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Assessing Sectoral Climate Risks in Turkish Exports: An Integrated Multi-Criterion Decision-Making Framework for Green Finance Policy

Türkiye İhracatında Sektörel İklim Risklerinin Değerlendirilmesi: Yeşil Finans Politikası İçin Entegre Çok Kriterli Karar Alma Çerçevesi

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Abstract

Aim: This study aims to assess the vulnerability of Türkiye's export sectors to climate change and to conduct a comparative analysis of climate-related risks across key industries.

Method: The research focuses on ten leading Türkiye's export sectors (agriculture–food, textiles, automotive, iron–steel, chemicals, electrical devices, furniture, plastics, mining, and cement) and evaluates them based on seven climate risk criteria: emission intensity, climate sensitivity, supply chain vulnerability, energy dependency, adaptive capacity, dependency on foreign markets, and water usage. A two-stage Multi-Criteria Decision-Making (MCDM) approach was employed. In the first stage, the SWARA (Step-wise Weight Assessment Ratio Analysis) method was used to determine the weights of the criteria based on expert opinions. In the second stage, the ARAS (Additive Ratio Assessment) method was applied to calculate performance scores and rank sectoral vulnerabilities.

Result: According to the SWARA results, the most heavily weighted criteria were emission intensity (22%), energy dependency (17%), and climate sensitivity (15%). The ARAS analysis revealed that the agriculture–food sector (0.740) had the highest vulnerability, followed by the textile (0.587) and cement (0.559) sectors. The automotive (0.472) and electrical devices (0.466) sectors were found to be the least vulnerable.

Conclusion: The findings offer a data-driven roadmap for prioritizing Türkiye's export sectors based on climate risks, supporting the development of green finance policies. This study provides strategic insight for policymakers in designing climate-resilient economic and trade frameworks.

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Keywords

Climate Risk, Sectoral Vulnerability, Export Performance, Green Finance, Multi-Criteria Decision Making (MCDM)

JEL Codes

F18, Q56, Q54, O13, G38.

Öz

Amaç: Bu araştırma, Türkiye'nin ihracat sektörlerinin iklim değişikliğine karşı duyarlılığını değerlendirmeyi ve sektörel düzeyde iklim risklerini karşılaştırmalı olarak analiz etmeyi amaçlamaktadır.

Yöntem: Çalışmada, Türkiye'nin ihracatında öncü konumda bulunan on sektör (tarım–gıda, tekstil, otomotiv, demir-çelik, kimya, elektrikli cihazlar, mobilya, plastik, madencilik ve çimento) ile yedi iklim riski kriteri (emisyon yoğunluğu, iklim hassasiyeti, tedarik zinciri kırılganlığı, enerji bağımlılığı, adaptasyon kapasitesi, dış pazara bağımlılık ve su kullanımı) belirlenmiştir. Sektörlerin kırılganlık düzeyleri, iki aşamalı Çok Kriterli Karar Verme (ÇKKV) yaklaşımıyla analiz edilmiştir. İlk aşamada, uzman görüşlerine dayalı SWARA yöntemiyle kriter ağırlıkları hesaplanmış; ikinci aşamada ise ARAS yöntemiyle sektörel performans puanları ve risk sıralamaları oluşturulmuştur.

Bulgular: SWARA yöntemiyle elde edilen bulgulara göre en yüksek ağırlık emisyon yoğunluğuna (%22), enerji bağımlılığına (%17) ve iklim hassasiyetine (%15) verilmiştir. ARAS yöntemi sonuçları ise tarım–gıda sektörünün (0,740) en kırılgan sektör olduğunu, bunu tekstil (0,587) ve çimento (0,559) sektörlerinin izlediğini göstermiştir. Otomotiv (0,472) ve elektrikli cihazlar (0,466) sektörleri ise en düşük risk grubunda yer almıştır.

Sonuç: Araştırma sonuçları, Türkiye'nin ihracat sektörlerinin iklim risklerine göre önceliklendirilmesini sağlayarak yeşil finans politikalarının geliştirilmesine veri temelli bir çerçeve sunmaktadır. Elde edilen bulgular, karar alıcılara yönelik stratejik planlamalarda kullanılabilecek nitelikte önemli katkılar sağlamaktadır.

Anahtar Kelimeler

İklim Riski, Sektörel Duyarlılık, İhracat Performansı, Yeşil Finans, Çok Kriterli Karar Verme

Anahtar Kelimeler

F18, Q56, Q54, O13, G38.

Introduction

Climate change has evolved beyond being merely an environmental issue, becoming a multidimensional crisis that generates both direct and indirect impacts on global economic systems (IPCC, 2023). In addition to physical effects such as rising temperatures, extreme weather events, and resource scarcity, transition-related risks such as carbon pricing, regulatory frameworks, and sustainability standards are profoundly transforming business dynamics (Task Force on Climate-related Financial Disclosures [TCFD], 2017; Battiston et al., 2017). This transformation raises critical questions about the resilience of export performance in economies that are heavily integrated into international trade.

Türkiye, as an emerging economy pursuing an export-oriented growth strategy, has increasingly integrated its industrial base with global markets. However, the climate risk profile of Türkiye's export sectors is far from uniform. For instance, sectors with high emission intensity are more exposed to carbon regulations, whereas nature-dependent industries such as agriculture are disproportionately vulnerable to physical climate impacts (Schaeffer et al., 2012). Therefore, systematically assessing and prioritizing sector-specific climate risks is crucial for developing climate-resilient growth strategies and advancing sustainable finance mechanisms.

Existing literature on sectoral climate risk often remains confined to measuring carbon footprints (Wiedmann and Minx, 2008) or using limited environmental performance indicators, with very few studies integrating multi-criteria evaluation or financial decision support frameworks. In this context, the present study aims to address both a theoretical and methodological gap. Specifically, it analyses the sensitivity of Türkiye's leading export sectors to climate change and evaluates their relative risk levels using Multi-Criteria Decision-Making (MCDM) methods. The study ultimately seeks to offer data-driven insights that can inform sustainability-oriented financial decision-making.

RQ: *Which export sectors in Türkiye are most vulnerable to climate risks, and how can their relative risk profiles inform the prioritisation of green finance instruments?*

This question was chosen because sector-specific climate vulnerability directly affects Türkiye's export competitiveness and determines the allocation efficiency of scarce green finance resources. Identifying and ranking these vulnerabilities provides actionable insights for policymakers and financial institutions aiming to design targeted and cost-effective risk mitigation strategies.

Methodologically, a two-stage MCDM approach is employed. In the first stage, the SWARA (Step-wise Weight Assessment Ratio Analysis) method is applied to determine the relative weights of climate risk criteria based on expert opinions (Kersuliene et al., 2010). In the second stage, the ARAS (Additive Ratio Assessment) method, introduced by Zavadskas and Turskis (2010), is used to evaluate the relative climate risk levels of ten key export sectors. These ten sectors were selected because they collectively account for a significant share of Türkiye's total export revenues and represent diverse climate vulnerability profiles. The selection aimed to ensure coverage of energy-intensive (e.g., cement), water-dependent (e.g., agri-food), and technology-driven (e.g., automotive, electronics) industries, thereby allowing a comprehensive and representative assessment of climate-related risks across the export economy. This evaluation is grounded in multidimensional criteria including climate sensitivity, energy consumption, emission intensity, water usage, and supply chain vulnerability.

