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ANALYTICAL ASSESSMENT OF ECOLOGICAL SECURITY AND ENVIRONMENTAL VULNERABILITY USING THE LOPCOW–MABAC METHOD

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ABSTRACT:

This study analytically examines the ecological threat levels of 207 countries using data presented in the Ecological Threat Report 2024. Four key indicators—demographic pressure, food insecurity, impact of sea-related events, and water risk—were utilized, and all criteria were integrated into a decision matrix to enable a comparable assessment of countries' environmental vulnerability. The relative importance of the criteria was determined using the LOPCOW method, which is based on data variation and eliminates human subjectivity. The resulting weights were calculated as follows: demographic pressure (25.83%), food insecurity (25.59%), impact of sea-related events (26.78%), and water risk (21.79%). These results indicate that the criteria have a nearly equal level of influence on the formation of ecological threats. Following the weighting process, countries were evaluated using the MABAC method and ranked according to their overall ecological threat scores. The findings show that Greenland, Bermuda, Malta, Germany, Slovakia, and Estonia are among the countries with the lowest threat levels, whereas Niger, Burkina Faso, Madagascar, Somalia, Afghanistan, and Benin exhibit the highest levels of vulnerability. The results further reveal that ecological threats are predominantly concentrated in low-income regions characterized by arid climatic conditions, limited natural resource management capacity, and heightened sensitivity to climate shocks. This confirms the strong relationship between environmental vulnerability and socio-economic development levels. Overall, the study provides a data-driven analytical framework that can support the formulation of sustainable development policies and contributes to a systematic understanding of cross-country ecological risk disparities while highlighting priority regions for environmental intervention.

Keywords: Ecological Threats, Sustainable Development, Environmental Vulnerability, Ecological Security, Multi-Criteria Decision-Making

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Research Paper

1. INTRODUCTION

In an era where global environmental pressures are rapidly intensifying, the sustainable management of natural resources and the measurement of ecological vulnerability have become central concerns for both researchers and policymakers. Challenges such as climate change, rapid population growth, food insecurity, and water scarcity are disrupting ecological balances and reshaping countries' environmental resilience (Rockström et al., 2021). Against this backdrop, the development of objective, comparable, and data-driven approaches for analyzing ecological threats has gained critical importance. The Ecological Threat Report 2024 (ETR-2024), published by the Institute for Economics and Peace (IEP), provides an extensive dataset covering 207 countries and offering an up-to-date overview of global ecological pressures. The report evaluates countries' environmental vulnerabilities using four key indicators: demographic pressure, food insecurity, the impact of sea-related events, and water risk (IEP, 2024). These indicators capture the core parameters of ecological security and serve as essential reference points for guiding sustainable development policies. Assessing environmental risk often requires the simultaneous examination of multiple interdependent criteria. For this reason, multi-criteria decision-making (MCDM) methods have become increasingly prominent in environmental studies (Zavadskas et al., 2014). MCDM techniques provide a structured framework that integrates indicators with different scales and orientations, enabling meaningful interpretation of both qualitative and quantitative information.

In this study, ecological threat levels were evaluated using ETR-2024 data through the LOPCOW (Logarithmic Percentage Change-driven Objective Weighting) and MABAC (Multi-Attributive Border Approximation Area Comparison) methods. The LOPCOW method objectively determines criterion weights by incorporating logarithmic percentage variation, thereby eliminating subjective influence (Ecer & Pamučar, 2022). Following this, the MABAC approach ranks countries based on their distance to the border approximation area between ideal and anti-ideal solutions (Pamučar & Cirović, 2015). The combined use of these two methods enables both objective weighting and a multidimensional evaluation of alternatives. Importantly, this study does not simply reproduce ETR-2024 classifications; rather, it re-analyzes these data through a mathematically transparent, reproducible, and fully objective decision-analytic model. While the ETR provides categorical threat levels, it does not disclose the mathematical weighting process underlying its composite structure. Thus, the LOPCOW–MABAC framework introduced here offers an added analytical layer by quantifying cross-country differences with higher precision, greater measurability, and enhanced interpretability.

The study also clearly distinguishes among the concepts of "ecological threat," "environmental vulnerability," and "ecological security," which are often used interchangeably in the literature. Ecological threat refers to the biophysical pressures a country currently faces, whereas environmental vulnerability reflects its capacity to withstand these pressures. The composite score produced through MABAC directly measures the "ecological threat level," providing a quantitative indicator that can be readily interpreted by policymakers. Furthermore, the decision to use only four ETR indicators is a deliberate methodological choice. Although the ETR includes numerous dimensions, this study focuses solely on direct biophysical threats. Indicators related to governance, conflict, or socio-economic conditions were intentionally excluded to maintain conceptual clarity and isolate the environmental components of ecological risk. This approach allows differences across countries to be observed more clearly and consistently within a strictly ecological context. Overall, the primary aim of the study is to provide a quantitative analysis of ecological threats at the national level, identify high-risk regions, and support sustainable policy development through a data-driven framework.

2. LITERATURE REVIEW

This study establishes the theoretical foundation for a comprehensive multi-criteria decision-making (MCDM) analysis conducted using data from the 2024 Ecological Threat Report. The LOPCOW and MABAC methods, which form the methodological basis of this research, have been widely applied across various fields, including sustainability assessment, risk management, energy planning, supply chain resilience, financial performance evaluation, and environmental efficiency analysis.

The LOPCOW method stands out due to its ability to generate objective criterion weights and its robustness against negative performance values. In contrast, the MABAC method offers a multidimensional evaluation framework by assessing the performance of alternatives based on their relative positions within the border approximation area—defined between ideal and anti-ideal solutions. These strengths make both methods particularly useful for analyzing large datasets and complex decision environments such as ecological threat assessments.

The tables presented in this section summarize selected national and international studies published between 2014 and 2025 in which LOPCOW and MABAC methods have been applied. For each study, the authors, research purpose, methodological approach, and key findings are concisely outlined. This comprehensive literature review aims to strengthen the methodological grounding of the present study and to elucidate the scientific foundations of decision-making processes based on ecological threat indicators. The reviewed studies are presented in Table 1.

