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From resource to innovation: A decision framework for sustainable boron research infrastructure

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ABSTRACT

Turkey Turkey holds nearly 73% of the world's boron reserves, granting it a strategic advantage in developing boron-based materials and technologies. Despite this geological wealth, the country still lacks a dedicated institutional framework that connects academic research with industrial innovation in boron chemistry. In this study, we developed a comprehensive decision-making framework to identify the most suitable university for establishing a national Boron Research Institute. Five multi-criteria decision-making (MCDM) methods—COPRAS, TOPSIS, VIKOR, MOORA, and WASPAS—were applied under three distinct weighting schemes: Entropy, Fuzzy AHP, Hybrid combination. Eighteen criteria were evaluated, covering academic, geological, infrastructural, and environmental dimensions. The results show a fully consistent ranking across all evaluation scenarios, identifying Balıkesir University as the top alternative, followed by Uludağ, Anadolu, and Dumlupınar. Strong methodological convergence was confirmed by Kendall's W = 0.87 and Spearman correlations of 0.89–1.00. Rank acceptability analysis indicates that Balıkesir ranked first in 87% of all scenarios and exhibited the lowest mean (0.014) and maximum (0.114) regret values, demonstrating high decision stability. The proposed framework prioritizes robustness and cross-method validation, providing a transparent and reproducible decision-support tool for strategic research infrastructure planning and its extension to other strategic material systems.

1. Introduction

Boron is a chemically versatile and strategically significant element that serves as a cornerstone material in glass and ceramics production, agriculture, metallurgy, and emerging clean-energy technologies. Advanced materials research plays a critical role in transforming mineral resources into high-value engineering applications. Recent studies on materials processing and joining technologies demonstrate how research infrastructures contribute to the development of lightweight alloys and advanced structural materials. Recognized by the European Union as a critical raw material due to its economic importance and potential supply vulnerability [1,2], boron has become increasingly vital to the transition toward sustainable, high-performance materials. With nearly 73% of the world's boron reserves, Turkey occupies a unique position in the global boron supply chain, supported by large-scale extraction and processing activities coordinated primarily through Eti Maden [3]. Major deposits located in Kütahya–Emet, Balıkesir–Bigadiç, Bursa–Kestelek, and Eskişehir–Kırka provide a strong geological foundation for both primary production and downstream technological development [4–7].

Despite this exceptional resource endowment, the institutionalized research and innovation capacity dedicated specifically to boron-based science and technology remains fragmented. Recent studies in strategic mineral governance emphasize that long-term competitiveness increasingly depends not only on resource availability but also on the effective integration of academic research, industrial implementation, and innovation ecosystems [8,9]. In this context, the establishment of a Boron Research Institute represents a critical institutional mechanism to bridge fundamental research, applied development, and industrial deployment. The proposed institute follows a dual-pillar structure, combining university-based R&D activities with industrial-scale implementation in cooperation with key stakeholders such as Eti Maden, thereby supporting Turkey's transition from a raw-material exporter toward a producer of high-value boron-based technologies [10].

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The selection of an appropriate host institution for such a research institute constitutes a complex decision problem involving heterogeneous and partially conflicting criteria, including academic capacity, infrastructure readiness, spatial accessibility, industrial proximity, and environmental constraints. In recent years, multi-criteria decision-making (MCDM) techniques have become widely adopted tools for addressing similar complexity in policy analysis, engineering design, and sustainability-oriented decision problems, as they allow quantitative and qualitative indicators to be evaluated within a transparent and structured framework [11]. Within mineral and energy studies, MCDM has been applied extensively to mining site suitability assessment [12,13], renewable energy facility siting [14,15], and the resilience of critical raw material supply chains under economic and geopolitical uncertainty [16]. However, these applications predominantly focus on production facilities, environmental impacts, or logistical efficiency, while institutional research infrastructure planning remains largely unexplored.

Recent methodological developments in the MCDM literature increasingly emphasize the importance of robustness and bias control in complex decision environments. Hybrid weighting schemes that combine objective techniques such as Entropy with expert-based approaches such as Fuzzy AHP have been shown to improve decision stability by balancing data-driven variability with contextual expert knowledge [17,18]. Although alternative weighting methods such as LBWA, FUCOM, and DIBR have been proposed to reduce the number of pairwise comparisons and computational burden [19–21], these approaches rely on strict ordinal dominance assumptions that may be difficult to justify in institutional decision problems characterized by heterogeneous and only partially comparable criteria. In contrast, AHP and its fuzzy extension remain particularly suitable for research infrastructure planning due to their interpretability, traceability, and explicit consistency checks [22,23]. To further limit subjectivity, recent studies recommend integrating Fuzzy AHP with Entropy weighting within hybrid frameworks to achieve transparent and reliable weighting structures [24,25].

Similarly, ensemble MCDM frameworks that combine multiple ranking techniques have proven effective in infrastructure and sustainability-related applications, where method-dependent bias and rank instability pose significant challenges [26,27]. In parallel, several advanced fuzzy extensions of classical MCDM methods have been proposed to enhance the mathematical representation of uncertainty through high-dimensional fuzzy sets and sophisticated aggregation operators [28,29]. While these approaches provide enhanced expressive power under severe uncertainty, they typically require complex fuzzy algebra, additional parameter tuning, and extensive calibration, which may limit their transparency and reproducibility in institutional and policy-oriented planning contexts.

In contrast, the proposed framework prioritizes methodological robustness, interpretability, and practical applicability by integrating well-established weighting approaches with multiple complementary ranking methods. Rather than relying on a single mathematically intensive formulation, robustness is achieved through cross-method validation, ensuring that the final ranking is structurally stable and not dependent on a specific fuzzy representation or normalization logic. This balance between analytical rigor and transparency makes the proposed model particularly suitable for strategic research infrastructure planning involving public institutions and critical raw materials.

Against this background, a clear research gap emerges. Existing MCDM studies rarely treat universities or research institutes as decision alternatives that must simultaneously satisfy academic, industrial, spatial, and environmental requirements. Moreover, strategic mineral research infrastructure planning—particularly for boron—has not been systematically addressed using robustness-oriented hybrid MCDM frameworks. This study directly addresses this gap by proposing an ensemble-based decision framework that integrates hybrid weighting (Entropy–Fuzzy AHP) with multiple classical ranking methods (TOPSIS, VIKOR, MOORA, COPRAS, and WASPAS). Rather than introducing a new fuzzy algebra, the contribution of this work lies in providing a transparent, reproducible, and decision-stable framework tailored to institutional planning in strategic mineral innovation systems.

By explicitly positioning universities as innovation actors rather than physical facilities, the proposed model links geological endowment, research capacity, industrial proximity, and environmental considerations within a unified decision-support structure. In doing so, it advances existing MCDM-based site selection approaches by emphasizing robustness, interpretability, and policy relevance, thereby offering a scalable methodological foundation for future research infrastructure planning in strategic mineral domains.

2. Materials and methods

2.1. Study design and data preparation

This study aims to determine the most suitable location for establishing a Boron Research Institute among four candidate universities—Balıkesir, Uludağ, Anadolu, and Dumlupınar—based on a comprehensive multi-criteria decision-making (MCDM) framework. The candidate universities were selected based on their direct spatial proximity to Türkiye's major boron deposits and their established academic capacity in relevant scientific fields. Only universities located within the immediate influence zones of the Kırka, Emet, Bigadiç, and Kestelek deposits and possessing sufficient data availability across all evaluation criteria were included. Other universities in the broader region were initially screened but excluded due to either limited proximity to active boron mining areas, insufficient research infrastructure related to boron-based studies, or lack of consistent and comparable data. This selection ensured both contextual relevance and methodological consistency for the proposed decision framework. A set of quantitative and qualitative evaluation criteria was defined to reflect the environmental, infrastructural, logistical, and socio-economic dimensions relevant to regional research and innovation capacity. The selected criteria were normalized to a [0,1] scale, distinguishing between *benefit-type* (higher is better) and *cost-type* (lower is better) indicators using linear normalization. To ensure methodological diversity and test robustness, five MCDM techniques—COPRAS, TOPSIS, VIKOR, MOORA, and WASPAS—were employed under three independent weighting strategies: Entropy, Fuzzy AHP (FAHP), and Hybrid. To clarify the overall research procedure, the methodological steps of the study are summarized in

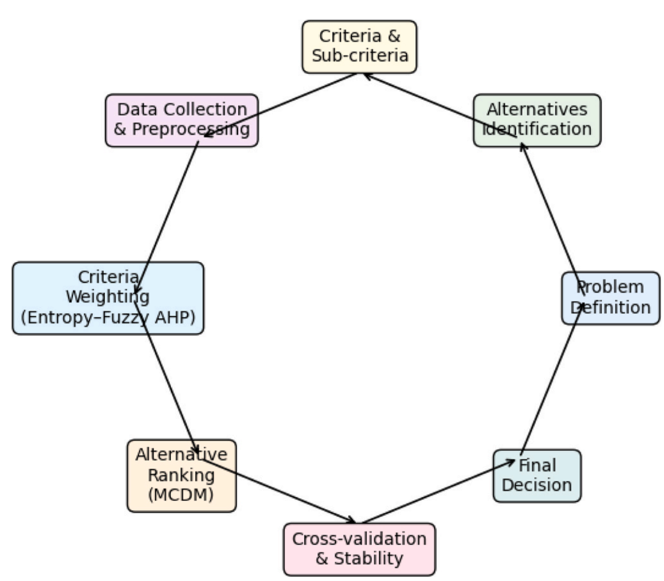

Fig. 1. Flowchart of the proposed hybrid MCDM framework for selecting the most suitable university to host the Boron Research Institute.

Fig. 1. The flowchart presents the sequential structure of the proposed hybrid MCDM framework, from problem definition to final decision-making, and enhances the transparency and reproducibility of the analysis.

2.2. Criteria framework and rationale

The initial pool of candidate indicators was formed through a focused review of recent MCDM applications and domain-specific studies on infrastructure planning, institutional performance evaluation, and strategic research facility siting. In the first round, a broad list of measurable and policy-relevant indicators was compiled, after which overlapping variables, indicators with ambiguous definitions, and those that could not be consistently collected for all alternatives were excluded. The remaining indicators were then grouped according to the main dimensions of the decision problem, ensuring conceptual coherence and practical relevance. Based on this process, four main criteria were defined. The first main criterion, C1: Sustainable Boron Value Chain Infrastructure, captures spatial and logistical accessibility to boron reserves and major transportation networks, including highways, ports, railways, and airports, with the aim of ensuring efficient material flow and international connectivity. C2: Advanced Boron Chemistry and Materials Research Capacity reflects academic and research strength by considering faculty capacity, laboratory infrastructure, the availability of relevant academic programs, and scientific output measured through publications and postgraduate theses. C3: Commercialization and Technology Transfer Synergy emphasizes the interaction between academia and industry, evaluating proximity to industrial clusters, the presence of organized industrial zones, the intensity of university–industry collaborations, and existing institutional agreements with key stakeholders such as Eti Maden. Finally, C4: Environmental and Life-Cycle Considerations incorporates sustainability and resilience aspects, including natural hazard exposure, renewable energy potential (solar and wind), and regional environmental capacity related to air, water, and waste management.