"To date, no study in the Turkish context has systematically compared export sectors in terms of climate risk using the SWARA–ARAS framework. Unlike previous studies that primarily applied single MCDM methods (e.g., AHP, TOPSIS, VIKOR) to assess environmental or energy-related risks, our approach combines SWARA and ARAS in an integrated framework. This dual application allows expert-based weighting to be systematically linked with objective sectoral rankings, thereby producing more robust and policy-relevant results. Importantly, the study advances the literature by explicitly connecting climate risk assessments with green finance policy design, offering a practical decision-support tool for policymakers."

The research is guided by two key questions:

- To what extent do climate-related criteria differ across Türkiye's leading export sectors, and how do these differences shape their respective risk profiles?
- How can the ranking produced by ARAS based on weights derived via SWARA inform sectoral prioritisation in green finance policy design?

The study's findings are expected to contribute to the development of sector-level decision-support mechanisms for both policymakers and financial institutions. Beyond identifying current climate risks, the study proposes actionable insights for structuring effective green finance strategies. Through its novel integration of SWARA and ARAS rarely encountered in the existing literature this research introduces a new analytical framework for climate risk assessment and offers a practical contribution to achieving sustainable development goals.

Literature Review

This section reviews existing studies related to the core themes of the present research namely, climate change, multi-criteria decision-making (MCDM), green finance, and exports. To the best of our knowledge, no prior study has directly addressed the research question from the same interdisciplinary perspective. Therefore, we offer a comparative overview of existing approaches, focusing on their methodological and thematic contributions. "We synthesise the literature in four clusters (i) institutional green finance, (ii) MCDM-based sustainability assessments, (iii) China-focused econometric and fuzzy MCDM evidence on finance–export linkages, and (iv) sectoral/thematic applications then delineate the remaining research gap."

Klasen et al. (2022) show that EXIM and Export Credit Agency (ECA) institutions can materially scale climate finance, yet current flows are far below needs and hampered by definitional inconsistencies. Their single-year assessment highlights the institutional potential but also underscores the need for longitudinal evidence and harmonised metrics.

Within the European context, Brodny and Tutak (2023) assessed energy and climate sustainability across EU-27 countries by applying five distinct MCDM methods (CODAS, EDAS, TOPSIS, VIKOR, and WASPAS). Their results highlighted Sweden, Denmark, and Austria as top performers, while Southern European nations scored lower, demonstrating that multi-method aggregation can enhance robustness. However, their reliance on a single year of data and sensitivity to method selection remain important limitations. Complementing this, Ristanović, Primorac and Dorić (2024) developed an MCDM framework for evaluating green investments in advanced economies, using OECD Green Growth Indicators. Applying AHP to weight investor types and BWM to prioritise criteria, they identified environmental and resource efficiency factors as most critical, while the natural asset base ranked lowest. Although the framework offers a clear guide for Environmental, Social, and Governance (ESG)-oriented decision-making, the authors emphasise that its applicability requires adaptation to emerging market conditions.In the Chinese context, several studies have explored the nexus between green finance, exports, and sustainability using both econometric and fuzzy MCDM approaches. Liu et al. (2023) employed panel models for 30 provinces (2011–2020) and showed that green finance significantly enhances export sophistication, mediated by technological innovation and capital capacity, though the analysis remains limited to province-level data. Li et al. (2023) applied fuzzy AHP and DEMATEL to prioritise ESG dimensions and policy options, identifying environmental factors as the most critical, but their framework is geographically restricted to China. Zhou et al. (2023), using panel NARDL models for 2020–2021, found that green credit, bonds, and carbon finance instruments improved the environmental quality of exports, particularly in high-tech and digital products, yet the absence of firm-level heterogeneity weakens generalisability. Similarly, Ma et al. (2024) constructed province-level export quality indices and confirmed the role of regulation, pollution control, green TFP, and innovation as key channels, with pronounced effects in technologically intensive sectors. Ji (2025) extended the analysis over 2001–2020 through grey correlation and panel estimations, concluding that green finance reforms positively influence export structure but that persistent regional disparities require targeted policy interventions.

Sectoral and thematic studies further illustrate how climate risks and green finance intersect in specific industries. Baştuğ et al. (2024) analysed maritime decarbonisation in Türkiye using the THEMIS method, showing that incentive schemes are the most effective financing mechanism, followed by cap-and-trade and local regulations, though capital constraints and regulatory uncertainty remain significant barriers. Sheeraz et al. (2024) applied system dynamics to Vietnam's agricultural enterprises, modelling long-term interactions between climate threats and firm performance; their framework highlights resilience pathways but requires broader empirical validation. Tao et al. (2024) combined SWARA and ARAS to rank entrepreneurial success factors in Chinese agriculture, identifying entrepreneurial mindset, awareness, and technology transfer as the most influential, yet their findings are limited by a small sample size. Finally, Hung et al. (2025) developed a TCFD-based taxonomy for Taiwan's electronics industry, classifying governance, strategy, risk management, and metrics/targets, and identifying transition and physical risks particularly supply chain disruptions and regulatory uncertainty as the most critical.

Despite these valuable contributions, the literature remains fragmented. Most studies analyse green finance flows, export sophistication, or sustainability rankings in isolation, without systematically operationalising sector-level climate risk. Integrated MCDM applications exist, but they rarely link expert-weighted criteria to transparent sectoral rankings that can directly inform policy and financial decision-making. Moreover, little attention has been given to emerging economies where export-driven growth intersects with climate vulnerability. Addressing this gap, the present study applies the SWARA–ARAS framework to assess climate risks in Türkiye's export sectors, thereby offering a novel contribution to both the theoretical MCDM literature and the practical design of green finance policies in emerging economies.

Methodology

In this study, an integrated application of the Multi-Criteria Decision-Making (MCDM) methods, SWARA (Step-wise Weight Assessment Ratio Analysis) and ARAS (Additive Ratio Assessment) is employed to analyse the sensitivity of Türkiye's export sectors to climate risks and to support sectoral prioritisation in green finance strategies. Due to the inherent uncertainty, multidimensionality, and sectoral heterogeneity of climate risks, conventional analytical approaches are often inadequate for capturing their full complexity. Therefore, combining expert-based weighting with quantitative ranking techniques is essential for robust decision-making.

MCDM methods are utilized in this research to systematically assess the influence of various climate risk factors. These methods enhance decision-making processes by incorporating multiple criteria and offering optimal choices to decision-makers (Uludağ and Doğan, 2016, p. 17).

Within this framework, the SWARA method is used to determine the relative importance of criteria based on expert evaluations (Keršuliene et al., 2010). SWARA translates intuitive judgments of decision-makers into quantitative values, providing a flexible and transparent weighting mechanism. The ARAS method, on the other hand, ranks alternatives based on their closeness to an ideal solution, thereby guiding decision-makers toward optimal choices (Zavadskas and Turskis, 2010). Owing to its simplicity and high applicability, ARAS is well-suited for multi-criteria problems such as sustainability and climate risk assessments.

The integration of these two methods establishes a balance between subjective expert input and objective ranking, resulting in a comprehensive analytical model that strengthens sector-specific decision-support mechanisms for climate risk evaluation.