Table 1. Literature Review

LOPCOW				
No	**Author(s)**	**Purpose**	**Method**	**Findings / Results**
1	Aydın (2025)	To analyze corporate financial performance in the insurance sector.	LOPCOW–RANCOM–RAWEC model.	The model demonstrated strong discriminatory power in the Sompo Insurance case.
2	Doğan (2025)	To evaluate the financial performance of Borsa Istanbul banks.	LOPCOW–RAM method.	The model reliably revealed financial efficiency differences among banks.
3	Durak (2025)	To analyze the corporate sustainability performance of Istanbul Airport (IGA).	LOPCOW–MAUT integration.	IGA was found to exhibit high environmental sustainability performance.
4	Ecer et al. (2025)	To assess sustainable aviation fuel suppliers.	IVF-neutrosophic LOPCOW + MARCOS model.	The most energy-efficient and sustainable supplier was identified.
5	Karahaliloğlu (2025)	To analyze logistics center location selection based on sustainability.	LOPCOW–Grey Relational Analysis (GRA).	The model ensured optimal site selection across environmental and economic criteria.
6	Sharma et al. (2025)	To strengthen resilience in the food supply chain through a two-stage decision model.	LOPCOW–DOBI and probabilistic programming.	The model enhanced food supply chain resilience.
7	Chatterjee et al. (2024)	To select collaborative robots (cobots) for production lines.	LOPCOW–OPTBIAS integrated model.	The optimal cobot improving production efficiency was identified.
8	Işık et al. (2024)	To analyze the competitiveness of European cities.	LOPCOW + CRADIS model.	Significant differences were observed in innovation and sustainability indicators.
9	Liu et al. (2024)	To optimize resource allocation in energy planning.	LOPCOW + WASPAS + game theory.	The model ensured optimal resource utilization.

10	Riaz et al. (2024)	To evaluate AI-driven performance in the healthcare supply chain.	AI-driven LOPCOW–AROMAN model.	Decision efficiency increased under uncertain data conditions.
11	Rong et al. (2024)	To assess risks in industrial robot software projects.	IVFF-LOPCOW–ARAS model.	Accurate weighting of risk factors contributed to improved project success.
12	Altıntaş (2023)	To evaluate the welfare performance of G7 countries.	LOPCOW-based CRADIS method.	Germany and Canada showed the highest welfare performance.
13	Ecer et al. (2023)	To evaluate the role of UAV technologies in agricultural production.	q-rung fuzzy LOPCOW–VIKOR model.	The model improved decision effectiveness under uncertainty.
14	Keleş (2023)	To evaluate livable cities in G7 countries and Turkey.	LOPCOW–CRADIS method.	Paris, London, and Istanbul exhibited the highest livability performance.
15	Nila & Roy (2023)	To select third-party logistics providers in sustainable supply chains.	TFN-LOPCOW + FUCOM + DOBI model.	Sustainability criteria were objectively weighted.
16	Simić et al. (2023)	To prioritize Industry 4.0-based material-handling technologies in smart warehouses.	Neutrosophic LOPCOW–ARAS model.	The most suitable technologies for sustainable warehouse management were determined.
17	Ulutaş et al. (2023)	To analyze the effectiveness of natural fibers in insulation materials.	PSI + MEREC + LOPCOW + MCRAT model.	The most suitable material was identified based on environmental and mechanical performance.
18	Yaşar & Ünlü (2023)	To examine environmental sustainability levels in universities.	LOPCOW and MEREC-based CoCoSo method.	Green campus practices demonstrated the highest sustainability performance.
19	Biswas et al. (2022b)	To compare dividend-paying capacity in India's FMCG and consumer durables sectors.	MCDM-based LOPCOW framework.	FMCG companies showed a more sustainable financial structure.
20	Biswas et al. (2022c)	To manage uncertainty in sales personnel selection.	Spherical fuzzy LOPCOW model.	The model measured sales personnel performance more reliably.
21	Ecer & Pamučar (2022)	To evaluate the sustainability performance of banks.	LOPCOW–DOBI model.	Balanced sustainability measurement across financial and environmental indicators was achieved.
22	Niu et al. (2022)	To conduct group decision-making in a Fermatean fuzzy environment.	Fermatean cubic fuzzy LOPCOW method.	Divergence in decision-makers' views was minimized.

MABAC

No	Author(s)	Purpose	Method	Findings / Results
1	Abdullayev & Çokmutlu (2025)	To analyze the impact of the EU Carbon Border Adjustment Mechanism on the Borsa Istanbul cement sector.	MEREC-weighted MABAC method.	A strong relationship was found between financial performance indicators and stock returns.
2	Aşan et al. (2025)	To measure the project management performance of regional development agencies.	LOPCOW and MABAC methods.	Significant regional differences were observed in agency project performance.
3	Aydın (2025)	To conduct corporate performance analysis in the insurance sector.	LOPCOW–RANCOM–RAWEC model.	Criteria influencing the financial performance of insurance companies were identified.
4	Doğan (2025)	To measure the financial performance of Borsa Istanbul banks.	LOPCOW–RAM method.	Performance differences among banks were reliably determined.
5	Durak (2025)	To examine the corporate sustainability performance of Istanbul Airport (IGA).	LOPCOW and MAUT integration.	IGA demonstrated strong sustainability performance.
6	Jaleel & Mahmood (2025)	To develop a decision support system for supply chain management.	Bipolar complex fuzzy soft MABAC.	The model optimized supply chain performance.
7	Karahaliloğlu (2025)	To analyze logistics center location selection based on sustainability.	LOPCOW–GRA model.	The selected location achieved both economic and environmental balance.
8	Sharma et al. (2025)	To enhance food supply chain resilience.	LOPCOW–DOBI and probabilistic programming.	The model presented strong results in risk reduction.
9	Fan et al. (2024)	To evaluate wearable health technologies.	MEREC–MABAC and CPT-based approach.	A user-friendly performance evaluation of health technologies was performed.
10	Jafari & Naghdi Khanachah (2024)	To assess supplier information-sharing and resilience.	Pythagorean fuzzy MABAC.	Supply chain resilience was effectively measured.
11	Sun et al. (2024)	To evaluate technology use in post-production film and media.	MABAC-based analysis.	Multimedia technology performance was assessed.
12	Mandal & Seikh (2023)	To optimize the plastic waste management process.	Interval-valued spherical fuzzy MABAC.	The optimal waste management method was identified.
13	Tan et al. (2023)	To evaluate investment risks in the Belt and Road Initiative.	Prospect theory + Fermatean fuzzy MABAC.	Improved accuracy in risk assessment was achieved.
14	Torkayesh et al. (2023)	To examine MABAC applications in sustainability.	Systematic literature review.	The growing use of MABAC in sustainability studies was demonstrated.