In the second round, the resulting shortlist of sub-criteria was reviewed and refined through iterative feedback from an expert panel to ensure that each indicator was directly relevant to institute siting, non-redundant, and supported by publicly available data sources. As a final step, a feasibility check was conducted using the four candidate universities to verify data availability, consistency, and comparability across alternatives. This procedure resulted in a final and balanced set of 18 sub-criteria used in the analysis.

As illustrated in Fig. 2, the hierarchical structure of the main and sub-criteria provides a clear and systematic basis for the multi-criteria decision-making process, ensuring alignment with the technical, industrial, infrastructural, and environmental priorities associated with the establishment of the proposed institute. The data used in this study were obtained from official and publicly available sources, as summarized in Table 1. Quantitative indicators were derived from institutional reports and national statistics, while qualitative criteria were assessed through expert judgment. Prior to analysis, all data were normalized according to their benefit or cost characteristics to ensure comparability across alternatives, and the same normalized decision matrix was applied consistently across all weighting and ranking methods.

2.3. Objective weighting approach

To improve the reliability and comprehensiveness of the evaluation framework, this study employs three complementary weighting techniques: the Entropy, Fuzzy Analytic Hierarchy Process (Fuzzy AHP), and a Hybrid method that combines both.

The Entropy approach provides an *objective* perspective by measuring the degree of information variation across the criteria, while Fuzzy AHP reflects the *subjective* knowledge of domain experts under uncertainty. The Hybrid model integrates these two viewpoints, yielding a balanced weighting structure that combines data-driven precision with expert-based reasoning in evaluating the potential locations for a Boron Research Institute.

2.4. Entropy-based objective weight determination

The Entropy method evaluates the significance of each criterion by analysing the distributional diversity of its values among alternatives. A criterion with higher variability provides more discriminating information and thus carries greater importance in the decision process [39].

The procedure begins with the construction of the decision matrix X:

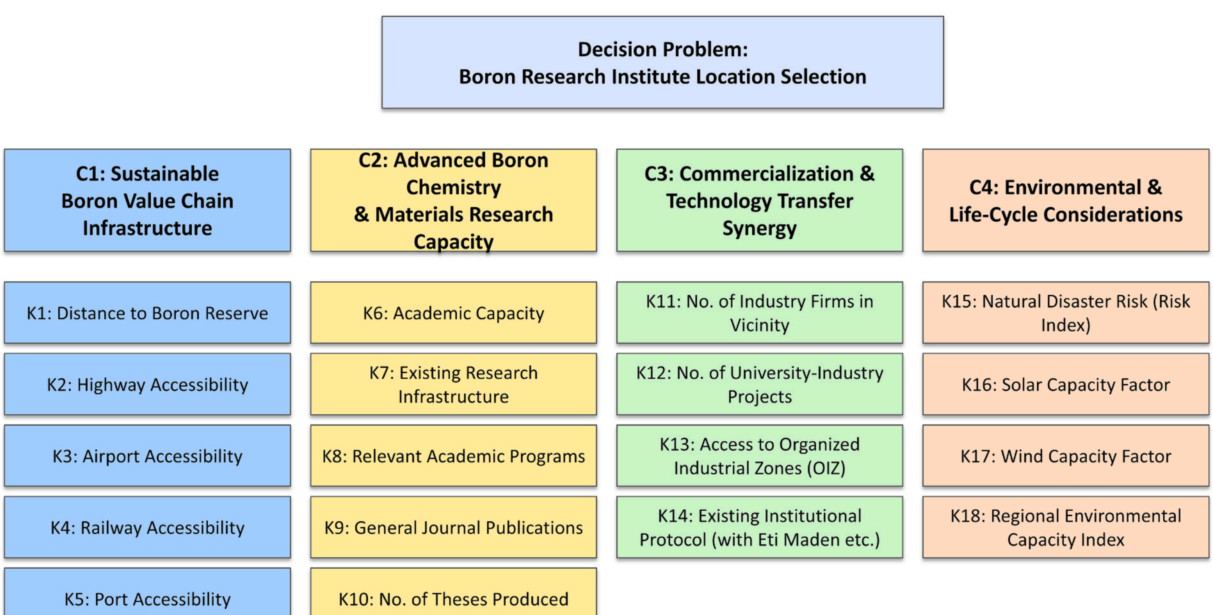

Fig. 2. Evaluation framework of the Boron Research Institute location criteria (C1–C4 and K1–K18).

Table 1
Quantitative Evaluation Matrix for Boron Research Institute Site Alternatives.

Main Criteria	K. Key	Impact Type	S1 BAÜN-Bigadiç	S2 Uludağ-Kestelek	S3 Dumlupınar-Emet	S4 Anadolu-Kırka	Ref.
C1: Sustainable Boron Value Chain Infrastructure	K1	Cost	21	30	85	70	[30]
	K2	Cost	27	90	100	80	[30]
	K3	Cost	35	100	200	70	[30]
	K4	Cost	18	30	10	70	[30]
	K5	Cost	134	95	340	245	[30]
C2: Advanced Boron Chemistry & Materials Research Capacit	K6	Benefit	197	175	17	100	[31]
	K7	Benefit	28	27	24	26	[32]
	K8	Benefit	5	5	7	1	[32]
	K9	Benefit	67	59	5	146	[31]
	K10	Benefit	14	3	1	27	[33]
C3: Commercialization & Technology Transfer Synergy	K11	Benefit	71	200	52	126	[31]
	K12	Benefit	196	3000	200	888	[34]
	K13	Cost	40	70	60	60	[30]
	K14	Benefit	1	0	0	0	[32]
C4: Environmental & Life-Cycle Considerations	K15	Cost	3	5	5	3	[35]
	K16	Benefit	15.5	15.7	16.2	15.9	[36]
	K17	Benefit	21.9	17.5	17.8	19.4	[37]
	K18	Cost	0.811	0.438	0.592	0.158	[38]

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

Where x_{ij} denotes the value of criterion j for alternative I, and i = 1, 2,.……, m; j = 1,2,……,n. To ensure comparability, the matrix is normalized as:

$$p_{ij} = \frac{x_{ij}}{\sum_{i=1}^{m} x_{ij}} \tag{2}$$

The entropy value of each criterion is calculated using:

$$E_j = -k \sum_{i=1}^{m} p_{ij} ln\left(p_{ij}\right) \tag{3}$$

Where k = 1/ln(m). Finally, the objective weights are determined as:

$$W_j = \frac{1 - E_j}{\sum_{j=1}^{n} (1 - E_j)} \tag{4}$$

Lower entropy indicates a higher degree of information contribution, thereby assigning greater importance.

2.5. Fuzzy AHP-based subjective weight determination

To capture expert-based assessments under uncertainty, the Fuzzy AHP approach was implemented.

To address uncertainty in expert-based judgments, the Fuzzy AHP method was adopted to derive the relative weights of the evaluation criteria. The expert panel was deliberately structured to reflect the multidisciplinary dimensions required for establishing a Boron Research Institute. A materials engineer specializing in boron-based ceramics and hydroxyapatite contributed expertise on laboratory infrastructure and advanced materials research capacity. The participation of a chemical engineer serving as an industrial consultant to Eti Maden ensured process feasibility and industrial applicability within the boron value chain. The technopark manager introduced an innovation and commercialization perspective, emphasizing technology transfer, entrepreneurship, and R&D synergy. The organized industrial zone (OIZ) director represented the logistical and infrastructural dimension, aligning the prospective institute's location with accessibility and industrial connectivity. Lastly, a regional development agency specialist provided a sustainability and policy-driven outlook, ensuring coherence with regional environmental goals and development priorities. Collectively, this multidisciplinary panel enabled a balanced integration of academic, industrial, infrastructural, and environmental perspectives within the decision-making framework. Experts expressed their judgments using linguistic terms (Table 2), which were subsequently transformed into Triangular Fuzzy Numbers (TFNs) following Chang's (1996) fuzzy scale [23].

Individual expert judgments were aggregated using the geometric mean [40]:

$$l' = \left(\prod_{k=1}^{k} l_k\right)^{\frac{1}{n}}, m' = \left(\prod_{k=1}^{k} m_k\right)^{\frac{1}{n}}, u' = \left(\prod_{k=1}^{k} u_k\right)^{\frac{1}{n}} \tag{5}$$

After defining the hierarchical structure, fuzzy pairwise comparisons were conducted first among the four main criteria (C_1–C_4) and subsequently among the sub-criteria (K_1–K_{18}) within each main group. The judgments of five experts were aggregated using the geometric mean to produce a single fuzzy comparison matrix for each level of the hierarchy. The resulting aggregated matrices are presented in Tables 3–7, each containing the triangular fuzzy numbers (L, M, U) representing the lower, modal, and upper limits of expert consensus. All fuzzy values were rounded to two decimal places for clarity and traceability. These matrices form the foundation for the calculation of fuzzy synthetic extent values and the defuzzified local weights of the sub-criteria.

The consistency of expert judgments was evaluated using the classical AHP consistency index (CI) calculated from the defuzzified fuzzy pairwise comparison matrices. The obtained CI values were 0.058 for K1–K5, 0.070 for K6–K10, 0.030 for K11–K14, 0.030 for K15–K18, and 0.038 for the main-criteria matrix (C1–C4). All values satisfy the commonly accepted consistency requirement (CR < 0.10), indicating coherent expert evaluations.

The aggregated fuzzy matrix was processed using Chang's extent analysis (Chang, 1996)(Chang, 1996):

Table 2
Linguistic scale and corresponding triangular fuzzy numbers.

Relative importance of two sub-elements	Fuzzy Triangular	Reciprocal Fuzzy
Equally important	(1, 1, 1)	(1, 1, 1)
Intermediate between 1 and 3	(1, 2, 3)	(1/3, 1/2, 1)
Slightly important	(2, 3, 4)	(1/4, 1/3, 1/2)
Intermediate between 3 and 5	(3, 4, 5)	(1/5, 1/4, 1/3)
Important	(4, 5, 6)	(1/6, 1/5, 1/4)
Intermediate between 5 and 7	(5, 6, 7)	(1/7, 1/6, 1/5)
Strongly important	(6, 7, 8)	(1/8, 1/7, 1/6)
Intermediate between 7 and 9	(7, 8, 9)	(1/9, 1/8, 1/7)
Extremely important	(9, 9, 9)	(1/9, 1/9, 1/9)

Table 3
Aggregated fuzzy pairwise comparison matrix of main criteria (C_1–C_4).