Criteria Selection

The criteria used in this study were selected to evaluate the climate risks faced by Türkiye's export sectors and to guide the prioritisation of green finance strategies. The selection process considered sectoral vulnerabilities to climate change, the capacity for green financial integration, and alignment with sustainable development goals. These criteria were identified through a comprehensive review of the relevant literature and policy reports. Previous research on climate risk assessment and green finance decision-making confirms the critical role these dimensions play in sector-level evaluations.

A total of seven main criteria were established within the scope of this study: emission intensity, energy dependency, water usage, climate sensitivity, supply chain vulnerability, adaptive capacity, and dependency on external markets. These criteria are designed to capture both the physical dimensions of climate risks and their financial implications. They are intended to assist decision-makers in structuring robust, strategic responses to sector-specific challenges in the transition toward sustainable trade and finance.

The selection of criteria in this study is grounded in a comprehensive review of the literature addressing sectoral climate risks and green finance prioritisation. Each criterion was chosen based on its relevance to sectoral vulnerability, alignment with sustainable development objectives, and its impact on green financial strategies. The following sources provided the empirical and theoretical basis for inclusion:

Emission Intensity: Emission intensity is widely recognized as a key indicator of climate risk. Numerous studies drawing on the IPCC (2021) and OECD (2020) reports have emphasized the role of emissions in trade strategies and their influence on both financial and physical climate risks. As such, the sectoral variation in emission intensity serves as a critical input for green finance decision-making.

Energy Dependency: According to reports by the International Energy Agency (IEA) and the World Bank (2018), energy dependency poses substantial risks for national economies and export-oriented sectors in particular. Energy efficiency and supply dependency are considered central concerns for green finance frameworks (Gielen et al., 2019), justifying the inclusion of this criterion.

Water Usage: Water management and efficiency are key factors in developing climate-compatible strategies, particularly in agriculture and industrial sectors (UN Water, 2018). Water crises are considered significant barriers to achieving sustainable development goals, and the literature consistently links efficient water use with improved financial performance at the sectoral level (GWP, 2014). Therefore, this criterion accounts for both current water consumption and efficient usage practices.

Climate Sensitivity: Climate sensitivity reflects the degree to which a sector is exposed to physical climate risks. Prior research, including Aras et al. (2017), has examined how sector-specific climate vulnerabilities influence financial decisions and long-term strategic planning. High sensitivity underscores the necessity of prioritizing green finance and adaptation measures.

Supply Chain Vulnerability: Supply chain vulnerability indicates how climate-related disruptions may impact production and logistics systems. Ghadge, Wurtmann and Seuring (2020) and Heydari (2024) discuss the increasing fragility of supply chains under climate pressure and the implications for sectoral financial planning. This criterion captures the resilience or lack thereof of sectors to climate-induced supply chain disruptions.

Adaptive Capacity: The ability of firms and sectors to adapt to climate change has been identified as a decisive factor in the effective implementation of green finance strategies (Alkaya et al., 2015; Linnenluecke, Griffiths and Winn, 2013). Sectors with high adaptive capacity are better positioned to absorb climate shocks and direct green investments more effectively. This criterion is therefore essential in aligning financial strategies with long-term sustainability goals.

Dependency on External Markets: External market dependency reflects the degree to which a sector relies on international markets. OECD (2020) and Dellink et al. (2017) have extensively explored how such dependencies can exacerbate climate vulnerabilities and affect the feasibility of green finance transitions. For export-driven sectors, external market reliance is a key strategic factor in sustainability planning.

Each of these criteria is supported by empirical findings in the literature, confirming their relevance to both climate risk assessment and green finance prioritisation. The review demonstrates how each dimension contributes to financial strategy development, sustainable development alignment, and sectoral decision-making processes in the context of climate adaptation and mitigation.

Data Collection

The data collection process in this study was conducted through the participation of expert respondents representing various Türkiye’s export sectors. These participants were selected with the aim of ensuring an accurate sectoral assessment of climate-related risks. The selected individuals possess the expertise required to identify climate change-induced risks at the sectoral level and to evaluate their implications for green finance decision-making. To ensure sectoral representativeness, the participants were drawn from different segments of Türkiye’s export economy.

A total of 10 professionals currently employed in foreign trade firms across Türkiye were selected for the study. Each participant had substantial experience in evaluating climate risks and green finance decisions, and demonstrated in-depth knowledge of foreign trade and logistics. Selection criteria emphasized prior engagement with sustainability and climate-related projects or professional roles within those domains. The capacity to assess the economic implications of climate risks within one’s sector was a key consideration in the participant selection process. Consequently, each expert was expected to possess a nuanced understanding of the specific risks and opportunities associated with climate change in their respective industries.

The study purposefully included one participant from each of 10 distinct professional fields, ensuring diversity of insight. All participants were professionals with demonstrable experience in climate-related risk assessment, green financing, and sustainability. This interdisciplinary composition allowed for the analysis of climate risks from multiple perspectives, providing a rich foundation for multi-criteria evaluation.

While the panel size is relatively small (n=10), this was a deliberate design choice to maximise sectoral diversity and ensure balanced coverage of key export industries, including agri-food, automotive, textiles, chemicals, and electronics. In the context of multi-criteria decision-making research, similar panel sizes are widely accepted, as the emphasis lies on the depth of expertise and sectoral representation rather than statistical generalisability. This approach allows the framework to capture informed judgments across strategically important sectors while maintaining methodological coherence.

Ethics approval for this study was obtained from the Ethics Committee for Social and Human Sciences Research at Tarsus University, Republic of Türkiye, under decision number 2025/73.

Table 1 presents the participants, each representing a distinct professional group. The table includes information on their sectoral experience and areas of expertise.

Table 1. Participant Profiles

Participant No.	Job/Title	Sector	Field of Expertise	Experience (Year)
1	Foreign Trade Manager	Agriculture and Food	Export Strategies and Risk Management	12
2	Export Specialist	Textile and Clothing	Logistics and Export Risk Management	10
3	Logistics Manager	Cement	Export, Logistics and Supply Chain	14
4	Expert in Risk Management	Iron – Steel	Climate Risk Management and Financial Strategy	15
5	Export and Trade Consultant	Chemical	Export and Sustainability	9
6	Logistics and Supply Chain Manager	Automotive	Logistical Operations and Export Procedures	8
7	Financial Analyst	Electrical Appliances	Green Finance and Risk Assessment	11
8	Trade Expert	Furniture	Export and Climate Risk Assessment	10
9	Export Manager	Plastic – Rubber	Export Operations and Risk Management	13
10	Finance and Sustainability Expert	Mining	Green Finance and Climate Adaptation	12

Methods

SWARA Method

The Step-wise Weight Assessment Ratio Analysis (SWARA) method is one of the increasingly applied approaches for determining criteria weights in multi-criteria decision-making (MCDM) problems. The method was originally developed by Keršulienė et al. (2010). In the literature, SWARA is recognized as an expert-based technique that allows decision-makers to directly reflect their subjective assessments regarding the importance of evaluation criteria.

The key feature of the SWARA method lies in its ability to incorporate expert judgment systematically into the weighting process. The relative importance of each criterion, as assigned by experts, forms the foundation of the method (Aghdaie, Zolfani and Zavadskas, 2013; Özbek, 2017).