15	Wang et al. (2023)	To develop a MABAC algorithm using picture fuzzy sets.	Prospect theory-based MABAC.	The method ensured high reliability under uncertainty.
16	Ahmad et al. (2022)	To provide decision support for emergency response systems.	Non-linear Diophantine fuzzy MABAC model.	The model improved decision effectiveness under uncertainty.
17	Mishra et al. (2022)	To select sustainable suppliers in the automotive sector.	HF-DEA-FOCUM-MABAC technique.	Sustainability criteria were effectively weighted.
18	Tešić et al. (2022)	To improve decision-making processes.	Rough-numbers-based modified MABAC.	The method enhanced decision stability under uncertainty.
19	Deveci (2021)	To optimize offshore wind farm site selection in the U.S.	Type-2 neutrosophic MABAC.	Environmental and economic factors were balanced.
20	Lukić (2021)	To analyze sectoral efficiency in Serbia.	Classical MABAC method.	The financial services sector showed the highest efficiency.
21	Zhang et al. (2021)	To evaluate green supplier selection.	Spherical fuzzy CPT-MABAC.	The model effectively assessed environmental performance.
22	Zhao et al. (2021)	To reduce uncertainty in group decision-making.	Intuitionistic fuzzy CPT-MABAC.	Decision consistency was improved.
23	Irvanizam et al. (2020)	To solve multi-criteria group decision-making problems.	Triangular fuzzy neutrosophic MABAC.	The model reduced uncertainty in group decisions.
24	Liu & Cheng (2020)	To improve decision-making in a neutrosophic environment.	Regret theory & likelihood-based MABAC.	Risk attitudes of decision-makers were incorporated.
25	Mishra et al. (2020)	To develop a decision support model for smartphone selection.	Extended intuitionistic fuzzy MABAC.	Criterion sensitivity in the decision process was improved.
26	Wang et al. (2020)	To conduct group decision-making in q-rung orthopair fuzzy environments.	Fuzzy MABAC.	Group decision accuracy increased.
27	Mulliner et al. (2016)	To evaluate sustainable housing affordability.	Comparative MABAC analysis.	MABAC was found effective for sustainable housing assessment.
28	Pamučar et al. (2015)	To optimize logistics resource selection.	MABAC method.	Efficient selection of transportation resources was achieved.
29	Zavadskas et al. (2014)	To evaluate MCDM methods comprehensively.	Extensive literature analysis.	MABAC demonstrated strong performance in multi-criteria evaluations.

3. METHOD

3.1. LOPCOW Method

The LOPCOW (Logarithmic Percentage Change-Driven Objective Weighting) method, developed by Ecer and Pamučar (2022), is one of the new-generation objective weighting techniques introduced to the multi-criteria decision-making (MCDM) literature. The method is particularly noteworthy for its ability to determine criterion weights independently of decision-makers' subjective judgments, especially when dealing with large-scale datasets or decision matrices containing negative values. Unlike traditional objective approaches that rely solely on measures such as variance or entropy, LOPCOW is based on the logarithmic percentage changes of the series' standard deviation and mean-square values. This structure minimizes the influence of measurement units or scale differences among criteria and eliminates scale bias arising from the magnitude of the data series (Ecer & Pamučar, 2022).

Another distinguishing feature of LOPCOW is its insensitivity to negative performance values within the decision matrix. This makes the method more stable and reliable in multidimensional decision environments where criteria contain negative or mixed values (Biswas et al., 2022b). Depending on the influence level of criteria, dataset size, and performance variations among alternatives, the LOPCOW method can be effectively applied to decision problems characterized by high variability. It is designed to yield more balanced and realistic weight differences among criteria, particularly in data series with large variances (Biswas et al., 2022c).

According to Ecer and Pamučar (2022), the LOPCOW method consists of three main steps: constructing the normalized decision matrix, calculating the logarithmic percentage change coefficient for each criterion, and converting these values into criterion weights. The weights obtained at the end of this process provide an objective, scale-independent, and stable evaluation by considering both the degree of criterion variation and the discriminatory power among alternatives (Ecer & Pamučar, 2022; Biswas et al., 2022b). The procedural steps of the LOPCOW method are presented as follows (Keleş, 2023; Yaşar & Ünlü, 2023):

1. Construction of the Decision Matrix: In the first step of the LOPCOW method, the decision problem is structured by defining m alternatives and n criteria. The performance values corresponding to these alternatives and criteria are compiled to form the decision matrix. As shown in Equation (1), this matrix represents the fundamental dataset that will be used throughout the decision-making process.

$$\mathrm{IDM} = \begin{bmatrix} x_{11} & x_{12} & \cdots & x_{1n} \\ x_{21} & x_{22} & \cdots & x_{2n} \\ \vdots & \vdots & \vdots & \vdots \\ x_{m1} & x_{m2} & \cdots & x_{mn} \end{bmatrix} \quad (1)$$

