reveal that China, India, and Peru have higher forest protection performance compared to other countries. This highlights the effectiveness of these countries' forest protection policies and their commitment to sustainable forest management. On the other hand, the consistent rankings of countries such as Peru, Indonesia, the USA, the Democratic Republic of Congo, Canada, Brazil, and Russia in both methods indicate that these countries have achieved a certain level of stability in their forest protection policies. However, these countries need to exert more effort to improve their forest protection performance. In this context, based on the forest conservation performance evaluations of the countries, it is observed that the performance levels of countries other than China, Peru, and India remain below the average value. This situation highlights the necessity of strengthening forest conservation efforts in these countries. In this context, it is recommended to expand the implementation of digital monitoring systems, especially for countries with low performance. The use of digital technologies is expected to enable real-time and precise monitoring of forest areas, thereby contributing to the prevention of illegal logging and other harmful activities. Furthermore, community-based land tenure reforms should be implemented to encourage the participation of local populations in forest management. This approach not only facilitates the integration of local knowledge and experience into conservation strategies but also promotes the sustainable use of forest resources, enhancing social ownership. Consequently, it will provide a foundation for developing more comprehensive and effective policies aimed at improving forest conservation performance in the respective countries.

The findings of this study offer significant insights for policymakers and decision-makers. Countries with low forest protection performance should develop more effective policies to reduce forest loss. These policies should aim to promote sustainable forest management practices, ensure the participation of local communities, and protect the ecosystem services provided by forests.

In addition to these findings, it is essential to interpret the results from the perspective of forest economics and governance. The structural differences in forest ownership and management across the countries including the proportions and functions of private, communal, and state-owned forests likely influenced the observed performance levels. Countries with a higher share of well-regulated private or community-managed forests may benefit from more localized and adaptive management practices, whereas nations with centralized forest governance systems might face challenges in implementation efficiency and stakeholder engagement. Therefore, future studies should consider incorporating variables related to forest tenure systems, institutional capacity, and economic incentives in order to better understand the underlying drivers of forest protection performance. This broader perspective can enhance the strategic formulation of policies tailored to each country's governance model and socio-economic context.

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Only one author contributed to this study.

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CONFLICT OF INTEREST STATEMENT

The author declare no conflict of interest.

ETHICS COMMITTEE APPROVAL

This study does not require any ethics committee approval.

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