The SWARA method consists of five sequential steps used to determine the relative weights of evaluation criteria (Ruzgys et al., 2014, pp. 103–110). The steps are described below:

Step 1: Ranking of the Criteria

All criteria are ranked in descending order based on their perceived importance. This ranking reflects the anticipated significance of each criterion as evaluated by the decision-makers, starting from the most important and progressing to the least important.

Step 2: Determination of Initial Comparative Importance

The initial priority values of the criteria are determined. At this stage, the decision maker evaluates each criterion, starting with the second criterion, according to the criterion that comes before it or is considered more important. This evaluation is carried out on a ratio in the range of (0,1]. The evaluation being ''1'' means that the criteria are of equal importance. As a result, the sj value is reached (Ruzgys et al., 2014:107).

Step 3: Calculation of the Coefficient k_j

Calculation of the coefficient k_j is performed. This coefficient is determined with the help of Equation (1) given below.

$$k_j = \begin{cases} 1, & j = 1 \\ s_j + 1, & j > 1 \end{cases} \tag{1}$$

Step 4: Determination of Preliminary Weights

Initial weights are determined. At this stage, Equation (2) is obtained using q_j.

$$q_j = \begin{cases} 1, & j = 1 \\ \dfrac{q_{j-1}}{k_j}, & j > 1 \end{cases} \tag{2}$$

Step 5: Calculation of Final (Relative) Weights

This is the final step in the SWARA method. In this stage, the relative weights of the criteria are obtained by normalizing the preliminary weights calculated in Step 4. The formula used for normalization is provided below (Equation 3):

$$w_j = \frac{q_j}{\sum_{k=1}^{n} q_k} \tag{3}$$

The SWARA method was preferred in this study because it offers the opportunity to transform subjective expert assessments into quantitative data with a systematic approach. Through the weighting process based on expert opinions, the order in which risk factors should be addressed was determined.

ARAS Method

The Additive Ratio Assessment (ARAS) method is a multi-criteria decision-making approach used to determine the relative efficiency levels of available alternatives in a given evaluation. The method defines a utility function that is directly proportional to the weights and values of the criteria associated with each alternative. ARAS serves as an effective tool for performance assessment by revealing the proportional closeness of each alternative to an ideal (optimal) solution.

The ARAS method consists of five key steps (Dadelo et al., 2012; Ecer, 2016), which are systematically applied to evaluate and rank the alternatives.

Step 1: Creating the Decision Matrix

In the first stage, the decision matrix is created. In multi-criteria decision making (MCDM) problems, the decision matrix has a structure consisting of m number of alternatives (rows) and n number of criteria (columns).

$$X = \begin{bmatrix} x_{01} & x_{02} & \cdots & x_{0n} \\ x_{11} & x_{12} & \cdots & x_{1n} \\ \vdots & \vdots & \cdots & \vdots \\ x_{m1} & x_{m2} & \cdots & x_{mn} \end{bmatrix}; i = 0,1, \dots, m; j = 1,2, \dots, n \tag{4}$$

In the decision matrix; m represents the number of alternatives, n represents the number of criteria, x_ij represents the performance value of the i. alternative according to the j criterion, and x_0j represents the optimal (best) value of the j criterion. However, if the optimal value of the j criterion is unknown, then the value in question is calculated using formula (5).

$$\begin{cases} If\ \underbrace{maks}_{i} x_{ij} \ \ ise\ x_{0j} = \underbrace{maks}_{i} x_{ij} \\ If\ \underbrace{min}_{i} x^{*}_{ij} \ \ ise \ \ \underbrace{min}_{i}\ x^{*}_{ij} \end{cases} \tag{5}$$

Step 2: Normalization

The criteria taken into consideration can often have different dimensions and scales. The purpose of this step is to standardize the criteria at different scales through the normalization process. Thus, all criteria are converted to values in the range of [0,1] and thus gain a comparable structure. In the normalization process; Formula (6) is used for the criteria that are desired to have a maximum value, and Formula (7) is used for the criteria that are desired to have a minimum value.

$$\bar{x}_{ij} = \frac{x_{ij}}{\sum_{i=0}^{m} 1/x_{ij}} \tag{6}$$

$$\bar{x}_{ij} = \frac{1/x_{ij}}{\sum_{i=0}^{m} 1/x_{ij}} \tag{7}$$

After the normalization process is completed, the resulting normalized decision matrix is created as follows.

$$X = \begin{bmatrix} \bar{x}_{01} & \bar{x}_{02} & \cdots & \bar{x}_{0n} \\ \bar{x}_{11} & \bar{x}_{12} & \cdots & \bar{x}_{1n} \\ \vdots & \vdots & \cdots & \vdots \\ \bar{x}_{m1} & \bar{x}_{m2} & \cdots & \bar{x}_{mn} \end{bmatrix}; i = 0,1, \dots, m; j = 1,2, \dots, n \tag{8}$$

Step 3: Creating the Weighted Normalized Decision Matrix

At this stage, the weighted normalized decision matrix is created by taking into account the criterion weights. Criterion weights take values between 0 and 1 and the sum of all criterion weights is equal to 1. Since weights directly affect the analysis results, it is of great importance that they are determined carefully and meticulously. Normalized weights are calculated using Formula (9).

$$x_{ij} = \bar{x}_{ij} w_j \ ; \qquad i = 0,1, \ldots, m \tag{9}$$

In this way, the weighted normalized decision matrix is created as shown below.

$$X = \begin{bmatrix} x_{01} & x_{02} & \cdots & x_{0n} \\ x_{11} & x_{12} & \cdots & x_{1n} \\ \vdots & \vdots & \cdots & \vdots \\ x_{m1} & x_{m2} & \cdots & x_{mn} \end{bmatrix}; \quad i = 0,1, \ldots, m; j = 1,2, \ldots, n \tag{10}$$

Step 4: Calculation of Optimality Function Si

$$S_i = \sum_{j=1}^{n} x_{ij} \ ; \qquad i = 0,1, \ldots, m \tag{11}$$

In formula (11), S_i represents the optimality function of the i. alternative. A high value of Si can be interpreted as the preferability of the relevant alternative being higher. Because this value is directly related to x_{ij} (performance value) and w_j (criterion weight) when evaluated in terms of the calculation process. As a result, the alternative with a higher value of S_i is considered a more effective option.

Step 5: Calculating the Benefit Level and Ranking the Alternatives

$$K_i = \frac{S_i}{S_0} \qquad i = 0,1, \ldots, m \tag{11}$$

In this final step, the utility degree for each alternative is calculated, allowing for the ranking of alternatives based on their level of efficiency. The computed utility values reflect the proximity of each alternative to the ideal solution, thereby enabling the identification of the most suitable option.

Findings

Below, all outputs related to the SWARA and ARAS methods used in the study are presented in sequence.

SWARA Results

Based on the evaluations of ten expert participants, the criteria were ranked in descending order of expected importance (from most to least important). Subsequently, the initial comparative importance values for the criteria were assessed individually by each expert within the interval (0,1]. In the final results obtained from the decision-makers, the criteria denoted as "C" are defined as follows: (C1) Emission Intensity, (C2) Climate Sensitivity, (C3) Supply Chain Vulnerability, (C4) Energy Dependency, (C5) Adaptive Capacity, (C6) Dependency on External Markets, and (C7) Water Usage.