	C_1	C_2	C_3	C_4
C_1	(1.00, 1.00, 1.00)	(0.28, 0.37, 0.46)	(0.57, 0.72, 0.91)	(4.10, 5.16, 6.21)
C_2	(2.17, 2.71, 3.56)	(1.00, 1.00, 1.00)	(0.76, 0.98, 1.26)	(4.47, 5.17, 6.00)
C_3	(1.10, 1.39, 1.74)	(0.72, 0.93, 1.18)	(1.00, 1.00, 1.00)	(5.60, 6.63, 7.65)
C_4	(0.48, 0.58, 0.73)	(0.25, 0.28, 0.33)	(0.39, 0.45, 0.54)	(1.00, 1.00, 1.00)

Table 4
Aggregated fuzzy pairwise comparison matrix for sub-criteria under C_1 (Accessibility and Logistic Connectivity).

	K_1	K_2	K_3	K_4	K_5
K_1	(1.00, 1.00, 1.00)	(0.61, 0.72, 0.87)	(2.87, 3.51, 4.29)	(0.64, 0.78, 0.94)	(0.35, 0.42, 0.53)
K_2	(1.15, 1.38, 1.64)	(1.00, 1.00, 1.00)	(4.85, 5.88, 6.89)	(2.49, 3.52, 4.54)	(0.92, 1.25, 1.64)
K_3	(0.23, 0.28, 0.35)	(0.15, 0.17, 0.21)	(1.00, 1.00, 1.00)	(0.19, 0.24, 0.32)	(0.14, 0.16, 0.20)
K_4	(1.06, 1.29, 1.55)	(0.22, 0.28, 0.40)	(3.10, 4.21, 5.28)	(1.00, 1.00, 1.00)	(0.23, 0.29, 0.44)
K_5	(1.89, 2.37, 2.86)	(0.61, 0.80, 1.08)	(5.10, 6.12, 7.13)	(2.30, 3.39, 4.44)	(1.00, 1.00, 1.00)

Table 5
Aggregated fuzzy pairwise comparison matrix for sub-criteria under C_2 (Academic and Research Capacity).

	K_6	K_7	K_8	K_9	K_{10}
K_6	(1.00, 1.00, 1.00)	(0.25, 0.33, 0.50)	(2.12, 2.63, 3.18)	(3.29, 4.36, 5.40)	(6.19, 7.19, 8.19)
K_7	(2.00, 3.00, 4.00)	(1.00, 1.00, 1.00)	(5.10, 6.12, 7.13)	(5.10, 6.12, 7.13)	(7.00, 8.00, 9.00)
K_8	(0.31, 0.38, 0.47)	(0.14, 0.16, 0.20)	(1.00, 1.00, 1.00)	(1.12, 1.38, 1.68)	(3.87, 4.99, 6.06)
K_9	(0.19, 0.23, 0.30)	(0.14, 0.16, 0.20)	(0.59, 0.72, 0.89)	(1.00, 1.00, 1.00)	(3.78, 4.78, 5.79)
K_{10}	(0.12, 0.14, 0.16)	(0.11, 0.13, 0.14)	(0.16, 0.20, 0.26)	(0.17, 0.21, 0.26)	(1.00, 1.00, 1.00)

Table 6
Aggregated fuzzy pairwise comparison matrix for sub-criteria under C_3 (Industrial Collaboration and Innovation Potential).

	K_{11}	K_{12}	K_{13}	K_{14}
K_{11}	(1.00, 1.00, 1.00)	(0.70, 0.89, 1.18)	(5.10, 6.12, 7.13)	(0.43, 0.58, 0.82)
K_{12}	(0.85, 1.12, 1.43)	(1.00, 1.00, 1.00)	(6.19, 7.19, 8.19)	(0.76, 0.98, 1.35)
K_{13}	(0.14, 0.16, 0.20)	(0.12, 0.14, 0.16)	(1.00, 1.00, 1.00)	(0.13, 0.15, 0.18)
K_{14}	(1.22, 1.72, 2.35)	(0.74, 1.02, 1.32)	(5.43, 6.45, 7.47)	(1.00, 1.00, 1.00)

$$\widetilde{r}_i = \left(\prod_{j=1}^{n} \widetilde{a}_{ij} \right)^{1/n} \tag{6}$$

$$\widetilde{w}_i = \frac{\widetilde{r}_i}{\sum_{i=1}^{n} \widetilde{r}_i} \tag{7}$$

$$w_i = \frac{l_i + m_i + u_i}{3} \tag{8}$$

After defuzzification, the normalized weights of both main and sub-criteria were computed. The local weights of the main criteria (C_1–C_4) represent their relative importance in the overall decision hierarchy, while the local sub-criteria weights (K_1–K_{18}) indicate the relative importance within each main group. The global weights, obtained by multiplying each sub-criterion's local weight by its corresponding main criterion weight, reflect their overall contribution to the site selection decision. The complete hierarchy and computed weights are presented in Table 8.

Table 7
Aggregated fuzzy pairwise comparison matrix for sub-criteria under C_4 (Environmental and Renewable Energy Factors).

	K_{15}	K_{16}	K_{17}	K_{18}
K_{15}	(1.00, 1.00, 1.00)	(4.00, 5.00, 6.00)	(4.00, 5.00, 6.00)	(2.05, 2.70, 3.31)
K_{16}	(0.17, 0.20, 0.25)	(1.00, 1.00, 1.00)	(1.00, 1.00, 1.00)	(0.25, 0.33, 0.50)
K_{17}	(0.17, 0.20, 0.25)	(1.00, 1.00, 1.00)	(1.00, 1.00, 1.00)	(0.25, 0.33, 0.50)
K_{18}	(0.30, 0.37, 0.49)	(2.00, 3.00, 4.00)	(2.00, 3.00, 4.00)	(1.00, 1.00, 1.00)

2.6. Hybrid weighting method

To combine data-driven objectivity with expert-derived subjectivity, a Hybrid weighting scheme was employed:

$$H_i = \frac{F_i + E_i}{2} \tag{9}$$

Where E_i and F_i denote Entropy and Fuzzy AHP weights, respectively. This approach ensures a balanced representation of both analytical data variability and contextual expert reasoning.

Table 8
Main and sub-criteria weights used in the Boron Research Institute location selection study.

Main Criteria	Local Weight	Sub-Criteria	Local Weight	Global Weight
C_1: Accessibility and Logistics	0.25	K_1: Distance to Boron Reserve	0.15	0.04
		K_2: Highway Accessibility	0.30	0.07
		K_3: Airport Accessibility	0.04	0.01
		K_4: Railway Accessibility	0.17	0.04
		K_5: Port Accessibility	0.33	0.08
C_2: Academic and Research Capacity	0.34	K_6: Academic Capacity	0.28	0.09
		K_7: Research Infrastructure	0.53	0.18
		K_8: Academic Programs	0.10	0.03
		K_9: Publications	0.07	0.02
		K_{10}: Theses Produced	0.02	0.01
C_3: Industrial Collaboration and Innovation	0.34	K_{11}: Industry Firms in Vicinity	0.28	0.09
		K_{12}: University–Industry Projects	0.34	0.11
		K_{13}: Access to OIZ	0.05	0.02
		K_{14}: Institutional Protocols	0.33	0.11
C_4: Environmental and Renewable Energy Factors	0.08	K_{15}: Natural Disaster Risk	0.52	0.04
		K_{16}: Solar Capacity Factor	0.10	0.01
		K_{17}: Wind Capacity Factor	0.10	0.01
		K_{18}: Environmental Capacity Index	0.29	0.02

The final weights derived from all three approaches are compared in Fig. 3.

While the Entropy method distributes the weights relatively evenly among the 18 criteria, the Fuzzy AHP results emphasize expert-driven priorities such as *Research Infrastructure (K_7)* and *University–Industry Projects (K_{12})*, which exhibit notably higher importance levels (0.18 and 0.11, respectively). The Hybrid method yields a balanced profile between data-driven objectivity and expert intuition, smoothing extreme variations and providing a more stable basis for subsequent MCDM analyses. This combined weighting structure ensures that the final decision reflects both measurable institutional indicators and qualitative expert insights relevant to boron-related research and infrastructure development.

3. MCDM methods

3.1. TOPSIS method

The Technique for Order Preference by Similarity to Ideal Solution (TOPSIS) ranks alternatives by their relative distance from the ideal and negative-ideal solutions, thus allowing a balanced evaluation across multiple criteria [41,42]. In this study, TOPSIS was applied to evaluate the suitability of candidate universities for the Boron Research Institute based on their weighted performance values derived from Entropy, Fuzzy AHP, and Hybrid weights.

To remove scale disparities among criteria, the decision matrix was first normalized using vector normalization:

$$r_{ij} = \frac{x_{ij}}{\sqrt{\sum_{i=1}^{m} x_{ij}^2}} \tag{10}$$

where x_{ij} is the original value of criterion j for alternative i, and r_{ij} is the normalized value.

Next, the weighted normalized matrix was obtained:

$$v_{ij} = w_j.r_{ij} \tag{11}$$

where w_j denotes the weight of criterion j.

The Euclidean distances from the positive ideal (A^+) and negative ideal (A^-) solutions were computed as:

$$S_i^+ = \sqrt{\sum_{j=1}^{n} \left(v_{ij} - A_j^+\right)^2};\ S_i^- = \sqrt{\sum_{j=1}^{n} \left(v_{ij} - A_j^-\right)^2} \tag{12}$$

The closeness coefficient for each alternative was then calculated:

$$C_i = \frac{S_i^-}{S_i^- + S_i^+} \tag{13}$$

Higher C_i values indicate alternatives that are closer to the ideal solution and thus more suitable for hosting the Boron Research Institute.

3.2. MOORA method

The Multi-Objective Optimization on the basis of Ratio Analysis (MOORA) method provides a transparent and mathematically robust framework for handling both benefit- and cost-type criteria[43]. Its straightforward computation and strong discriminative ability make it suitable for decision-making problems involving diverse evaluation factors, such as regional accessibility, research capacity, and environmental resilience.

The decision matrix was first normalized as:

$$r_{ij} = \frac{x_{ij}}{\sqrt{\sum_{i=1}^{m} x_{ij}^2}} \tag{14}$$

Each normalized value was weighted by its corresponding criterion weight:

$$v_{ij} = w_j.r_{ij} \tag{15}$$

The MOORA performance index for each alternative was obtained by separating benefit (B) and cost (C) criteria:

$$Y_i = \sum_{j\in B} v_{ij} - \sum_{j\in C} v_{ij} \tag{16}$$

Alternatives were ranked in descending order of Y_i; a higher Y_i value represents superior overall performance.