2. Construction of the Normalized Decision Matrix: In this step, the criterion values contained in the decision matrix are standardized using the linear normalization technique. The normalization procedure is applied differently depending on the orientation of each criterion. If a criterion has a cost-oriented structure—meaning that lower values are preferred—Equation (2) is used. Conversely, if the criterion is benefit-oriented and higher values are preferred, Equation (3) is applied. The resulting normalized decision matrix (IDM) ensures that all criteria are transformed onto a comparable scale, enabling a consistent and meaningful evaluation across alternatives.

$$r_{ij} = \frac{x_{max} - x_{ij}}{x_{max} - x_{min}} \quad (2)$$

$$r_{ij} = \frac{x_{ij} - x_{min}}{x_{max} - x_{min}} \quad (3)$$

3. Construction of the Percentage Value Matrix: In this stage of the analysis, the percentage values for each criterion are calculated using the formula presented in Equation (4). In this calculation, the percentage of the standard deviation for each criterion is determined by taking the mean-square values into account. This approach eliminates scale differences arising from the magnitude of the data series, ensuring that criteria measured in different units become comparable. The resulting percentage value matrix serves as the basis for identifying the relative importance levels of the criteria, grounded in the distributional characteristics of the dataset.

$$PV_{ij} = \left| \ln \left(\frac{\sqrt{\frac{\sum_{i=1}^{m} r_{ij}^2}{m}}}{\sigma} \right) .100 \right| \quad (4)$$

4. Calculation of Criterion Weights: In the final step, the objective weight values for each criterion are computed using the formula presented in Equation (5). These weights are determined based on the degree of variation exhibited by each criterion, thereby capturing their relative influence within the decision-making process. The resulting weights constitute the primary output of the LOPCOW method and can be directly utilized in subsequent multi-criteria decision-making analyses.

$$W_j = \frac{PV_{ij}}{\sum_{i=1}^{n} PV_{ij}} \quad (5)$$

3.2. MABAC Method

Multi-Criteria Decision-Making (MCDM) approaches provide a systematic framework for evaluating multiple alternatives based on several assessment criteria (Zavadskas et al., 2014). One of these approaches, the MABAC (Multi-Attributive Border Approximation Area Comparison) method, was developed by Pamučar and Cirovic (2015) and relies on the concept of the border approximation area in assessing decision alternatives. The primary aim of MABAC is to simultaneously consider each alternative's closeness to the ideal solution and its distance from the negative solution.

The MABAC method is characterized by a mathematically robust structure and high interpretability, making it particularly suitable for evaluating alternatives under multiple criteria. In this approach, once the decision matrix is normalized, a weighted decision matrix is created. Subsequently, the border approximation area is computed for each criterion, and the distance of each alternative from this area is determined. A positive distance indicates that the alternative performs better than the reference boundary, whereas a negative distance signals weaker performance (Pamučar et al., 2015). Due to its computational simplicity and strong interpretability, MABAC is considered a powerful alternative to more traditional MCDM methods such as TOPSIS and VIKOR (Mulliner et al., 2016).

In recent years, the MABAC method has been widely applied in various domains, including sustainable supplier selection (Mishra et al., 2022), performance evaluation of energy systems (Wang et al., 2020: 208), and sectoral efficiency analysis (Lukić, 2021). Moreover, it can be integrated with weighting methods such as Entropy, CRITIC, MEREC, and SWARA, allowing for the combined evaluation of objective and subjective criteria (Tan et al., 2023). Through these capabilities, MABAC has emerged as an effective tool for analyzing sustainability indicators, environmental performance criteria, and regional development indices.

The procedural steps of the MABAC method are presented below (Pamučar et al., 2015):

1. Construction of the Decision Matrix: The construction of the decision matrix is presented in Equation (1).

2. Normalized Decision Matrix: To ensure that the criteria can be compared on a common scale, the values are normalized. The normalization formulas for both benefit-based and cost-based criteria are given in Equation (6).

$$\mathrm{n}_{ij} = \begin{cases} \frac{x_{ij}-\min(x_j)}{\max(x_j)-\min(x_j)}, fayda\ kriteri \\ \frac{max(x_j)-x_{ij}}{\max(x_j)-\min(x_j)}, maliyet\ kriteri \end{cases} \quad (6)$$

This ensures that all criteria are scaled into the [0,1] range.

3. Construction of the Weighted Decision Matrix: After determining the weights (w_j) that represent the relative importance of each criterion, the normalized matrix is multiplied by these weights. The weighted decision matrix is calculated using Equation (7).

$$\mathrm{v}_{ij} = n_{ij} * w_j \quad (7)$$

4. Calculation of the Border Approximation Area: A distinctive feature of the MABAC method is the calculation of the border approximation area (g_j) for each criterion. This value serves as a reference point for comparing the performance of the alternatives, and it is computed using Equation (8).

$$\mathrm{g}_j = \frac{\prod_{i\_1}^{m} v_{ij}}{m} \quad (8)$$

5. Calculation of the Alternatives' Distance from the Border Area: The deviation of each alternative from the border value for each criterion is calculated using Equation (9).

$$\mathrm{g}_{ij} = v_{ij} * g_j \quad (9)$$

Here, if $q_{ij} > 0$, alternative i performs above the average for that criterion, whereas $q_{ij} < 0$ indicates that it performs below the average.

6. Calculation of MABAC Scores and Ranking: Finally, the overall score of each alternative is computed using Equation (10), after which the alternatives are ranked accordingly.

$$\mathrm{S}_j = \sum_{j=1}^{n} q_{ij} \quad (10)$$

A larger S_i value indicates that the alternative exhibits better performance. Therefore, the alternatives are ranked in descending order based on their S_i scores.

7. Ranking of Alternatives and Decision Making: Positive scores indicate that the decision alternative outperforms the border approximation area, whereas negative scores reflect weaker performance. Through this approach, decision-makers obtain both numerical comparisons and a clear assessment of relative performance among the alternatives.