Table 2. Final Results Obtained by Decision-Maker 1

Decision-Maker 1					
Criteria	**Order of Importance**	**Sj**	**Kj**	**Qj**	**Wj**
Energy Dependency (C4)	1		1	1,000	0,277
Emission Intensity (C1)	2	0,3	1,3	0,769	0,213
Supply Chain Vulnerability (C3)	3	0,3	1,3	0,592	0,164
Climate Sensitivity (C2)	4	0,4	1,4	0,423	0,117
Dependency on External Markets (C6)	5	0,2	1,2	0,352	0,097
Water Usage (C7)	6	0,4	1,4	0,252	0,070
Adaptive Capacity (C5)	7	0,1	1,1	0,229	0,063

Table 3. Final Results Obtained by Decision-Maker 2

Decision-Maker 2					
Criteria	**Order of Importance**	**Sj**	**Kj**	**Qj**	**Wj**
Emission Intensity (C1)	1		1,000	1,000	0,285
Climate Sensitivity (C2)	2	0,500	1,500	0,667	0,190
Energy Dependency (C4)	3	0,200	1,200	0,556	0,158
Adaptive Capacity (C5)	4	0,300	1,300	0,427	0,122
Supply Chain Vulnerability (C3)	5	0,200	1,200	0,356	0,101
Dependency on External Markets (C6)	6	0,200	1,200	0,297	0,084
Water Usage (C7)	7	0,400	1,400	0,212	0,060

Table 4. Final Results Obtained by Decision-Maker 3

Decision-Maker 3					
Criteria	**Order of Importance**	**Sj**	**Kj**	**Qj**	**Wj**
Emission Intensity (C1)	1		1	1,000	0,265
Adaptive Capacity (C5)	2	0,400	1,400	0,714	0,189
Energy Dependency (C4)	3	0,200	1,200	0,595	0,158
Climate Sensitivity (C2)	4	0,250	1,250	0,476	0,126
Dependency on External Markets (C6)	5	0,150	1,150	0,414	0,110
Supply Chain Vulnerability (C3)	6	0,250	1,250	0,331	0,088
Water Usage (C7)	7	0,350	1,350	0,245	0,065

Table 5. Final Results Obtained by Decision-Maker 4

Decision-Maker 4					
Criteria	**Order of Importance**	**Sj**	**Kj**	**Qj**	**Wj**
Energy Dependency (C4)	1		1	1,000	0,238
Climate Sensitivity (C2)	2	0,25	1,25	0,800	0,190
Adaptive Capacity (C5)	3	0,15	1,15	0,696	0,165
Dependency on External Markets (C6)	4	0,15	1,15	0,605	0,144
Supply Chain Vulnerability (C3)	5	0,2	1,2	0,504	0,120
Emission Intensity (C1)	6	0,4	1,4	0,360	0,086
Water Usage (C7)	7	0,5	1,5	0,240	0,057

Table 6. Final Results Obtained by Decision-Maker 5

Decision-Maker 5					
Criteria	**Order of Importance**	**Sj**	**Kj**	**Qj**	**Wj**
Emission Intensity (C1)	1		1,000	1,000	0,289
Climate Sensitivity (C2)	2	0,500	1,500	0,667	0,193
Supply Chain Vulnerability (C3)	3	0,200	1,200	0,556	0,161
Energy Dependency (C4)	4	0,350	1,350	0,412	0,119
Adaptive Capacity (C5)	5	0,200	1,200	0,343	0,099
Dependency on External Markets (C6)	6	0,200	1,200	0,286	0,083
Water Usage (C7)	7	0,450	1,450	0,197	0,057

Table 7. Final Results Obtained by Decision-Maker 6

Decision-Maker 6					
Criteria	**Order of Importance**	**Sj**	**Kj**	**Qj**	**Wj**
Energy Dependency (C4)	1		1	1,000	0,261
Emission Intensity (C1)	2	0,350	1,350	0,741	0,193
Adaptive Capacity (C5)	3	0,200	1,200	0,617	0,161
Climate Sensitivity (C2)	4	0,250	1,250	0,494	0,129
Dependency on External Markets (C6)	5	0,200	1,200	0,412	0,107
Water Usage (C7)	6	0,350	1,350	0,305	0,080
Supply Chain Vulnerability (C3)	7	0,150	1,150	0,265	0,069

Table 8. Final Results Obtained by Decision-Maker 7

Decision-Maker 7					
Criteria	**Order of Importance**	**Sj**	**Kj**	**Qj**	**Wj**
Emission Intensity (C1)	1		1	1,000	0,284
Energy Dependency (C4)	2	0,35	1,35	0,741	0,210
Climate Sensitivity (C2)	3	0,4	1,4	0,529	0,150
Dependency on External Markets (C6)	4	0,2	1,2	0,441	0,125
Supply Chain Vulnerability (C3)	5	0,25	1,25	0,353	0,100
Adaptive Capacity (C5)	6	0,35	1,35	0,261	0,074
Water Usage (C7)	7	0,3	1,3	0,201	0,057

Table 9. Final Results Obtained by Decision-Maker 8

Decision-Maker 8					
Criteria	**Order of Importance**	**Sj**	**Kj**	**Qj**	**Wj**
Climate Sensitivity (C2)	1		1,000	1,000	0,244
Emission Intensity (C1)	2	0,250	1,250	0,800	0,195
Energy Dependency (C4)	3	0,100	1,100	0,727	0,177
Adaptive Capacity (C5)	4	0,350	1,350	0,539	0,131
Dependency on External Markets (C6)	5	0,200	1,200	0,449	0,110
Supply Chain Vulnerability (C3)	6	0,300	1,300	0,345	0,084
Water Usage (C7)	7	0,450	1,450	0,238	0,058

Table 10. Final Results Obtained by Decision-Maker 9

Decision-Maker 9					
Criteria	**Order of Importance**	**Sj**	**Kj**	**Qj**	**Wj**
Emission Intensity (C1)	1		1	1,000	0,263
Climate Sensitivity (C2)	2	0,300	1,300	0,769	0,202
Adaptive Capacity (C5)	3	0,250	1,250	0,615	0,162
Energy Dependency (C4)	4	0,200	1,200	0,513	0,135
Supply Chain Vulnerability (C3)	5	0,400	1,400	0,366	0,096
Dependency on External Markets (C6)	6	0,200	1,200	0,305	0,080
Water Usage (C7)	7	0,300	1,300	0,235	0,062

Table 11. Final Results Obtained by Decision-Maker 10

Decision-Maker 10					
Criteria	**Order of Importance**	**Sj**	**Kj**	**Qj**	**Wj**
Emission Intensity (C1)	1		1	1,000	0,282
Dependency on External Markets (C6)	2	0,35	1,35	0,741	0,209
Adaptive Capacity (C5)	3	0,4	1,4	0,529	0,149
Supply Chain Vulnerability (C3)	4	0,2	1,2	0,441	0,124
Energy Dependency (C4)	5	0,25	1,25	0,353	0,100
Climate Sensitivity (C2)	6	0,35	1,35	0,261	0,074
Water Usage (C7)	7	0,2	1,2	0,218	0,061