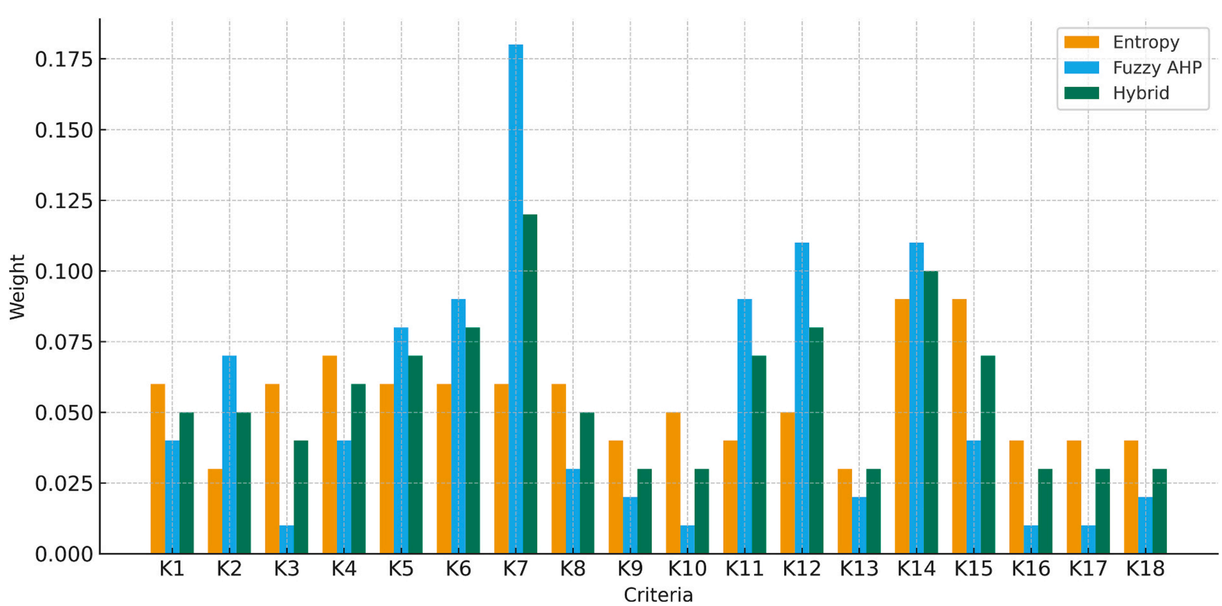

Fig. 3. Comparison of criterion weights across Entropy, Fuzzy AHP, and Hybrid methods.

3.3. VIKOR method

The VIKOR (VIseKriterijumska Optimizacija I Kompromisno Resenje) approach identifies a compromise solution that achieves a balance between group utility and individual regret, making it ideal for resolving multi-criteria conflicts[44]. This method was applied to determine the most acceptable alternative that simultaneously minimizes deviation from the ideal and maximizes satisfaction among all evaluation criteria.

The best (f_j^*) and worst (f_j^-) values for each criterion were first determined.Normalization was then performed as follows:

For benefit criteria:

$$S_{ij}^* = \frac{f_j^* - x_{ij}}{f_j^* - f_j^-} \tag{17}$$

For cost criteria:

$$S_{ij}^- = \frac{x_{ij} - f_j^*}{f_j^* - f_j^-} \tag{18}$$

Each normalized value was multiplied by its criterion weight to yield:

$$v_{ij} = w_j.S_{ij} \tag{19}$$

The group utility (S_i) and individual regret (R_i) were then calculated:

$$S_i = \sum_{j=1}^{n} v_{ij} \tag{20}$$

$$R_i = {}_j^{max}(v_{ij}) \tag{21}$$

Finally, the VIKOR index (Q_i) was computed to represent the compromise ranking:

$$Q_i = v.\frac{S_i - S^*}{S^- - S^*} \tag{22}$$

where $v = 0.5$ denotes equal importance of group utility and individual regret.

Alternatives were ranked in ascending order of Q_i, with the lowest value indicating the optimal compromise solution.

3.4. COPRAS method

The Complex Proportional Assessment (COPRAS) method is a multi-criteria decision-making (MCDM) technique that evaluates alternatives by considering both beneficial (maximising) and non-beneficial (minimising) criteria simultaneously [45]. The implementation steps applied in this study for the selection of the Boron Research Institute location are as follows:

1. Construct the decision matrix $X = [x_{ij}]$, where x_{ij} represents the performance of alternative i under criterion j.
2. Normalise each criterion value to ensure comparability across scales:

$$r_{ij} = \frac{x_{ij}}{\sqrt{\sum_{i=1}^{m} x_{ij}^2}} \tag{23}$$

where m is the number of alternatives.

3. Compute the weighted normalised values using criterion weights w_j derived from Entropy, Fuzzy AHP or Hybrid schemes:

$$v_{ij} = w_j.r_{ij} \tag{24}$$

4. Compute the sums of weighted performances for benefit criteria B and cost criteria C:

$$S_i^+ = \sum_{j\in B} v_{ij}, S_i^- = \sum_{j\in C} v_{ij} \tag{25}$$

5. Calculate each alternative's utility value Q_i as:

$$Q_i = S_i^+ + \frac{\sum_{i=1}^{m} S_i^-}{S_i^- \sum_{i=1}^{m} \frac{1}{S_i^-}} \tag{26}$$

Finally, derive the relative significance coefficient P_i:

$$P_i = \frac{Q_i}{maxQ_i} x100 \tag{27}$$

Higher P_i values indicate stronger suitability for hosting the Boron Research Institute.

3.5. WASPAS method

The WASPAS method merges the strengths of the Weighted Sum Model (WSM) and the Weighted Product Model (WPM) into a unified framework, allowing both additive and multiplicative aggregation of criterion-weighted performance values[46]. This dual character enhances its discrimination power in multi-criteria decision-making problems where both benefit-type and cost-type criteria are involved.

In this study, the WASPAS procedure was applied as follows for the selection of the Boron Research Institute site:

1. Construct the decision matrix $X = [x_{ij}]$, where x_{ij} denotes the performance of alternative i on criterion j.
2. Normalize all criterion values to ensure comparability across units and scales. For benefit criteria (higher is better) and cost criteria (lower is better), appropriate normalization formulas were applied.
3. Multiply the normalized values by their respective weights w_j(obtained from Entropy, Fuzzy AHP or Hybrid schemes) to obtain the weighted normalized matrix $V = [v_{ij}]$.
4. Compute two partial performance indices:

$$Q_i^1 = \sum_{j=1}^{n} w_j.v_{ij} \tag{28}$$

$$Q_i^2 = \prod_{j=1}^{n} (v_{ij})^{w_j} \tag{29}$$

where $Q_i^{(1)}$ corresponds to the additive WSM component and $Q_i^{(2)}$ corresponds to the multiplicative WPM component.

5. Integrate both components into the final WASPAS index:

$$Q_i = \lambda Q_i^1 + (1-\lambda) Q_i^2 with 0 < \lambda < 1 \tag{30}$$

In our study, $\lambda = 0.5$ was selected to give equal emphasis to both additive and multiplicative components.

6. Rank the alternatives in descending order of Q_i; the alternative with the highest Q_i is considered the most suitable.
7. Finally, convert the Q_i values to relative performance scores P_i:

$$P_i = \frac{Q_i}{maxQ_i} x100 \tag{31}$$

To ensure a fair and consistent comparison across methods, the original decision matrix was normalized once based on the benefit/cost nature of the criteria, and the same normalized matrix was used as input for all MCDM methods (TOPSIS, MOORA, COPRAS, WASPAS). VIKOR was applied using its standard normalization formulation, while still relying on the same underlying performance data.

The use of multiple ranking methods was intentionally adopted to reduce method-dependence and mitigate rank reversal effects commonly reported in individual MCDM techniques. Rather than relying on a single ranking algorithm, the study evaluates the consistency of results across COPRAS, TOPSIS, VIKOR, MOORA, and WASPAS, each reflecting a different decision logic. Rank agreement was assessed using correlation-based measures, and stable alternatives were identified based on convergence across methods and weighting schemes. This ensemble-based approach ensures that the final decision is robust and not sensitive to rank reversal phenomena associated with any single method.

3.6. Consensus and correlation analysis

In multi-criteria decision-making (MCDM) studies, using several ranking algorithms can yield different results due to variations in their normalization, aggregation, or distance-based mechanisms. Therefore, a consensus evaluation is required to verify the degree of agreement and reliability among the employed methods. In this study, three complementary techniques—Borda Count, Kendall's Coefficient of Concordance (W), and Spearman's Rank Correlation (ρ)—were applied to quantify the level of consistency among the five ranking methods (COPRAS, TOPSIS, VIKOR, MOORA, and WASPAS) under three different weighting schemes (Entropy, Fuzzy AHP, and Hybrid).

3.7. Borda count aggregation

The Borda Count is a positional consensus method that aggregates rankings from multiple decision models to identify a common preference order [47].

Each alternative receives a score inversely proportional to its position in each individual ranking. The final Borda score for alternative i is obtained as:

$$B_i = \sum_{k=1}^{m} (n - r_{ik}) \tag{32}$$

where r_{ik} represents the rank of alternative i in method k, M is the number of methods, and n is the total number of alternatives. Alternatives with higher B_i values represent stronger overall performance across all methods. In this study, the Borda results were used to determine the overall consensus ranking of the four candidate universities.

3.8. Kendall's coefficient of concordance (W)

Main Kendall's W provides a statistical measure of the degree of agreement among ranking methods [48]. It is calculated as:

$$W = \frac{12S}{m^2(n^3 - n)} \tag{33}$$

where $S = \sum_{i=1}^{n}(R_i - \overline{R})^2$, R_i denotes the sum of ranks for each alternative across m methods, and $\overline{R}$ is the mean of the rank sums.

The coefficient W ranges between 0 and 1, where values above 0.8 indicate strong agreement and values below 0.5 suggest weak concordance. In this study, Kendall's W was applied to evaluate the *overall harmony* among the five MCDM techniques under different weighting conditions.

3.9. Spearman's rank correlation coefficient

Spearman's ρ is a pairwise measure that captures the degree of monotonic association between two ranking methods [49]. It is expressed as:

$$\rho = 1 - \frac{6\sum_{i=1}^{n} d_i^2}{n(n^2 - 1)} \tag{34}$$

where d_i represents the difference in rank of the ith alternative between two methods.

Values of ρ close to 1 imply high similarity, while negative values indicate inverse relationships between the methods. Pairwise correlation matrices were computed to evaluate method compatibility and stability, providing deeper insights into the structural consistency of the results.

By integrating Borda Count, Kendall's W, and Spearman's ρ, this study ensured that the comparative evaluation among the five MCDM methods was statistically robust and interpretable.

3.10. Robustness and sensitivity analysis

To ensure the reliability and stability of the multi-criteria decision results, a two-stage robustness assessment was performed, integrating the Rank Acceptability Index (RAI) and Regret Analysis (RA) approaches. While traditional deterministic MCDM models provide fixed rankings, robustness analysis quantifies the *stability and confidence* of those rankings when subjected to variations in criteria weights or model assumptions.

