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Consensus-based GIS–MCDM model for hydrogen infrastructure in Southern Marmara, Türkiye

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ABSTRACT

This study develops a spatial multi-criteria decision-making (SMCDM) framework integrating Geographic Information Systems (GIS) with three MCDM methods (TOPSIS, MOORA, VIKOR) and three weighting strategies (Entropy, Fuzzy AHP (FAHP), Hybrid) to identify optimal green hydrogen production sites in Southern Marmara, Türkiye. Thirteen criteria were structured into five dimensions: technical, environmental, infrastructural, logistic/industrial, and socio-economic. The framework evaluates 4,795 candidate locations, capturing both objective data variability and expert-informed priorities. Comparative analysis across nine ranking scenarios reveals both method-independent high-potential clusters and ranking variability depending on weighting strategy. Entropy emphasizes data-driven consistency, FAHP reflects expert-defined perspectives, and the Hybrid approach balances the two. Consensus ranking identifies Bandırma's industrial-port zone as the most robust site, aligning with the location of Türkiye's first hydrogen facility. These findings validate the methodological framework and demonstrate how integrating consensus-based MCDM with GIS can guide resilient energy infrastructure planning. The proposed approach offers a flexible analytical structure that could be *considered* in the development of national or regional hydrogen roadmaps. While this study does not quantitatively model CBAM-related dynamics, the methodological framework can potentially support future clean energy planning efforts that aim to align with EU sustainability and trade mechanisms.

1. Introduction

Green hydrogen, produced by water electrolysis powered by renewable energy, is now widely seen as one of the key pathways toward achieving net-zero emissions and building a sustainable global energy model [1]. Among the available options, hybrid wind–photovoltaic systems stand out because they reduce the intermittency of renewables, allow surplus power to be stored as hydrogen, and increase both flexibility and reliability in energy supply [2,3]. Beyond balancing supply and demand, these systems offer a clean alternative to fossil fuels and contribute to decarbonization across several sectors such as transport, industry, and power, including more challenging areas like steel, chemicals, and large-scale logistics [4].

Although the environmental advantages of green hydrogen are clear, its production cost is still higher than that of fossil-based hydrogen. This makes careful planning and optimization of system design essential. One of the most critical parameters is site selection, which directly influences both economic performance and long-term project viability [3,5]. Unlike conventional energy facilities, hydrogen plants require a much broader evaluation that takes into account renewable resource potential, industrial demand, accessibility to infrastructure, environmental conditions, and overall feasibility. Poor siting choices may increase transport costs and environmental impacts or limit operational efficiency, which in turn affects the competitiveness of hydrogen systems [6,7].

Choosing suitable locations for green hydrogen production is therefore a multi-dimensional problem, involving technical, economic, environmental, social, and policy-related factors. Proximity to renewable energy sources—especially solar and wind—is one of the key determinants since local resource potential strongly affects system performance. However, most previous studies have concentrated on single-resource projects, either solar [8,9] or wind [10], typically using GIS–MCDM frameworks. While these approaches have improved our

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understanding of renewable energy potential [5,11], While such GIS–MCDM analyses have provided valuable insights into renewable energy potential [5,11], their scope remains narrow. Studies that evaluate both resources together are still limited because integrating multiple renewable sources increases methodological complexity [12].

In addition to energy potential, infrastructure and environmental aspects also play an important role. Accessibility to transmission lines, natural gas networks, roads, ports, and industrial zones significantly influences logistics and hydrogen transport costs. For example, India has located hydrogen hubs close to refineries and fertilizer plants to improve distribution efficiency [13]. Environmental and social dimensions are equally important: Thailand's studies on hydrogen infrastructure have included protected-area buffers to minimize ecological impact [14,15]. On a larger scale, energy security and trade also add strategic complexity. Pinto et al. [16] showed that including geopolitical factors in a GIS–AHP model for North Africa significantly changed site rankings, underlining the importance of such dimensions.