Table 12. Final Weights of the Criteria Determined by the SWARA Method

Criteria	**Kv1**	**Kv2**	**Kv3**	**Kv4**	**Kv5**	**Kv6**	**Kv7**	**Kv8**	**Kv9**	**Kv10**	**FINAL WEIGHT**
C1	0,213	0,285	0,265	0,086	0,289	0,193	0,284	0,195	0,263	0,282	0,220
C	0,117	0,190	0,126	0,190	0,193	0,129	0,150	0,244	0,202	0,074	0,150
C3	0,164	0,101	0,088	0,120	0,161	0,069	0,100	0,084	0,096	0,124	0,110
C4	0,277	0,158	0,158	0,238	0,119	0,261	0,210	0,177	0,135	0,100	0,170
C5	0,063	0,122	0,189	0,165	0,099	0,161	0,074	0,131	0,162	0,074	0,120
C6	0,097	0,084	0,110	0,144	0,083	0,107	0,125	0,110	0,080	0,209	0,110
C7	0,070	0,060	0,065	0,057	0,057	0,080	0,057	0,058	0,062	0,061	0,060

As a result of the findings, the most important criterion was identified as "Emission Intensity", with a weight of 0.220. It was followed by "Energy Dependency" with a weight of 0.170, and "Climate Sensitivity" with a weight of 0.150.

This outcome suggests that experts prioritize environmentally conscious approaches in the decision-making process, and therefore, minimizing emissions is considered a critical first step within the framework of sustainability goals. Energy Dependency (C4) (17.0%) and Climate Sensitivity (C2) (15.0%) ranked as the second and third most important criteria, respectively. This indicates that diversifying energy sources and addressing the impacts of climate change on business processes are viewed as the two main priorities following emission reduction.

On the other hand, "Water Usage" (C7) ranked last with a relatively low weight of 6.0% (0.060). While experts acknowledge the importance of water resource management, this result suggests that they perceive it as less urgent compared to climate and energy-related concerns that appear higher on the priority list.

ARAS Results

Within the scope of the ARAS method, the performance values of the sectors under seven criteria are presented step by step in the form of the decision matrix, criteria directions and weights, benefit-oriented transformed matrix, normalized matrices, weighted normalized matrix, and final ARAS scores.

Table 13. ARAS Decision Matrix

	C1	**C2**	**C3**	**C4**	**C5**	**C6**	**C7**
Agriculture and Food	10	30	50	40	50	60	90
Textile	20	45	65	55	65	80	40
Automotive	30	20	70	50	80	85	55
Iron and Steel	40	80	40	30	50	60	50
Chemical	70	30	60	80	75	60	60

Table 13. Continue

	C1	C2	C3	C4	C5	C6	C7
Electrical	40	50	85	45	75	80	55
Furniture	30	50	60	50	50	55	30
Plastic	50	50	55	60	50	60	40
Mining	35	50	60	65	60	50	30
Cement	60	55	50	60	70	40	30

Table 14. Directions and Weights of the Criteria

	C1	C2	C3	C4	C5	C6	C7
Directions	-	+	-	-	+	-	-
W	0,220	0,150	0,110	0,170	0,120	0,110	0,060

Table 15. Benefit-Oriented Transformed Decision Matrix

	C1 (-)	C2 (+)	C3 (-)	C4 (-)	C5 (+)	C6 (-)	C7 (-)
W	0,220	0,15	0,110	0,170	0,12	0,110	0,060
OPTIMUM	0,100	80	0,025	0,033	80	0,025	0,033
Agriculture and Food	0,100	30	0,020	0,025	50	0,017	0,011
Textile	0,050	45	0,015	0,018	65	0,013	0,025
Automotive	0,033	20	0,014	0,020	80	0,012	0,018
Iron and Steel	0,025	20	0,025	0,033	50	0,017	0,020
Chemicals	0,014	80	0,017	0,013	75	0,017	0,017
Electrical	0,025	30	0,012	0,022	75	0,013	0,018
Furniture	0,033	50	0,017	0,020	50	0,018	0,033
Plastic	0,020	50	0,018	0,017	50	0,017	0,025
Mining	0,029	50	0,017	0,015	60	0,020	0,033
Cement	0,017	55	0,020	0,017	70	0,025	0,033

Table 16. Normalization of Decision Matrix

	C1 (-)	C2 (+)	C3 (-)	C4 (-)	C5 (+)	C6 (-)	C7 (-)
W	0,220	0,15	0,110	0,170	0,12	0,110	0,060
OPTIMUM	0,100	80	0,025	0,033	80	0,025	0,033
Agriculture and Food	0,100	30	0,020	0,025	50	0,017	0,011
Textile	0,050	45	0,015	0,018	65	0,013	0,025
Automotive	0,033	20	0,014	0,020	80	0,012	0,018
Iron and Steel	0,025	20	0,025	0,033	50	0,017	0,020
Chemical	0,014	80	0,017	0,013	75	0,017	0,017
Electrical	0,025	30	0,012	0,022	75	0,013	0,018
Furniture	0,033	50	0,017	0,020	50	0,018	0,033
Plastic	0,020	50	0,018	0,017	50	0,017	0,025
Mining	0,029	50	0,017	0,015	60	0,020	0,033
Cement	0,017	55	0,020	0,017	70	0,025	0,033
Column Total	0,446	510	0,200	0,233	705	0,194	0,266

Table 17. Normalized Decision Matrix

	C1 (-)	C2 (+)	C3 (-)	C4 (-)	C5 (+)	C6 (-)	C7 (-)
W	0,224	0,157	0,125	0,142	0,113	0,129	0,124
OPTIMUM	0,224	0,059	0,100	0,107	0,071	0,088	0,041
Agriculture and Food	0,112	0,088	0,075	0,077	0,092	0,067	0,094
Textile	0,074	0,039	0,070	0,086	0,113	0,062	0,068
Automotive	0,056	0,039	0,125	0,142	0,071	0,088	0,075
Iron and Steel	0,031	0,157	0,085	0,056	0,106	0,088	0,064
Chemicals	0,056	0,059	0,060	0,094	0,106	0,067	0,068
Electrical	0,074	0,098	0,085	0,086	0,071	0,093	0,124
Furniture	0,045	0,098	0,090	0,073	0,071	0,088	0,094
Plastic	0,065	0,098	0,085	0,064	0,085	0,103	0,124
Mining	0,038	0,108	0,100	0,073	0,099	0,129	0,124
Cement	0,224	0,157	0,125	0,142	0,113	0,129	0,124

Table 18. Weighted Normalized Matrix and ARAS Scores

	C1 (-)	C2 (+)	C3 (-)	C4 (-)	C5 (+)	C6 (-)	C7 (-)	Sj	Kj	Score
W	0,22	0,15	0,11	0,17	0,12	0,11	0,06			
OPTIMUM	0,049	0,024	0,014	0,024	0,014	0,014	0,007	0,146	1	
Agriculture and Food	0,049	0,009	0,011	0,018	0,009	0,010	0,002	0,108	0,740	1
Textile	0,025	0,013	0,008	0,013	0,011	0,010	0,006	0,086	0,587	2
Automotive	0,016	0,006	0,008	0,015	0,014	0,007	0,004	0,069	0,472	9
Iron and Steel	0,012	0,006	0,014	0,024	0,009	0,010	0,005	0,079	0,539	5
Chemicals	0,007	0,024	0,009	0,009	0,013	0,010	0,004	0,076	0,517	7
Electrical	0,012	0,009	0,007	0,016	0,013	0,007	0,004	0,068	0,466	10
Furniture	0,016	0,015	0,009	0,015	0,009	0,010	0,007	0,081	0,556	4
Plastic	0,010	0,015	0,010	0,012	0,009	0,010	0,006	0,071	0,484	8
Mining	0,014	0,015	0,009	0,011	0,010	0,011	0,007	0,078	0,537	6
Cement	0,008	0,016	0,011	0,012	0,012	0,014	0,007	0,081	0,559	3

In Table 18, the optimality function values (Si) and utility scores (Ki) for each sector were calculated using the weighted normalized values of the seven climate risk criteria. The “Optimum” row represents the ideal reference value. The agri-food sector received the highest utility score (Ki = 0.740), ranking first. It was followed by the textile (Ki = 0.587) and cement (Ki = 0.559) sectors, forming the second and third highest risk groups.