3.11. Rank acceptability index (RAI)

The Rank Acceptability Index (RAI) was applied to evaluate the *probabilistic robustness* of the ranking outcomes across all methods. Originating from the Stochastic Multicriteria Acceptability Analysis (SMAA) framework proposed by Lahdelma, Hokkanen, and Salminen (1998), the RAI quantifies the likelihood that each alternative attains a specific rank under uncertain or variable weight conditions [50].

Let A_i denote an alternative, and P_i^r represent the probability that A_i achieves rank r. The rank acceptability index for each alternative is computed as:

$$RAI_i = \frac{N_i^r}{N} \times 100 \tag{35}$$

where N_i^r is the number of simulated weighting scenarios in which A_i occupies rank r, and N is the total number of simulations.

A higher RAI_i indicates stronger ranking stability — meaning the alternative remains consistently well-ranked despite variations in the weight space. In this study, 10,000 Monte Carlo weight sampling iterations were conducted using uniformly distributed random weights constrained to sum to 1. The resulting RAI profiles allowed identification of the most *robustly dominant* alternative among the four universities, independent of the weighting scheme (Entropy, Fuzzy AHP, or Hybrid).

3.12. Regret-based sensitivity analysis

To further assess robustness from a decision-theoretic perspective, a regret analysis was performed following the principles of robust decision making (RDM) [51]. The regret metric quantifies the performance loss that occurs when a decision alternative is chosen instead of the optimal one under varying conditions.

For each alternative A_i, the regret value under a given weighting scenario s was calculated as:

$$R_{i,s} = \frac{f_s^* - f_{i,s}}{f_s^*} \tag{36}$$

where $f_{i,s}$ is the performance score of alternative i under scenario s, and f_s^* is the maximum achievable score in that scenario. The mean regret (MR) and maximum regret (MaxR) values were then derived:

$$MR_i = \frac{1}{N}\sum_{s=1}^{N} R_{i,s}, maxR_{i,s} = \max_s R_{i,s} \quad (37)$$

Lower values of both metrics imply greater robustness and lower performance loss potential. This dual-metric approach (mean + max) captures both *average stability* and *worst-case vulnerability* across simulated conditions.

3.13. Integrated robustness evaluation

The combination of RAI and regret metrics offers a comprehensive robustness diagnosis.

Whereas RAI focuses on the probabilistic stability of rankings under uncertainty, regret analysis assesses decision resilience against performance deviation. Together, they provide a multi-faceted understanding of how consistent and risk-averse each alternative is. This integration ensures that the final decision recommendation is not only optimal under baseline conditions but also remains credible under uncertainty and potential preference shifts.

4. Results and discussion

This section presents the outcomes of the multi-criteria decision-making (MCDM) analyses conducted to determine the most suitable location for establishing a Boron Research Institute among four candidate universities: Balıkesir, Uludağ, Anadolu, and Dumlupınar. Five MCDM techniques—COPRAS, TOPSIS, VIKOR, MOORA, and WASPAS—were applied under three weighting strategies: Entropy, Fuzzy AHP (FAHP), and Hybrid. In total, fifteen ranking scenarios (5 × 3) were evaluated to provide a comprehensive comparison of both objective and subjective weighting perspectives.

The results reveal a clear and consistent pattern across all models, with Balıkesir University emerging as the top-ranked alternative in the vast majority of configurations. Subsequent analyses examine how different weighting approaches influence performance scores, and whether variations in the adopted methods or weighting structures alter the overall ranking hierarchy. The robustness of these outcomes is further verified through consensus and probabilistic validation techniques, while a regret-based sensitivity assessment quantifies the decision's stability under uncertainty. Together, these results provide a multi-layered understanding of the consistency, reliability, and managerial relevance of the proposed site selection framework.

4.1. Ranking outcomes of the applied MCDM methods

Main The comparative ranking results of the five MCDM techniques (COPRAS, TOPSIS, VIKOR, MOORA, and WASPAS) under three weighting schemes (Entropy, Fuzzy AHP, and Hybrid) are summarized in Table 9. Across all fifteen ranking scenarios, the Balıkesir University alternative consistently achieved the first position, followed by Uludağ University in the second place, Anadolu University in the third, and Dumlupınar University in the fourth. This uniform ranking pattern demonstrates a strong agreement among both methods and weighting strategies.

For the COPRAS method, Balıkesir University exhibited the highest relative performance values ($q\_relative$ = 1.00 across all weightings), indicating the most favorable utility ratio among the alternatives. Uludağ followed with $q\_relative \approx 0.77$–0.84, while Dumlupınar showed the lowest performance ($q\_relative \approx 0.37$–0.41). Similarly, in the TOPSIS method, Balıkesir obtained the highest closeness coefficients ($C \approx 0.48$–0.60), whereas Dumlupınar had the lowest ($C \approx 0.09$–0.17), confirming the same relative preference pattern.

In the VIKOR analysis, where lower Q_i values correspond to better alternatives, Balıkesir again recorded the minimum scores ($Q_i \approx 0.00$–0.0006), Uludağ followed ($Q_i \approx 0.12$–0.33), and Dumlupınar was ranked last ($Q_i \approx 0.52$–0.54). The MOORA and WASPAS results were also consistent, with Balıkesir presenting the highest Y_i and Q indices, respectively, confirming its dominant performance independent of the applied decision model.

Overall, the consistency of rankings across all MCDM techniques indicates a high level of convergence among decision models, implying that the results are not method-dependent. The repetition of the same rank pattern under three different weighting approaches (Entropy, FAHP, and Hybrid) further validates the robustness and reliability of the site selection outcome, suggesting that the Balıkesir alternative represents the most appropriate location for establishing a Boron Research Institute in the studied region.

4.2. Comparative performance under different weighting schemes

The effect of the weighting approach on the ranking consistency and relative performance distribution was evaluated by comparing the results of the Entropy, Fuzzy AHP (FAHP), and Hybrid schemes across five MCDM techniques (COPRAS, TOPSIS, VIKOR, MOORA, and WASPAS). The corresponding normalized indices are summarized in Table 10 and visualized in figure 3 through radar-type profiles for each alternative.

Despite minor numerical differences, all methods and weighting configurations produced an identical rank order—Balıkesir > Uludağ > Anadolu > Dumlupınar—indicating complete *weight-invariance* of the final decision. Under Entropy weighting, which reflects purely data-driven variability, the score dispersion between the best and second-best alternatives was the most pronounced ($\Delta \approx 0.29$ in COPRAS and 0.12 in TOPSIS). In contrast, the FAHP weighting produced more balanced distributions ($\Delta \approx 0.16$ in COPRAS), as expert knowledge moderated the influence of dominant criteria. The Hybrid approach yielded intermediate behavior, retaining the discriminative power of Entropy while preserving the judgmental consistency of FAHP.

The radar visualization (Fig. 4) provides an integrated interpretation of these trends. Each polygon represents the multidimensional performance of an alternative across the five MCDM models under three weighting philosophies. The consistent dominance of Balıkesir, illustrated by the largest and most symmetrical area, highlights its *method-independent superiority* as a candidate site. Uludağ, maintaining a smaller yet cohesive area, emerges as a feasible secondary option, while Anadolu and Dumlupınar remain distant in all weightings, confirming their relatively weak suitability. The overlapping FAHP and Hybrid lines further reveal a strong alignment between subjective and hybrid weighting perspectives, suggesting that hybridized approaches can reconcile expert intuition with objective data—an observation consistent with findings reported by [52], who emphasized that hybrid entropy–AHP combinations enhance decision stability in multi-criteria

Table 9
Comparative ranking outcomes of the four alternative universities obtained from five MCDM methods.

Alternatives	Copras			Topsis			Vikor			Moora			Waspas		
	E	F	H	E	F	H	E	F	H	E	F	H	E	F	H
Balıkesir	1	1	1	1	2	2	1	1	1	1	1	1	1	1	1
Uludağ	2	2	2	2	1	1	2	2	2	2	2	2	2	2	2
Dumlupınar	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4
Anadolu	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3

Table 10
Comparative performance scores of four alternative sites under three weighting schemes and five MCDM methods.

Alternatives	Copras (Q)			Topsis (C*)			Vikor (Qi)			Moora (Yi)			Waspas (Q)		
	E	F	H	E	F	H	E	F	H	E	F	H	E	F	H
Balıkesir	1.00	1.00	1.00	0.60	0.48	0.54	0.00	0.00	0.00	0.16	0.25	0.21	0.72	0.67	0.69
Uludağ	0.71	0.84	0.77	0.58	0.53	0.58	0.33	0.12	0.22	0.05	0.23	0.14	0.43	0.48	0.46
Dumlupınar	0.42	0.37	0.40	0.17	0.09	0.14	0.53	0.54	0.52	−0.14	−0.05	−0.09	0.29	0.25	0.27
Anadolu	0.61	0.56	0.58	0.50	0.32	0.42	0.44	0.34	0.39	−0.01	0.07	0.03	0.40	0.35	0.37