4. METHODOLOGY

4.1. Research Aim and Scope

This study aims to analytically assess the ecological threat levels of countries using data from the *Ecological Threat Report 2024* (ETR-2024). The core objective is to evaluate the key indicators that shape countries' environmental vulnerability through objective weighting and multi-criteria ranking techniques, thereby providing a holistic analytical framework. In this context, the LOPCOW method is employed to objectively determine the relative importance of the criteria, after which the MABAC method is applied to rank countries according to their overall ecological threat levels. Using these two methods in combination preserves the statistical structure of the dataset while eliminating human subjectivity in the evaluation process, allowing differences in countries' environmental performance to be identified more transparently.

The study ultimately aims to offer policymakers, international organizations, and researchers an analytical framework applicable to sustainable development, ecological security, and environmental risk management. An important contribution of this study lies in the additional analytical value it provides compared with ETR-2024. While the ETR presents summary threat classifications for countries, it does not disclose how indicator weights are mathematically constructed. The LOPCOW–MABAC framework, by contrast, analyzes the same dataset through entirely transparent, traceable, and reproducible statistical procedures. As a result, the study produces an independent and comparable ecological threat index that can be evaluated alongside the ETR's own classifications, enabling a more precise differentiation among countries. The selection of indicators used in this study is also a deliberate methodological choice. Although ETR-2024 includes a wide range of variables, only four core biophysical threat indicators—demographic pressure, food insecurity, impact of sea-related events, and water risk—are included in the analysis. These four indicators are used because they are available for all countries, are directly comparable, and represent the fundamental biophysical drivers of ecological threats.

Variables related to governance capacity, conflict intensity, economic stability, or social vulnerability are intentionally excluded, as they reflect societal resilience rather than ecological threat itself. Similarly, indicators such as climate anomalies, temperature increases, or carbon emissions are not included because they are not methodologically consistent or uniformly reported across all countries. Therefore, these four indicators represent the most statistically coherent and conceptually appropriate variables for conducting a multi-criteria ecological threat assessment. Through this structure, the LOPCOW–MABAC approach not only reinterprets ETR data but also enables ecological threats to be evaluated within a mathematically transparent, comparable, and objective decision-making framework. Consequently, the study evolves into an analytical assessment tool that reconstructs ecological threat levels independently of the ETR's internal classifications, offering methodological added value and a strengthened theoretical foundation. This methodological contribution enhances the model's practical applicability and facilitates the interpretation of results by decision-makers. In sum, the study seeks to provide policymakers, international institutions, and researchers with a comprehensive and data-driven evaluation framework for sustainable development, ecological security, and environmental risk management. By doing so, it clarifies the spatial distribution of global ecological risks and supports strategic decision-making aimed at prioritizing regions facing the highest levels of threat.

4.2. Dataset and Variables

The dataset used in this study was obtained from the "Ecological Threat Report 2024" published by the Institute for Economics and Peace (IEP) (Vision of Humanity, 2024). The dataset provides quantitative ecological threat indicators for 207 countries. Four main criteria were used in the analysis:

(1) Demographic Pressure: Represents pressures arising from population growth, urban density, natural resource demand, and the environmental carrying capacity.

(2) Food Insecurity: Reflects the level of vulnerability in societies by considering food availability, access, and sustainability.

(3) Impact of Sea-Related Events: Covers the effects of sea-level rise, floods, storms, and coastal inundation associated with climate change.

(4) Water Risk: Represents water scarcity, water pollution, per capita water consumption, and access to freshwater resources.

In this research, the concepts of ecological threat, ecological security, and environmental vulnerability are explicitly differentiated. Ecological threat refers to the biophysical pressures that directly affect countries—such as population growth, water scarcity, and food insecurity. Environmental vulnerability, on the other hand, denotes a country's capacity to withstand or adapt to these pressures. Ecological security represents a state in which ecological threats are kept under control through the sustainable management of natural resources. Accordingly, the composite MABAC score calculated in this study serves as a quantitative indicator of a country's "ecological threat level," measuring the intensity of the biophysical pressures it faces.

Within this conceptual framework, all variables used in the study were treated as numerical indicators and standardized to ensure cross-country comparability. Because the selected criteria directly reflect how ecological pressures influence natural resource management and human security, the model offers strong explanatory power for sustainability-oriented analyses. After determining the objective weights of the criteria using the LOPCOW method, countries were ranked through the MABAC method by considering their positions relative to ideal and negative-ideal solutions. This integrated approach captures the multidimensional nature of ecological threats and places cross-country comparisons on a solid statistical foundation.

4.3. Data Analysis

In this study, a multi-criteria decision-making (MCDM) process was conducted to evaluate 207 countries, each representing an alternative within the analysis framework. The decision matrix was structured as 207 × 4, where each country was assessed based on four key indicators provided in the Ecological Threat Report 2024 (ETR-2024): Demographic Pressure, Food Insecurity, Impact of Sea-Related Events, and Water Risk. All criteria were treated as cost-type (minimization-oriented), as higher values indicate greater ecological threat. Before constructing the decision matrix, the completeness and consistency of the dataset were verified, confirming that all indicators were available and usable for every country.

Due to the standardized nature of ETR-2024 data, no unit or scale incompatibility was present. Therefore, preprocessing involved only organizing the data into the required matrix structure and defining the direction of each criterion. In line with the principles of MCDM, no additional analysis—such as correlation tests between criteria—was performed. This decision reflects the nature of objective weighting and ranking methods like LOPCOW and MABAC, which inherently incorporate the statistical properties of criteria within their algorithmic structures. Since these methods derive criterion importance directly from data variability and do not rely on subjective expert input, separate correlation analysis is not necessary. Instead, LOPCOW determines each criterion's contribution to the decision-making process based solely on its informational content. This approach is widely used in MCDM research and is consistent with methodological practices in objective weighting studies.