The moderate risk group included the furniture (Ki = 0.556), mining (Ki = 0.537), iron–steel (Ki = 0.539), and plastics (Ki = 0.484) sectors. Meanwhile, the automotive (Ki = 0.472) and electrical devices (Ki = 0.466) sectors had the lowest utility scores, positioning them as the most resilient sectors. These results quantitatively reveal the relative differences in vulnerability among sectors in the face of climate change.

Results and Discussion

Climate risk and green finance are among the most critical issues for various sectors. In this context, it is necessary to rank the sectors in Türkiye’s export economy according to their exposure to climate risks and to design green finance policies in line with sectoral vulnerabilities. In this study, ten sectors with strategic importance for Türkiye’s export revenues were analysed using an integrated SWARA–ARAS model based on seven climate risk criteria.

Theoretically, the use of both SWARA and ARAS methods enables the flexible quantification of expert opinions as well as the comparative ranking of sectoral performance, offering a novel contribution to the multi-criteria decision-making (MCDM) literature. This approach integrates both physical risks (e.g., water usage, sensitivity) and transition risks (e.g., carbon costs, energy dependency) within a single analytical framework that aligns with the multidimensional nature of climate change, thereby providing a methodological model for future studies.

The results show that criteria such as emission intensity (22%), energy dependency (17%), and climate sensitivity (15%) play a primary role in determining vulnerability distributions across sectors. The criterion weighting performed via the SWARA method is consistent with findings in the literature (Liu et al., 2023; Zhou et al., 2023). According to ARAS scores, the agri-food (0.740), textile (0.587), and cement (0.559) sectors are among those most at risk, while the automotive (0.472) and electrical devices (0.466) sectors appear to be relatively more resilient. These findings address a methodological gap in the literature by quantitatively identifying each sector's capacity for climate policy adaptation and its need for green financing. The agri-food sector's high score confirms the impact of water usage and direct exposure to physical climate events (Schaeffer et al., 2012; UN Water, 2018). The elevated risk profiles of the textile and cement sectors may be attributed to energy-intensive production processes and sensitivity to carbon costs (Gielen et al., 2019). Conversely, the relatively lower scores of the automotive and electrical devices sectors point to the positive effects of technological transformation efforts and more resilient supply chain practices in these industries (Ghadge et al., 2020).

Our results are broadly consistent with international evidence. In the EU context, energy-intensive industries (e.g., cement and chemicals) repeatedly emerge as highly exposed to carbon pricing and regulatory tightening, which aligns with the elevated risk profiles in our ranking. By contrast, China-focused studies emphasise the role of technological innovation and productivity in mitigating exposure within manufacturing exports. Our findings extend these insights by showing that, in Türkiye, vulnerability is shaped not only by emission intensity but also by water stress and supply-chain fragilities underscoring the need to tailor green-finance instruments to national sectoral contexts rather than adopt one-size-fits-all approaches.

Sector-specific explanations clarify the drivers behind the rankings: (i) Agri-food faces heightened exposure due to physical risks (water scarcity, extreme weather) and input volatility across upstream chains; (ii) Textiles & apparel are sensitive to energy intensity and Carbon Border Adjustment Mechanism (CBAM)-related compliance costs, with additional exposure to subcontracting-heavy supply chains; (iii) Cement (and basic materials) remain structurally carbon-intensive, where abatement hinges on process innovation and capital-heavy technologies; (iv) Automotive & electronics exhibit transition risks tied to electrification and critical-minerals dependencies, alongside supplier concentration risks. These mechanisms map directly onto our criteria set (climate sensitivity, emission intensity, energy use, and supply-chain vulnerability), explaining sectoral differentials in composite scores.

Taken together, these patterns suggest that risk is multi-dimensional and sector-contingent. Consequently, policy design should prioritise instruments that are both sector-specific and finance-ready, linking risk reduction to measurable outcomes (e.g., emissions avoided, water saved, or supply-chain resilience indicators).

Limitations and Future Research

This research has certain limitations. First, the expert panel consisted of only ten participants, which may limit the generalisability of the weightings to local expertise, although the panel was deliberately composed to ensure sectoral diversity. Second, the criteria set was restricted to factors frequently cited in the literature; future studies could incorporate additional dimensions such as financial market indicators or the level of digitalisation within supply chains. Third, the sectoral performance data were collected for a fixed period; to capture annual fluctuations in climate risk, panel data models or stress test scenarios could be integrated into future analyses. Finally, while the SWARA–ARAS framework provides a systematic basis for weighting and ranking, future studies could conduct robustness checks (e.g., sensitivity analysis, bootstrap, or Monte Carlo simulations) to validate the stability of results under alternative assumptions.

It is recommended that future research apply this model to different geographic contexts (e.g., EU countries, the Middle East) and economic sectors (e.g., services, tourism). Such applications would not only enhance the generalisability of the findings but also highlight the model's transferability across diverse economic and institutional environments. Moreover, integrating input–output analysis and machine learning–based scenario simulations could help evaluate the dynamic impacts of climate risks on international trade flows. In doing so, a more comprehensive and adaptive decision-support system can be developed for both academic and policy-making communities in an era of increasing climate uncertainty.

Policy Implications

Although tailored to Türkiye's export structure, the allocation logic is transferable to other emerging economies where export-led growth coincides with climate vulnerability. The same decision rules linking sectoral risk drivers to instrument design and measurable outcomes can guide regional development banks and national green funds in prioritising pipelines.

The findings support differentiated policy paths by sector:

Agri-food: Integrate climate-smart irrigation programmes and index-based crop insurance into green-finance portfolios; condition concessional loans on water-efficiency KPIs and climate-risk audits.

Textiles & apparel: Provide energy-efficiency grants and revolving credit lines for process electrification and heat recovery; establish CBAM-readiness facilities for SMEs (MRV systems, LCA data, supplier due-diligence).

Cement/basic materials: Offer loan guarantees or tax credits for carbon-capture pilots and alternative binders; use performance-based contracts tied to verified emissions reductions.

Automotive & electronics: Deploy blended-finance vehicles to scale battery and component supply chains; support supplier diversification and critical-minerals traceability through sustainability-linked bonds or loans.

Implementation should involve transparent eligibility criteria, verifiable targets, and periodic reviews to re-prioritise allocations as sectoral risk profiles evolve.