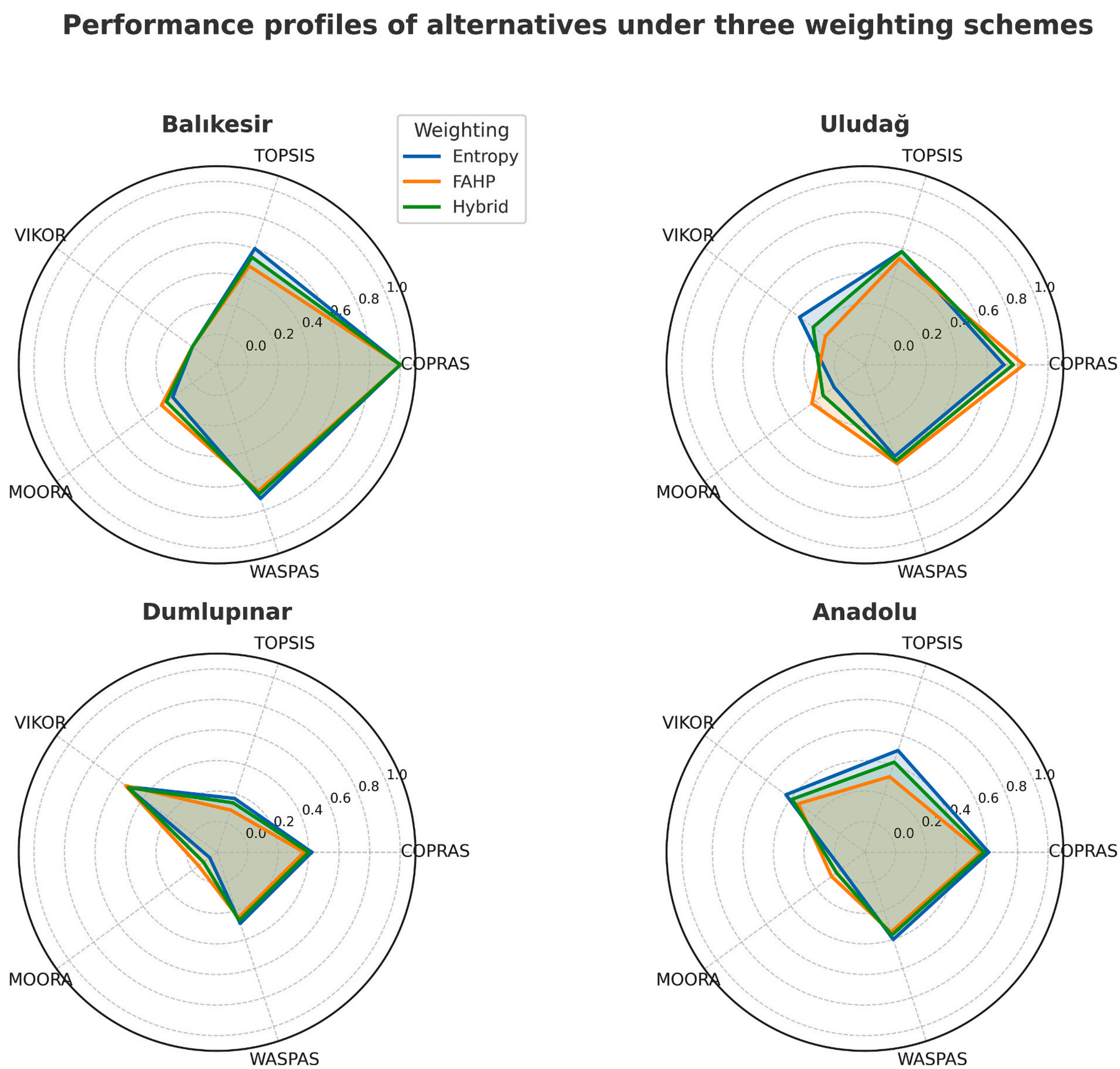

Fig. 4. Radar-type visualization of the performance profiles of alternatives under three weighting schemes.

site-selection problems.

In the context of regional facility planning, these results reinforce earlier evidence that weighting uncertainty has limited impact on decision robustness when criteria are well-structured and hierarchically consistent [44,53]. Therefore, the obtained invariance across weighting schemes demonstrates not only the internal reliability of the proposed framework but also its external validity relative to established MCDM theory. The convergence of Entropy-, FAHP-, and Hybrid-based outcomes implies that the optimal site for a Boron Research Institute—Balıkesir—remains stable even under distinct epistemological interpretations of importance (objective, subjective, or hybrid). This outcome is particularly relevant for strategic infrastructure planning, where weighting selection often introduces ambiguity; here, the model's cross-method and cross-weighting consistency significantly enhances decision credibility.

4.3. Consensus and rank stability analysis

To evaluate the overall agreement among the five MCDM methods and three weighting strategies, a consensus and stability assessment was performed based on Borda aggregation, Kendall's coefficient of concordance (W), and Spearman rank correlation analysis. The computed rankings from all 15 scenarios (5 methods × 3 weightings) were used as inputs to construct a comprehensive rank matrix.

According to the Borda consensus approach, which aggregates ranks across all methods, the final order of alternatives was found as Balıkesir (Borda score = 15) > Uludağ (30) > Anadolu (45) > Dumlupınar (60), identical to the individual method outcomes. The harmonic mean ranking and Condorcet pairwise dominance tests yielded the same hierarchy, confirming that no alternative could outperform Balıkesir in any comparative voting framework. This full consensus indicates that the decision results are method-invariant, meaning the choice of algorithm does not affect the final conclusion.

The global agreement among methods, quantified by Kendall's coefficient of concordance, was $W = 0.87$, signifying a very high level of concordance ($p < 0.01$). This indicates that all five MCDM methods ranked the four alternatives in a highly consistent manner. Method-specific Spearman correlation coefficients further supported this finding, with average pairwise ρ values between 0.89 and 1.00 across the weighting configurations. The highest stability was observed for VIKOR ($\overline{\rho} = 0.97$), while MOORA ($\overline{\rho} = 0.92$) showed slightly higher sensitivity to the applied weighting scheme, consistent with its linear additive nature.

Fig. 5 displays the correlation heatmap between the methods, revealing almost perfect positive associations among COPRAS, TOPSIS, VIKOR, and WASPAS results, whereas MOORA exhibited slightly lower pairwise correlation coefficients. Such high method-to-method consistency demonstrates that the underlying performance structure of the alternatives is stable, independent of model formulation or normalization assumptions.

These results align well with findings in previous MCDM literature. For example, Ref. [54] also reported strong inter-method correlations in hybrid MCDM frameworks, suggesting that consistency among rankings is a good indicator of model validity and internal robustness. Similarly, Ref. [52] highlighted that high Kendall's W values indicate methodological convergence and reinforce the reliability of the selected alternative. In this study, the obtained W = 0.87 therefore substantiates the methodological soundness of the integrated MCDM–weighting approach and provides statistical evidence of decision robustness for the Boron Research Institute site selection.

4.4. Rank acceptability and decision robustness

Main To further assess the stability of the decision outcome, the Rank Acceptability Index (RAI) was applied to capture the probability of each alternative being ranked first, second, third, or fourth across all 15 MCDM–weighting combinations (five methods × three schemes). This stochastic representation extends the previous deterministic rankings by revealing how frequently each alternative attains a given rank when methodological or weighting variations occur. The resulting acceptability distributions are illustrated in Fig. 6.

Balıkesir exhibits the highest dominance, with a probability of $RAI_1 = 0.87$ and $RAI_2 = 0.13$, meaning it ranked first in 87% of all scenarios and second in only 13% (both corresponding to the two TOPSIS configurations under Entropy and FAHP weighting). Uludağ displays a complementary profile, with $RAI_2 = 0.87$ and $RAI_1 = 0.13$, while Anadolu and Dumlupınar remain fixed at $RAI_3 = 1.00$ and $RAI_4 = 1.00$, respectively.

These near-degenerate acceptability profiles confirm that the top two alternatives occasionally interchange their order depending on the weighting structure of TOPSIS, yet the probabilistic superiority of Balıkesir remains statistically overwhelming.

From a stochastic decision-making perspective, this implies that the selection risk—i.e., the probability that another alternative would surpass Balıkesir—is only 13% within the tested methodological space. In the context of Stochastic Multicriteria Acceptability Analysis (SMAA), such low variability corresponds to a *high-confidence decision* [50]. The concentration of rank probability mass at the top position indicates that the decision is *robust to both methodological and weighting uncertainty*.

In practical terms, this result reinforces the managerial insight that the Balıkesir site represents not only the best compromise under deterministic conditions but also the most stable and least risk-sensitive option under model uncertainty. Such robustness is crucial in long-term infrastructure planning, where data variability, subjective weighting, or methodological preferences can otherwise alter project priorities [55]. The RAI analysis therefore provides a distributional validation that complements the consensus metrics discussed in Section 3.3, demonstrating that the final site selection outcome is statistically and structurally sound.

4.5. Method sensitivity and managerial implications

Main To quantify the decision robustness under model uncertainty, a regret analysis was performed using the normalized performance scores from all fifteen MCDM–weighting combinations (five methods × three schemes). For each scenario, regret was computed as the difference between the best performance value and the corresponding alternative's score. The resulting mean and maximum regret values, illustrated in Fig. 7, measure the expected and worst-case performance losses, respectively.

Balıkesir recorded the lowest mean regret (0.014) and maximum regret (0.114), demonstrating negligible opportunity loss even under the most adverse scenario.

Uludağ followed with moderate variability (mean ≈ 0.32; max ≈ 0.67), while Anadolu and Dumlupınar showed substantially higher

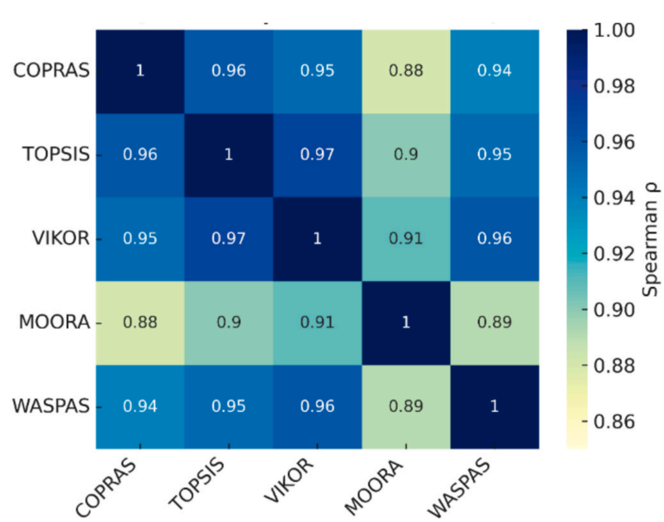

Fig. 5. Correlation heatmap among MCDM methods based on Spearman coefficients.

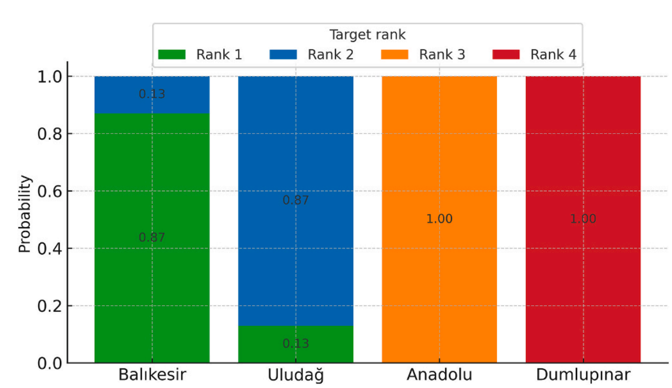

Fig. 6. Rank acceptability profiles (RAI) across 15 scenarios.