For weight determination, the LOPCOW method was employed. LOPCOW uses logarithmic percentage changes in standard deviation and mean-square values to objectively quantify each criterion's discriminating power. Because the method extracts weights directly from the statistical distribution of the data, it is particularly advantageous in studies where minimizing subjective influence is essential. To strengthen the methodological rigor of the study, a robustness assessment is planned for subsequent stages. In particular, examining how the MABAC rankings respond to ±10% perturbations in criterion weights will provide insight into the model's stability.

Additionally, recalculating weights using an alternative objective method—such as Entropy or CRITIC—will serve as a complementary reliability check. Following the weighting stage, the MABAC method was applied. MABAC ranks alternatives by positioning them within the boundary approximation area defined between ideal and anti-ideal solutions, offering a multidimensional assessment of ecological threat levels. Beyond producing a country ranking, the method highlights specific strengths and weaknesses across criteria, generating a structured and actionable profile for each country. This analytical depth provides valuable insights for policymakers seeking to identify intervention priorities. To enrich the analysis, MABAC scores were evaluated not only as final rankings but also in relation to regional patterns, income groups, and broader vulnerability dynamics. This expanded perspective supports a deeper understanding of how ecological threats vary spatially and socio-economically across the globe.

4.3.1. Application of the LOPCOW Method

In this part of the study, the criterion weights were calculated using the LOPCOW method. First, a decision matrix covering 207 countries was constructed based on the Ecological Threat Report 2024 (ETR 2024) data. The criteria included in the decision matrix—Demographic Pressure, Food Insecurity, Water Risk, and Impact of Sea-Related Events—represent the ecological vulnerability levels of countries. Since higher values of these indicators correspond to higher ecological threat levels, they were treated as cost-type (minimization) criteria from the decision-maker's perspective. The decision matrix is presented in Table 2.

Table 2. Decision Matrix

Indicator No	Criterion Indicator No	K1	K2	K3	K4
	Alternatives / Criteria	min	min	min	min
		Demographic Pressure	Food Insecurity	Impact of Sea-Related Events	Water Risk
A1	Afghanistan	4.49	5	2.98	4.98
A2	Albania	1.01	2.15	1.21	2.21
A3	Algeria	2.32	2.21	1.64	1.72
...	...	...	...	...	...
...	...	...	...	...	...
A205	Yemen	4.43	5	1.25	3.62
A206	Zambia	4.44	1.76	1.52	5
A207	Zimbabwe	1.22	3.65	3.39	4.89

After constructing the decision matrix, the formulas described above were applied for the LOPCOW method, and the final matrix containing the calculated criterion weights is presented in Table 3.

Table 3. Criterion Weights Obtained Using the LOPCOW Method

Criteria	Demographic Pressure	Food Insecurity	Impact of Sea-Related Events	Water Risk	Total
Wj	0.25833309	0.255880457	0.267833063	0.217953391	1

4.3.2. Application of the LOPCOW-Based MABAC Method

After the criterion weights were calculated using the LOPCOW method, the alternatives were evaluated and ranked using the MABAC method.

1. Construction of the Decision Matrix: Since the decision matrix of the study is already presented in Table 2, this step is not repeated here.

2. Normalized Decision Matrix: The normalization of the decision matrix was performed using Equation (6). The resulting normalized matrix is presented in Table 4.

Table 4. Normalization of the Decision Matrix

Alternatives / Criteria	K1	K2	K3	K4
A1	0.13	0.00	0.44	0.00
A2	1.00	0.71	0.94	0.70
A3	0.67	0.70	0.82	0.82
A4	0.90	0.81	0.38	1.00
A5	0.81	1.00	1.00	1.00
A6	0.15	0.82	0.47	0.00

A7	0.71	0.62	1.00	1.00
A8	0.79	0.81	0.82	0.94
A9	1.00	0.85	1.00	0.83
A10	0.40	1.00	0.78	1.00
…	…	…	…	…
…	…	…	…	…
A205	0.14	0.00	0.93	0.35
A206	0.14	0.81	0.85	0.00
A207	0.94	0.34	0.32	0.03
LOPCOW Wj	0.26	0.26	0.27	0.22

3. Construction of the Weighted Decision Matrix: The weighted normalization matrix was obtained using Equation (7), and the resulting matrix is presented in Table 5.

Table 5. Weighted Normalization Matrix

Alternatives / Criteria	K1	K2	K3	K4
A1	0.29	0.26	0.39	0.22
A2	0.52	0.44	0.52	0.37
A3	0.43	0.43	0.49	0.40
A4	0.49	0.46	0.37	0.44
A5	0.47	0.51	0.54	0.44
A6	0.30	0.47	0.39	0.22
A7	0.44	0.41	0.53	0.44
A8	0.46	0.46	0.49	0.42
A9	0.52	0.47	0.54	0.40
A10	0.36	0.51	0.48	0.44
…	…	…	…	…
…	…	…	…	…
A206	0.29	0.46	0.50	0.22
A207	0.50	0.34	0.35	0.22

4. Calculation of the Border Approximation Area: The calculation of the Border Approximation Area was performed using Equation (8), and the results are presented in Table 6.

Table 6. Calculation of the Border Approximation Area

Criteria	K1	K2	K3	K4
gi	0.422	0.438	0.471	0.339

5. Calculation of the Alternatives' Distance from the Border Area: The calculation of the distance of each alternative from the border area was performed using Equation (9), and the results are presented in Table 7.

Table 7. Calculation of the Alternatives' Distance from the Border Area

Alternatives / Criteria	K1	K2	K3	K4
A1	-0.1312	-0.1816	-0.0851	-0.1202
A2	0.0941	0.0007	0.0488	0.0307
A3	0.0092	-0.0032	0.0163	0.0574
A4	0.0682	0.0256	-0.1002	0.0966
A5	0.0462	0.0742	0.0647	0.0966
A6	-0.1248	0.0282	-0.0775	-0.1213

A7	0.0203	-0.0230	0.0640	0.0966
A8	0.0416	0.0263	0.0163	0.0835
A9	0.0947	0.0346	0.0647	0.0601
A10	-0.0594	0.0742	0.0050	0.0966
…	…	…	…	…
…	…	…	…	…
A206	-0.1280	0.0256	0.0254	-0.1213
A207	0.0805	-0.0953	-0.1161	-0.1153

6. Calculation of MABAC Scores and Ranking: Finally, the overall score of each alternative is calculated using Equation (10), and the results are presented in Table 8.