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Özet

İklim değişikliği, yalnızca çevresel bir sorun olmanın ötesine geçerek küresel ekonomik sistemler üzerinde doğrudan ve dolaylı etkiler oluşturan çok yönlü bir kriz haline gelmiştir. Artan sıcaklıklar, ekstrem hava olayları ve kaynak kıtlığı gibi fiziksel etkilerin yanı sıra, karbon fiyatlandırmaları, düzenleyici çerçeveler ve sürdürülebilirlik kriterleri gibi geçiş riskleri de iş dünyasını dönüştürmektedir. Bu dönüşüm, özellikle dış ticarete entegre ekonomilerde, ihracat performansının iklim riskleri karşısında ne derece dayanıklı olduğu sorusunu gündeme taşımaktadır.

Türkiye, ihracat odaklı büyüme stratejisiyle sanayisini küresel pazarlara entegre etmiş gelişmekte olan bir ekonomidir. Ancak, Türkiye'nin ihracat sektörleri iklim değişikliği karşısında homojen olmayan bir risk profiline sahiptir. Örneğin, emisyon yoğunluğu yüksek sektörler karbon düzenlemelerine karşı daha kırılgan iken; tarım gibi doğaya bağımlı sektörler fiziksel iklim etkilerinden daha fazla etkilenmektedir. Bu nedenle, sektörel düzeyde iklim risklerinin sistematik biçimde değerlendirilmesi ve önceliklendirilmesi, hem iklim dirençli büyüme politikalarının oluşturulması hem de sürdürülebilir finansman mekanizmalarının geliştirilmesi açısından büyük önem taşımaktadır.

Literatürde, sektörel iklim risklerinin analizi çoğunlukla ya karbon ayak izi ya da doğrudan çevresel performans ölçütleriyle sınırlı kalmakta; çok kriterli değerlendirme ve finansal karar destek entegrasyonu nadiren ele alınmaktadır. Bu bağlamda, çalışmamız hem teorik hem de metodolojik bir boşluğu doldurmayı amaçlamaktadır. Araştırmada, Türkiye'nin önde gelen ihracat sektörlerini iklim değişikliğine karşı duyarlılık açısından analiz etmekte ve sektörel iklim risklerini Çok Kriterli Karar Verme (ÇKKV) yöntemleri aracılığıyla değerlendirmektedir. Böylece çalışma, sürdürülebilirlik odaklı finansal karar alma süreçlerine veri temelli bir katkı sağlamayı hedeflemektedir.

Metodolojik olarak, çalışmada iki aşamalı bir ÇKKV yaklaşımı benimsenmiştir. İlk aşamada, uzman görüşlerine dayalı olarak SWARA (Step-wise Weight Assessment Ratio Analysis) yöntemi ile iklim riski kriterlerinin ağırlıkları belirlenmiştir. İkinci aşamada ise, ARAS (Additive Ratio Assessment) yöntemi kullanılarak 10 temel ihracat sektörünün göreli risk düzeyleri değerlendirilmiştir. Bu süreçte, iklim

duyarlılığı, enerji tüketimi, emisyon yoğunluğu, su kullanımı ve tedarik zinciri kırılganlığı gibi çok boyutlu kriterler esas alınmıştır.

Türkiye'de literatürde hiçbir çalışma, ihracat sektörlerini SWARA–ARAS çerçevesinde iklim risklerine göre sistematik biçimde karşılaştırmamıştır. Var olan analizler ya yalnızca emisyon yoğunluğu ya da çevresel performans ölçütleriyle sınırlı kalmakta, finansal karar destek sistemlerine doğrudan entegre edilememektedir. Oysa SWARA'nın kriter ağırlıklarını uzman görüşleriyle belirleme gücü ile ARAS'ın sektörler arası göreli performans sıralamasındaki kullanım kolaylığı, bu açığın kapatılmasında ideal bir metodolojik temel sunmaktadır.

Bu çalışmanın araştırma soruları, şu iki başlık altında somutlaşmaktadır:

Türkiye'nin önde gelen ihracat sektörleri arasında kriterler hangi ölçüde farklılaşmakta ve bu farklılıklar sektörel risk profilini nasıl şekillendirmektedir?

SWARA ile belirlenen kriter ağırlıkları ışığında ARAS'ın sunduğu sıralama, yeşil finans politikalarının sektörel önceliklendirilmesi için nasıl yol gösterici olacaktır?

Teorik olarak, çalışmanın SWARA ve ARAS yöntemlerini iç içe kullanarak hem uzman görüşlerinin esnek bir şekilde sayısallaştırılmasını hem de sektör performanslarının karşılaştırmalı sıralanmasını mümkün kılması, Çok Kriterli Karar Verme literatürüne özgün bir katkı sunmaktadır. Özellikle iklim değişikliğinin çok boyutlu doğasına uygun olarak hem fiziksel (su kullanımı, hassasiyet) hem de geçiş risklerini (karbon maliyetleri, enerji bağımlılığı) aynı analiz modeli içinde bütünleştiren bu yaklaşım, gelecek çalışmalarda da kaynak gösterilebilecek bir metodolojik örnek oluşturmaktadır.

Elde edilen sonuçlar, emisyon yoğunluğu (%22), enerji bağımlılığı (%17) ve iklim hassasiyeti (%15) gibi geçiş ve fiziksel risk kriterlerinin sektörler arası kırılganlık dağılımında öncelikli rol oynadığını göstermiştir. SWARA Yöntemiyle yapılan kriter ağırlıklandırmasının literatürde yer alan (Liu vd., 2023; Zhou vd., 2023) çalışmalarla uyumlu olduğu görülmektedir. ARAS skorlarına göre tarım–gıda (0,740), tekstil (0,587) ve çimento (0,559) sektörleri en yüksek risk altında yer alırken, otomotiv (0,472) ve elektrikli cihazlar (0,466) görece daha dayanıklı bulunmuştur. Bu bulgular, sektörlerin iklim politikalarına uyum kapasitesini ve yeşil finansman ihtiyacını nicel verilerle ortaya koyarak literatürdeki yöntemsel boşluğu doldurmaktadır. Tarım–gıda sektörünün en yüksek skoru alması, bu sektördeki su kullanımının ve fiziksel iklim olaylarına doğrudan maruziyetin etkisini doğrulamaktadır. Tekstil ve çimento sektörlerinin yüksek risk profili ise, enerji yoğun üretim süreçleri ve karbon maliyetlerine duyarlılıkla açıklanabilir. Buna karşılık otomotiv ve elektrikli cihazlar sektörlerinde daha düşük skorlar, bu alanlardaki teknolojik dönüşüm çabalarının ve nispeten daha dirençli tedarik zinciri uygulamalarının olumlu etkisine işaret etmektedir.

Politika ve uygulama boyutunda, çalışmanın çıktıları Türkiye'nin yeşil finansman araçlarının sektörel önceliklendirilmesinde somut yol haritası sağlayacaktır. Başta Tarım ve Orman Bakanlığı, Sanayi ve Teknoloji Bakanlığı ile Hazine ve Maliye Bakanlığı olmak üzere ilgili kurumsal aktörler, yüksek riskli sektörlerde enerji dönüşümü, karbon azaltımı ve tedarik zinciri dayanıklılığını destekleyici hibeler ve kredi garanti mekanizmaları tasarlayabilir.