To deal with these multi-layered challenges, combining Geographic Information Systems (GIS) with MCDM has become a common and effective approach in renewable energy siting studies [17,18]. This combination enables structured evaluation of many spatial and non-spatial factors—such as renewable resource availability, infrastructure, and environmental restrictions—within a single framework [8,9]. GIS–MCDM approaches are especially valuable because they make site selection decisions transparent, systematic, and reproducible through weighted overlay analysis of spatial layers [19,20].

Several regional studies have applied this approach to hydrogen-related projects. In Cameroon, AHP, Fuzzy Analytic Hierarchy Process (FAHP), and Monte Carlo FAHP were used to assess solar-based hydrogen potential, demonstrating the strength of fuzzy logic for handling uncertainty [21]. In Morocco's Souss-Massa region, GIS–AHP was applied to evaluate technical and environmental indicators, but it lacked sensitivity testing [22]. A similar limitation was observed in Thailand's hydrogen refuelling study [23] and in Iran's wind-based hydrogen site analysis [24]. These studies contributed useful regional insights but mainly relied on single weighting schemes or decision methods.

Although fuzzy-based MCDM approaches like FAHP can better capture uncertainty [25] most of the existing works share three limitations: (1) they use only a single decision-making method, (2) they apply a fixed or subjective weighting scheme without sensitivity checks, and (3) they generally focus on a single renewable resource instead of combining solar and wind data. Because of this, the relative consistency and robustness of different MCDM techniques under the same spatial conditions are still not well understood.

In Türkiye, research directly addressing hydrogen production site selection remains limited. Yılmaz [26] used a GIS–MCDM framework for solar-driven hydrogen production in Konya, while Karayel [27] examined national wind-based hydrogen potential without detailed spatial modelling. Broader renewable energy studies, such as those by Aydın et al. [28] and Emeksiz & Demirci [29], have contributed to hybrid and offshore wind planning, but they do not specifically focus on hydrogen. To date, there has been no comprehensive framework that integrates solar and wind potential together with technical, environmental, infrastructural, and logistic dimensions for hydrogen site selection in Türkiye.

This gap forms the main motivation of the present study. We aimed to answer the following research question: How can a multi-method, multi-weighting, and consensus-based GIS–MCDM framework be developed to provide robust and reproducible site selection for green hydrogen infrastructure in Türkiye?

To address this question, we developed a comprehensive spatial multi-criteria decision-making (SMCDM) framework that combines three well-known MCDM methods—TOPSIS, MOORA, and VIKOR—-with three different weighting schemes: Entropy (objective), Fuzzy AHP (expert-based), and a Hybrid Entropy–FAHP combination. This design created nine different model configurations (3×3) and made it possible to compare their performance and test the consistency, sensitivity, and robustness of the resulting spatial rankings. The inclusion of both objective and expert-based weights provided a balanced perspective between data-driven evaluation and human judgment.

A major methodological contribution of this work is the introduction of a consensus-based ranking approach that statistically aggregates the results of all nine configurations. This helps quantify the level of agreement among different methods and identify locations that remain stable across weighting and ranking scenarios. The approach strengthens the transparency and reproducibility of GIS–MCDM applications, which often depend heavily on a single decision logic.

From a practical perspective, this study also provides the first spatial validation of Türkiye's Hydrogen Valley Project in Balıkesir, one of the country's first large-scale green hydrogen initiatives. By comparing model outcomes with the existing facility, the analysis shows how a data-driven GIS–MCDM approach can support real-world planning decisions. Moreover, the proposed framework is scalable and transferable to other regional contexts, offering a methodological basis for future hydrogen roadmaps aligned with EU CBAM policies and broader clean-energy transition targets.

The remainder of this paper is structured as follows: Section 2 presents the data sources, criteria, and methodological workflow; Section 3 discusses the spatial results and comparative analyses; and Section 4 concludes with key findings, implications, and recommendations for future work.