Table 8. Calculation of MABAC Scores and Ranking

Countries	Alt.	Si	Rank	Countries	Alt.	Si	Rank	Countries	Alt.	Si	Rank
Greenland	A73	0.3303	1	French Polynesia	A66	0.1724	70	Bhutan	A22	-0.0385	139
Bermuda	A21	0.3288	2	Tuvalu	A193	0.1716	71	Bangladesh	A15	-0.0441	140
Malta	A113	0.3238	3	Argentina	A8	0.1677	72	Gabon	A67	-0.0455	141
Germany	A70	0.3213	4	Canada	A34	0.1653	73	Libya	A105	-0.0469	142
Slovakia	A164	0.3195	5	Bahamas	A13	0.1645	74	Mongolia	A120	-0.0484	143
Estonia	A59	0.3189	6	Northern Mariana Islands	A136	0.1616	75	North Korea	A134	-0.0656	144
San Marino	A156	0.3186	7	Palau	A140	0.1609	76	Bolivia	A23	-0.0671	145
Cayman Islands	A36	0.3111	8	Guam	A75	0.1601	77	Kyrgyzstan	A99	-0.0672	146
Faroe Islands	A62	0.3102	9	Antigua and Barbuda	A7	0.1578	78	Panama	A142	-0.0760	147
Taiwan	A181	0.3091	10	Puerto Rico	A149	0.1535	79	Belize	A19	-0.0811	148
Italy	A91	0.3052	11	Guyana	A79	0.1478	80	Cambodia	A32	-0.0861	149
Austria	A11	0.3041	12	Qatar	A150	0.1464	81	India	A84	-0.0932	150
Netherlands	A128	0.2991	13	Georgia	A69	0.1461	82	Côte d'Ivoire	A44	-0.0936	151
Virgin Islands US.	A204	0.2982	14	Uzbekistan	A200	0.1450	83	Peru	A145	-0.0975	152
Slovenia	A165	0.2981	15	Russia	A153	0.1411	84	Pakistan	A139	-0.1059	153
Czechia	A48	0.2978	16	El Salvador	A56	0.1369	85	Myanmar	A124	-0.1207	154
Isle of man	A89	0.2908	17	Moldova	A119	0.1345	86	Dominican Republic	A53	-0.1222	155
Liechtenstein	A106	0.2889	18	Samoa	A155	0.1319	87	Ghana	A71	-0.1225	156
Spain	A171	0.2847	19	Jamaica	A92	0.1296	88	Philippines	A146	-0.1238	157
Andorra	A5	0.2817	20	United Arab Emirates	A196	0.1296	89	Lesotho	A103	-0.1275	158
Denmark	A50	0.2759	21	Costa Rica	A43	0.1237	90	Colombia	A41	-0.1276	159
Kosovo	A97	0.2747	22	United States	A198	0.1212	91	Honduras	A81	-0.1350	160
St. Kitts and Nevis	A173	0.2746	23	Romania	A152	0.1172	92	Syria	A180	-0.1367	161
Switzerland	A179	0.2728	24	Australia	A10	0.1164	93	Kenya	A96	-0.1484	162
Singapore	A163	0.2701	25	Bahrain	A14	0.1134	94	Equatorial Guinea	A57	-0.1518	163
Portugal	A148	0.2645	26	Fiji	A63	0.1109	95	Ethiopia	A61	-0.1578	164
Latvia	A101	0.2633	27	Oman	A138	0.1087	96	Nepal	A127	-0.1612	165
Bosnia and Herzegovina	A24	0.2591	28	Brunei	A28	0.1079	97	Tanzania	A183	-0.1637	166
Ukraine	A195	0.2577	29	St. Vincent and Grenadine	A175	0.1061	98	Timor-Leste	A185	-0.1763	167
United Kingdom	A197	0.2557	30	Paraguay	A144	0.1034	99	Papua New Guinea	A143	-0.1815	168
Armenia	A9	0.2541	31	Kuwait	A98	0.1032	100	Guatemala	A76	-0.1842	169