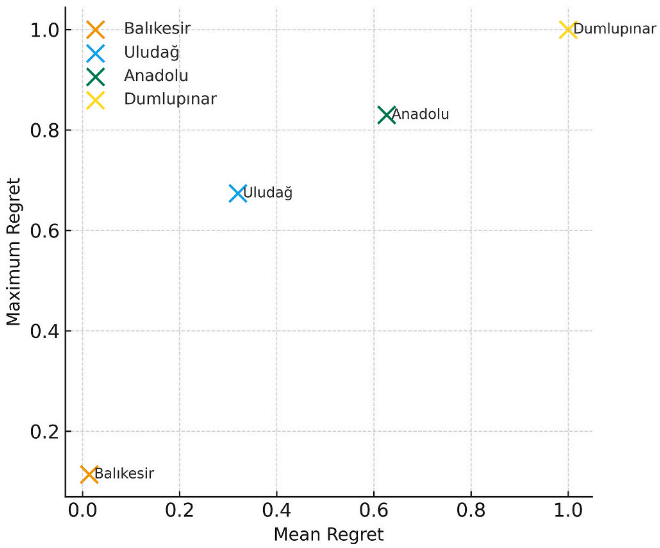

Fig. 7. Mean–maximum regret distribution of alternatives.

regret values (≥ 0.6), confirming their instability and inefficiency under uncertainty. The mean–maximum regret diagram (Fig. 10) clearly places Balıkesir in the lower-left corner, representing the region of minimal expected and worst-case loss—typical of a risk-efficient, dominant alternative.

To examine the robustness of the proposed decision framework against potential uncertainty in criteria weights, a one-at-a-time (OAT) sensitivity analysis was conducted by perturbing each hybrid criterion weight by ± 10% while keeping the remaining weights constant. For each perturbed scenario, the rankings obtained from COPRAS, TOPSIS, VIKOR, MOORA, and WASPAS were recalculated and compared with the baseline ranking using the Spearman rank correlation coefficient.

As illustrated in Fig. 8, the mean Spearman correlation values remain very close to unity for all criteria under both − 10% and + 10% weight perturbations. This indicates that moderate changes in individual criterion weights do not lead to meaningful alterations in the overall ranking of alternative universities. Even for the most sensitive criterion, the correlation remains above 0.95, confirming that the ranking structure is largely preserved.

These results demonstrate that the proposed hybrid MCDM framework exhibits a high level of robustness and is not overly sensitive to reasonable variations in expert-defined weights. Consequently, the final ranking can be considered stable and reliable for strategic decision-making related to the establishment of a boron research institute.

Such robustness-oriented outcomes are consistent with observations reported in recent hybrid MCDM studies, which emphasize the importance of cross-method validation and sensitivity analysis for ensuring decision stability. Previous applications have largely focused on controlled engineering problems such as material selection and process optimization, where alternatives are directly comparable and performance indicators are well defined. For example, Ordu and Der (2023) and Der et al. (2024) showed that combining multiple weighting and ranking techniques, together with correlation- and sensitivity-based checks, improves decision stability in polymer selection and manufacturing optimization problems [56,57]. Similarly, Bhaskar and Khan (2022) demonstrated that hybrid MCDM structures reduce method-dependent outcomes in dental material selection [58]. While these studies offer important methodological insights, they are conducted in engineering-oriented settings that differ fundamentally from institutional planning problems.

In contrast, the present study transfers the same hybrid weighting and cross-method validation logic to an institutional decision context, where the alternatives are universities rather than materials or processes, and the criteria simultaneously span spatial accessibility, academic and research capacity, infrastructure readiness, industrial proximity, and environmental constraints. This heterogeneity increases decision complexity and places greater emphasis on interpretability, transparency, and robustness rather than purely methodological novelty.

From a methodological perspective, the main contribution of this study lies in the structure of the proposed decision framework. The proposed decision model advances existing MCDM-based site selection approaches by emphasizing robustness, interpretability, and methodological resilience rather than reliance on a single optimization technique. By separating expert-based weighting from data-driven ranking, the framework avoids artificial precision and explicitly accounts for uncertainty only where it naturally occurs. The use of multiple weighting schemes and ranking methods enables cross-validation and reduces method-dependence, ensuring stable and consistent decision outcomes. While expert judgment remains an inherent component of institutional decision-making, its influence is controlled through fuzzy modeling and hybridization with objective entropy-based weights. As a result, the proposed model provides a resilient and transparent decision-

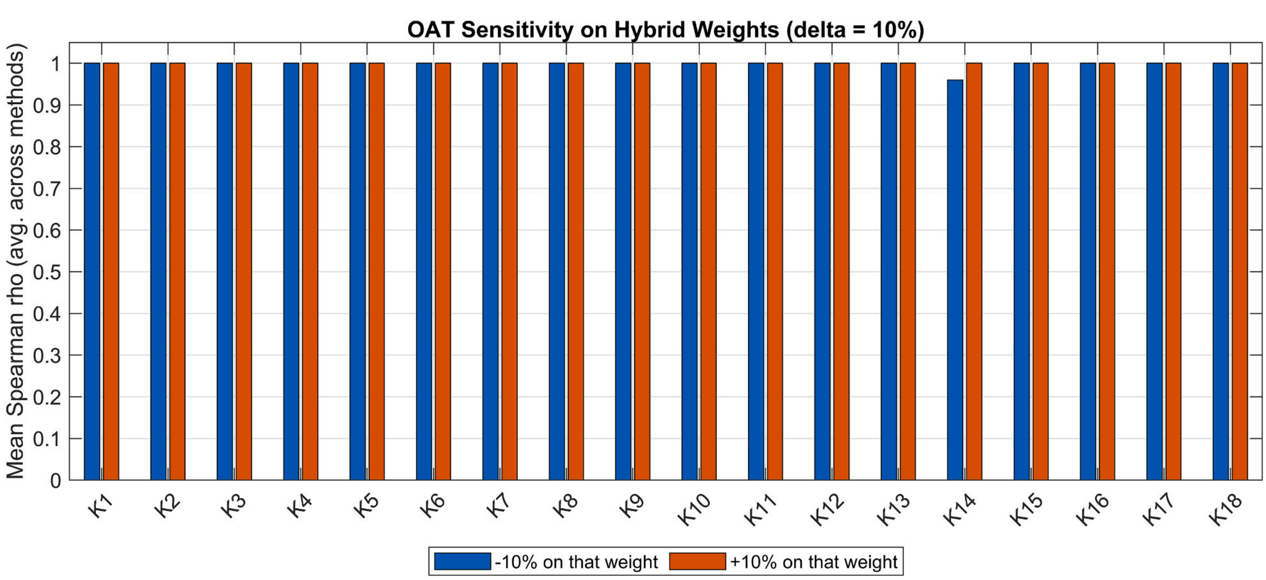

Fig. 8. Sensitivity of ranking results to ± 10% variations in hybrid criterion weights, evaluated using mean Spearman rank correlation across five MCDM methods.

support structure that is particularly suitable for strategic research infrastructure planning.

Despite the robustness of the proposed framework, some limitations should be noted. The analysis is based on a fixed set of 18 sub-criteria derived from the literature and expert input, and alternative indicator sets could slightly affect intermediate rankings. Expert judgment remains an inherent part of the weighting process, although its influence is moderated through fuzzy modeling and entropy-based weighting. In addition, the number of candidate universities is limited, and the use of static data reflects current conditions rather than future policy or infrastructure changes. Nevertheless, the sensitivity analysis indicates that these factors do not materially alter the final ranking, supporting the overall reliability of the results.

5. Conclusions

The present study provides a comprehensive and validated decision framework for selecting the optimal university location for establishing a national Boron Research Institute in Turkey. By integrating five complementary multi-criteria decision-making (MCDM) techniques—COPRAS, TOPSIS, VIKOR, MOORA, and WASPAS—with three distinct weighting strategies (Entropy, Fuzzy AHP, and Hybrid), we aimed to ensure both methodological diversity and analytical rigor. The results consistently highlighted Balıkesir University as the most suitable and stable alternative, with the same rank order (Balıkesir > Uludağ > Anadolu > Dumlupınar) reproduced across all fifteen scenarios. Such full convergence among methods demonstrates that the final outcome is not an artifact of model selection but a reflection of genuine performance dominance.

Statistical analyses further confirmed the internal validity of this conclusion, with high Kendall's concordance ($W = 0.87$) and nearly perfect Spearman correlations across the applied MCDM methods. In addition, stochastic and regret-based evaluations indicated that Balıkesir University not only performs best under deterministic conditions but also remains the most resilient and risk-averse choice under methodological uncertainty. From both a scientific and managerial standpoint, this means that the decision is not only optimal but also dependable.

Beyond its immediate implications for boron research infrastructure, the proposed framework offers a transferable and scalable decision-support tool for strategic research planning in other critical raw material domains. Future studies may extend this approach by incorporating dynamic or scenario-based data to capture long-term policy and infrastructure changes, expanding the set of decision alternatives to include international research hubs, or integrating advanced uncertainty and multi-objective optimization techniques. Such extensions would further enhance the applicability of the framework in supporting resilient, innovation-oriented, and policy-relevant institutional decision-making.

CRediT authorship contribution statement

Gülşah Çelik Gül: Writing – review & editing, Writing – original draft, Validation, Supervision, Project administration, Methodology, Funding acquisition, Formal analysis, Data curation. **Metin Gül:** Methodology, Formal analysis.

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Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.matdes.2026.115837.

Data availability

The data that has been used is confidential.