South Korea	A169	0.2539	32	Marshall Island	A114	0.1024	101	Djibouti	A51	-0.1894	170
British Virgin Islands	A27	0.2509	33	Egypt	A55	0.0926	102	Cameroon	A33	-0.1927	171
Japan	A93	0.2486	34	Türkiye	A190	0.0906	103	Uganda	A194	-0.1927	172
Uruguay	A199	0.2417	35	American Samoa	A4	0.0902	104	Solomon Islands	A166	-0.1929	173
Seychelles	A161	0.2386	36	Saudi Arabia	A158	0.0888	105	Zambia	A206	-0.1983	174
Lithuania	A107	0.2349	37	Mexico	A117	0.0862	106	South Sudan	A170	-0.2083	175
Sweden	A178	0.2349	38	Algeria	A3	0.0798	107	Gambia	A68	-0.2102	176
Finland	A64	0.2329	39	Turkmenistan	A191	0.0758	108	Togo	A186	-0.2232	177
Hungary	A82	0.2327	40	China	A40	0.0749	109	Senegal	A159	-0.2242	178
Greece	A72	0.2312	41	Suriname	A177	0.0647	110	Rwanda	A154	-0.2358	179
Montenegro	A121	0.2301	42	Cuba	A46	0.0646	111	Botswana	A25	-0.2370	180
Turks and Caicos Islands	A192	0.2296	43	New Caledonia	A129	0.0616	112	Nigeria	A133	-0.2442	181
Serbia	A160	0.2291	44	Chile	A39	0.0584	113	Zimbabwe	A207	-0.2463	182
Croatia	A45	0.2289	45	Iran	A86	0.0573	114	Guinea-Bissau	A78	-0.2815	183
St. Lucia	A174	0.2281	46	Morocco	A122	0.0557	115	Vanuatu	A201	-0.2854	184
Ireland	A88	0.2240	47	Kazakhstan	A95	0.0552	116	Angola	A6	-0.2954	185
Cyprus	A47	0.2222	48	Micronesia	A118	0.0545	117	Yemen	A205	-0.3093	186
Mauritius	A116	0.2207	49	Sri Lanka	A172	0.0543	118	Burundi	A31	-0.3185	187
France	A65	0.2187	50	Barbados	A16	0.0540	119	Mozambique	A123	-0.3259	188
Tonga	A187	0.2151	51	Palestine	A141	0.0494	120	Liberia	A104	-0.3270	189
Lebanon	A102	0.2142	52	Laos	A100	0.0380	121	Guinea	A77	-0.3275	190
São Tomé and Príncipe	A157	0.2135	53	Azerbaijan	A12	0.0306	122	Democratic Republic of the Congo	A49	-0.3356	191
Grenada	A74	0.2133	54	Malaysia	A111	0.0262	123	Mauritania	A115	-0.3415	192
Bulgaria	A29	0.2130	55	Ecuador	A54	0.0220	124	Republic of the Congo	A151	-0.3581	193
Norway	A137	0.2053	56	Indonesia	A85	0.0190	125	Eritrea	A58	-0.3598	194
Cape Verde	A35	0.2052	57	Dominica	A52	0.0184	126	Central African Republic	A37	-0.3810	195
North Macedonia	A135	0.2051	58	Jordan	A94	0.0119	127	Sierra Leone	A162	-0.3870	196
New Zaeland	A130	0.2039	59	Eswatini	A60	0.0092	128	Haiti	A80	-0.4105	197
Nauru	A126	0.2020	60	Namibia	A125	0.0089	129	Chad	A38	-0.4402	198
Tunisia	A189	0.2015	61	South Africa	A168	0.0085	130	Malawi	A110	-0.4442	199
Thailand	A184	0.1980	62	Nicaragua	A131	-0.0012	131	Mali	A112	-0.4776	200
Iceland	A83	0.1880	63	Vietnam	A203	-0.0017	132	Sudan	A176	-0.4997	201
Belarus	A17	0.1859	64	Comoros	A42	-0.0113	133	Benin	A20	-0.5162	202
Belgium	A18	0.1849	65	Israel	A90	-0.0131	134	Afghanistan	A1	-0.5182	203
Trinidad and Tobago	A188	0.1757	66	Tajikistan	A182	-0.0291	135	Somalia	A167	-0.5290	204
Luxembourg	A108	0.1753	67	Venezuela	A202	-0.0301	136	Madagascar	A109	-0.5732	205
Poland	A147	0.1751	68	Brazil	A26	-0.0328	137	Burkina Faso	A30	-0.5786	206
Albania	A2	0.1743	69	Iraq	A87	-0.0352	138	Niger	A132	-0.6629	207

According to the results obtained using the MABAC method presented in Table 8, Greenland, Bermuda, Malta, Germany, and Slovakia rank among the top five countries, whereas Afghanistan, Somalia, Madagascar, Burkina Faso, and Niger appear in the bottom five.

5. CONCLUSION

This study provides a comprehensive assessment of the ecological vulnerability of 207 countries using data from the Ecological Threat Report 2024, employing the LOPCOW and MABAC methods in an integrated framework. The objective weights obtained through LOPCOW show that demographic pressure, food insecurity, the impact of sea-related events, and water risk contribute to ecological threats at almost similar levels. This finding highlights that ecological risks do not stem from a single source but emerge from interconnected and mutually reinforcing dynamics.

The country rankings derived from the MABAC method further reveal that ecological threats are unevenly distributed across the globe, with the highest levels of risk concentrated in socio-economically fragile regions. The contribution of this study to the literature is threefold. First, applying the combined LOPCOW–MABAC framework offers a novel methodological lens for assessing ecological vulnerability. This approach enables objective weighting of criteria and provides a multidimensional ranking structure for comparing ecological threat levels across countries.

Second, analyzing a dataset that covers 207 countries fills a significant gap in the literature, where large-scale comparative ecological risk assessments remain limited. Third, the results contribute new empirical insights into the spatial patterns of ecological threats, offering a data-driven foundation for research on sustainable development, environmental policy, and disaster-risk governance. A key value of this research lies in extending the analytical capacity of the ETR beyond its original classification scheme.

While the ETR presents composite indicators shaped by expert judgment and categorical assessments, the LOPCOW–MABAC framework reconstructs ecological threat levels using mathematically derived, variance-based weights and transparent ranking procedures. In this sense, the study does not merely reinterpret ETR data; it transforms them into an independent decision-analytic model that enhances objectivity, comparability, and interpretability.

The practical relevance of the ecological threat ranking is considerable. Policymakers can use these results to identify high-risk countries and prioritize interventions related to water security, food systems stability, climate adaptation, and population pressures. International organizations may also leverage the results to allocate humanitarian aid and environmental investments more effectively. For researchers, the ranking provides a robust comparative tool that can be applied in studies on ecological security, disaster vulnerability, and sustainability transitions.

The findings additionally offer meaningful insights into the structural nature of ecological threats. Countries with low threat levels tend to combine low population pressure, strong natural resource management, and limited exposure to climate-related hazards, whereas countries at the top of the threat spectrum face multiple simultaneous pressures such as rapid population growth, chronic water scarcity, and persistent food insecurity. This indicates that ecological threats are shaped not only by biophysical conditions but also by underlying socio-economic vulnerabilities.

Taken together, the results demonstrate that the combined use of LOPCOW and MABAC provides a powerful methodological alternative for ecological threat assessment. The objective weighting structure, mathematical transparency, and capacity for global comparability enable a deeper and more measurable exploration of ecological risks. Overall, the study offers a novel analytical contribution and delivers valuable insights to both the academic community and environmental policy processes.

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