References

[1] European Commission. Critical Raw Materials Resilience: Charting a Path Towards Greater Security and Sustainability 2020.
[2] F. Tolun, Evaluation of welding parameters effects in friction stir welding of AZ31B Mg alloy, Kovove Materialy-Metallic Materials (2022) 60. https://doi.org/10.31577/km.2022.2.109.
[3] Eti Maden Operations General Directorate, 2023 Annual Activity Report, Ankara, Turkey, 2024.
[4] C. Helvacı, O. Alaca, Geology and Mineralogy of the Bigadiç Borate Deposıts and Vicinity, Bulletin of the Mineral Research and Exploration 113 (1991) 31–63.
[5] C. Helvacı, Geochemistry and origin of the Emet Borate Deposits, Western Turkey, Bulletin of the Faculty of Engineering, Cum Uni, Earthsciences 3 (1986) 49–73.
[6] A. Kilic, E. Kahraman, Ö. Kilic, M. Fakültesi, Place of Turkey in the, World Boron Production and Importance, 2018.
[7] T. Türkbay, B. Laratte, A. Çolak, S. Çoruh, B. Elevli, Life Cycle Assessment of Boron Industry from Mining to Refined Products, Sustainability 14 (2022) 1787, https://doi.org/10.3390/su14031787.
[8] Y. Liu, G.R. Madni, Role of scientific and technological innovations on industrial upgradation in China: A spatial econometric analysis, PLoS One 19 (2024) e0304344, https://doi.org/10.1371/journal.pone.0304344.
[9] Z. Zuo, J. Cheng, H. Guo, Y. Li, Knowledge mapping of research on strategic mineral resource security: A visual analysis using CiteSpace, Resources Policy 74 (2021) 102372, https://doi.org/10.1016/j.resourpol.2021.102372.
[10] B. Elevli, İ. Yaman, B. Laratte, Estimation of the Turkish Boron Exportation to Europe, Mining 2 (2022) 155–169, https://doi.org/10.3390/mining2020009.
[11] B. Mecca, Assessing the sustainable development: A review of multi-criteria decision analysis for urban and architectural sustainability, Journal of Multi-Criteria Decision Analysis 30 (2023) 203–218, https://doi.org/10.1002/mcda.1818.
[12] A.C. Özdemir, Use of Integrated AHP-Topsis Method in Selection of Optimum Mine Planning for Open-Pit Mines, Archives of Mining Sciences 68 (2023) 35–53. https://doi.org/10.24425/ams.2023.144316.
[13] F. Sitorus, J. Cilliers, P. Brito-Parada, Multi-Criteria Decision Making for the Choice Problem in Mining and Mineral Processing: Applications and Trends, Expert Syst Appl 121 (2019) 393–417, https://doi.org/10.1016/j.eswa.2018.12.001.
[14] Z.N. Shehab, R.M. Faisal, S.W. Ahmed, Multi-criteria decision making (MCDM) approach for identifying optimal solar farm locations: A multi-technique comparative analysis, Renew Energy 237 (2024) 121787, https://doi.org/10.1016/j.renene.2024.121787.
[15] T. Bulavskaya, F. Reynès, Job creation and economic impact of renewable energy in the Netherlands, Renew Energy 119 (2018) 528–538, https://doi.org/10.1016/j.renene.2017.09.039.
[16] R. Nagariya, S. Mukherjee, M.M. Baral, V. Chittipaka, Analyzing blockchain-based supply chain resilience strategies: resource-based perspective, International Journal of Productivity and Performance Management 73 (2024) 1088–1116, https://doi.org/10.1108/IJPPM-07-2022-0330.
[17] M. Alemi-Ardakani, A. Milani, S. Yannacopoulos, G. Shokouhi, On the effect of subjective, objective and combinative weighting in multiple criteria decision making: A case study on impact optimization of composites, Expert Syst Appl 46 (2015), https://doi.org/10.1016/j.eswa.2015.11.003.
[18] W. Mo, S. Xiao, Q. Li, AHP–Entropy Method for Sustainable Development Potential Evaluation and Rural Revitalization: Evidence from 80 Traditional Villages in Cantonese Cultural Region, China. Sustainability 17 (2025) 9582, https://doi.org/10.3390/su17219582.
[19] D. Pamucar, M. Deveci, I. Gokasar, M. Işık, M. Zizovic, Circular economy concepts in urban mobility alternatives using integrated DIBR method and fuzzy Dombi CoCoSo model, J Clean Prod 323 (2021) 129096, https://doi.org/10.1016/j.jclepro.2021.129096.
[20] M. Žižović, D. Pamučar, New model for determining criteria weights: Level Based Weight Assessment (LBWA) model, Decision Making: Applications in Management and Engineering (2019) 2. https://doi.org/10.31181/dmame1902102z.
[21] D. Pamučar, Ž. Stević, S. Sremac, A New Model for Determining Weight Coefficients of Criteria in MCDM Models: Full Consistency Method (FUCOM), Symmetry (Basel) 10 (2018) 393, https://doi.org/10.3390/sym10090393.
[22] R.W. Saaty, The analytic hierarchy process—what it is and how it is used, Mathematical Modelling 9 (1987) 161–176, https://doi.org/10.1016/0270-0255(87)90473-8.
[23] D.-Y. Chang, Applications of the extent analysis method on fuzzy AHP, Eur J Oper Res 95 (1996) 649–655, https://doi.org/10.1016/0377-2217(95)00300-2.
[24] P.H. Nyimbili, T. Erden, A Hybrid Approach Integrating Entropy-AHP and GIS for Suitability Assessment of Urban Emergency Facilities, ISPRS Int J Geoinf 9 (2020) 419, https://doi.org/10.3390/ijgi9070419.

[25] F. Zhou, T.-Y. Chen, A synergetic intuitionistic fuzzy model combining AHP, entropy, and ELECTRE for data fabric solution selection, Artif Intell Rev 58 (2025) 137, https://doi.org/10.1007/s10462-025-11128-7.
[26] F. Bandeiras, Á. Gomes, M. Gomes, P. Coelho, Multi-criteria sustainability assessment of energy resources in the energy supply chain of smart city ecosystems, Energy Nexus 18 (2025) 100441, https://doi.org/10.1016/j.nexus.2025.100441.
[27] T. Jameel, M. Riaz, M. Aslam, D. Pamucar, Sustainable renewable energy systems with entropy based step-wise weight assessment ratio analysis and combined compromise solution, Renew Energy 235 (2024) 121310, https://doi.org/10.1016/j.renene.2024.121310.
[28] R. Anjum, M.U. Mirza, N. Kausar, R. Ali, Decision-Making Framework for Urban Transportation Using Linear Diophantine Fuzzy Z-numbers with Dombi Aggregation, TOPSIS and VIKOR Methods, Spectrum of Operational Research (2025) 1–34. https://doi.org/10.31181/sor4155.
[29] Ullah K, Rehman N, Ali A. Business-oriented Stock Market Decision Analysis Using Circular Complex Picture Fuzzy Sets and Advanced MCDM Based on the CRITIC–WASPAS Method. Journal of Contemporary Decision Science n.d.;2:1–54.
[30] OpenStreetMap Contributors. Geospatial Infrastructure and Transport Data for Turkey 2025.
[31] C. Analytics, Web of Science Database, Research Output and Institutional Performance Data (2025).
[32] Balıkesir University Uludağ University Dumlupınar University Anadolu University. Institutional Websites and Academic Program Information 2025.
[33] Council of Higher Education (YÖK), National Thesis Center (YÖKTez) (2025).
[34] Republic of Türkiye M of I, Technology, Organized Industrial Zones and University-Industry Collaboration Reports (2025).
[35] AFAD. Türkiye Deprem Tehlike Haritası 2025.
[36] European Commission Joint Research Centre (JRC), PVGIS: Photovoltaic Geographical Information System (2025).
[37] World Bank Group ESMAP, Energy DTUW. Global Wind Atlas 4 (2025).
[38] Republic of Türkiye Ministry of Environment U, Change C, Environmental Indicators of Turkey: Air, Water and Waste Management Data (2025).
[39] S.K. Vaid, G. Vaid, S. Kaur, R. Kumar, M.S. Sidhu, Application of multi-criteria decision-making theory with VIKOR-WASPAS-Entropy methods: A case study of silent Genset, Mater Today Proc 50 (2022) 2416–2423, https://doi.org/10.1016/j.matpr.2021.10.259.
[40] T.-Y. Hsieh, S.-T. Lu, G.-H. Tzeng, Fuzzy MCDM approach for planning and design tenders selection in public office buildings, International Journal of Project Management 22 (2004) 573–584, https://doi.org/10.1016/j.ijproman.2004.01.002.
[41] F. Ye, Y. Li, An extended TOPSIS model based on the Possibility theory under fuzzy environment, Knowl Based Syst 67 (2014) 263–269, https://doi.org/10.1016/j.knosys.2014.04.046.
[42] M. Behzadian, S. Khanmohammadi Otaghsara, M. Yazdani, J. Ignatius, A state-of the-art survey of TOPSIS applications, Expert Syst Appl 39 (2012) 13051–13069, https://doi.org/10.1016/j.eswa.2012.05.056.
[43] W. Karel, W. Brauers, E. Zavadskas, The MOORA method and its application to privatization in a transition economy, Control and Cybernetics 35 (2006).
[44] S. Opricovic, G.-H. Tzeng, Compromise solution by MCDM methods: A comparative analysis of VIKOR and TOPSIS, Eur J Oper Res 156 (2004) 445–455, https://doi.org/10.1016/S0377-2217(03)00020-1.
[45] E. Zavadskas, A. Kaklauskas, V. Šarka, The new method of multicriteria complex proportional assessment of projects, Technological and Economic Development of Economy 1 (1994) 131–139.
[46] E.K. Zavadskas, Z. Turskis, J. Antucheviciene, A. Zakarevicius, Optimization of Weighted Aggregated Sum Product Assessment, Elektronika Ir Elektrotechnika 122 (2012) 3–6, https://doi.org/10.5755/j01.eee.122.6.1810.
[47] W. Sałabun, K. Urbaniak, A New Coefficient of Rankings Similarity in Decision-Making Problems (2020) 632–645, https://doi.org/10.1007/978-3-030-50417-5_47.
[48] M.G. Kendall, B.B. Smith, The Problem of m Rankings, The Annals of Mathematical Statistics 10 (1939) 275–287, https://doi.org/10.1214/aoms/1177732186.
[49] C. Spearman, The Proof and Measurement of Association between Two Things, Am J Psychol 15 (1904) 72, https://doi.org/10.2307/1412159.
[50] R. Lahdelma, J. Hokkanen, P. Salminen, SMAA - Stochastic multiobjective acceptability analysis, Eur J Oper Res 106 (1998) 137–143, https://doi.org/10.1016/S0377-2217(97)00163-X.
[51] R. Lempert, S. Popper, S. Bankes, Shaping the Next One Hundred Years: New Methods for Quantitative, Long-Term Policy Analysis, RAND Corporation (2003), https://doi.org/10.7249/MR1626.
[52] E.K. Zavadskas, Z. Turskis, MULTIPLE CRITERIA DECISION MAKING (MCDM) METHODS IN ECONOMICS: AN OVERVIEW / DAUGIATIKSLIAI SPRENDIMŲ PRIĖMIMO METODAI EKONOMIKOJE: APŽVALGA, Technological and Economic Development of Economy 17 (2011) 397–427, https://doi.org/10.3846/20294913.2011.593291.
[53] S. Chakraborty, E.K. Zavadskas, Applications of WASPAS Method in Manufacturing Decision Making, Informatica 25 (2014) 1–20. https://doi.org/10.15388/Informatica.2014.01.
[54] G.-H. Tzeng, J.-J. Huang, Multiple Attribute Decision Making, Chapman and Hall/CRC (2011), https://doi.org/10.1201/b11032.
[55] R. Lahdelma, P. Salminen, J. Hokkanen, Locating a waste treatment facility by using stochastic multicriteria acceptability analysis with ordinal criteria, Eur J Oper Res 142 (2002) 345–356, https://doi.org/10.1016/S0377-2217(01)00303-4.
[56] O. Der, M. Ordu, G. Basar, Optimization of cutting parameters in manufacturing of polymeric materials for flexible two-phase thermal management systems, Materials Testing 66 (2024) 1700–1719, https://doi.org/10.1515/mt-2024-0127.
[57] M. Ordu, O. Der, Polymeric Materials Selection for Flexible Pulsating Heat Pipe Manufacturing Using a Comparative Hybrid MCDM Approach, Polymers (Basel) 15 (2023) 2933, https://doi.org/10.3390/polym15132933.
[58] A. Siva Bhaskar, A. Khan, Comparative analysis of hybrid MCDM methods in material selection for dental applications, Expert Syst Appl 209 (2022) 118268, https://doi.org/10.1016/j.eswa.2022.118268.