2. Materials and methods

The methodological framework of this study integrates spatial analysis, multi-criteria decision-making, and sensitivity testing to systematically evaluate potential green hydrogen production plants. The process begins with the identification of 13 evaluation criteria derived from technical, environmental, infrastructural, and socio-economic factors. These criteria are spatially analysed via GIS, weighted using both objective (Entropy) and subjective (FAHP) techniques, and used to rank potential sites through multiple decision models. Additionally, sensitivity and variable importance analyses are conducted to enhance the robustness of the findings.

2.1. The study area

The study is conducted in Balıkesir Province, situated in the western part of Turkey within the Southern Marmara Region. It lies between latitudes 39°06′N and 40°38′N and longitudes 26°38′E and 28°43′E, covering an area of approximately 14,500 km^2. The province features a diverse landscape encompassing coastal zones along both the Aegean and Marmara Seas, as well as mountainous and agricultural inland areas. Balıkesir has a population of over 1.2 million and benefits from rich renewable energy resources, especially wind speeds suitable for utility-scale energy generation. Its strategic location near major industrial zones, transportation corridors (including highways, railways, and ports), and its proximity to Europe enhance its suitability for sustainable energy projects, including green hydrogen production [30].

2.2. Criteria definition and spatial data processing

The methodological process begins with the definition of thirteen spatial evaluation criteria aimed at determining the suitability of potential sites for green hydrogen production plants. The selection of criteria in this study was guided by an extensive review of the relevant academic literature, national and international policy frameworks, technical documentation, and insights from experts in areas such as energy systems, spatial planning, and environmental engineering [18, 31,32].

To capture the multi-dimensional nature of green hydrogen site selection, the evaluation criteria were organized into five overarching categories: (i) technical aspects, (ii) environmental aspects, (iii) infrastructure-related factors, (iv) logistics and industrial accessibility, and (v) socio-economic considerations. This structure enables a comprehensive assessment that accounts for resource potential, ecological constraints, infrastructure availability, logistical practicality, and regional development conditions. The inclusion of each criterion is based on both practical and strategic considerations. For instance, although hydrogen does not directly depend on natural gas infrastructure, proximity to gas pipelines was retained as a criterion because such corridors often overlap with established rights-of-way and may facilitate future hydrogen blending or pipeline repurposing. Similarly, logistic and port access criteria were included to reflect Türkiye's export ambitions under EU CBAM regulations, while settlement-related indicators capture potential conflicts and socio-economic co-benefits.

2.3. Data sources and GIS environment

The spatial database used in this study was constructed from multiple validated open-access and institutional datasets to ensure spatial consistency and thematic reliability. Land use and land cover data were obtained from the CORINE Land Cover (CLC) 2018, Version 2020_20u1 produced by the European Environment Agency (EEA) under the Copernicus Land Monitoring Service [33]. Topographic variables, including elevation and slope, were derived from the Digital Elevation Model (DEM) accessed via the USGS Earth Explorer platform [34]. Solar energy potential layers were retrieved from the PVGIS (Photovoltaic Geographical Information System) [35], while wind energy data were extracted from the Global Wind Atlas [36]. Geological and fault-line information was collected from the General Directorate of Mineral Research and Exploration (MTA) [37]. Transportation and infrastructure layers, such as road networks, urban areas, and industrial zones, were obtained from OpenStreetMap contributors and cross-checked using Google Earth Pro (v7.3) imagery [38].

All spatial data were projected to the WGS 84/UTM Zone 35 N coordinate system to maintain spatial uniformity. The spatial analyses—including raster standardization, reclassification, weighted overlay, and proximity analysis—were performed using ArcGIS Pro 3.2 and QGIS 3.34 environments.

A detailed overview of the criteria, their classification within these dimensions, and the spatial data sources employed in the GIS-based analysis is provided in Table 1.

Table 1
Overview of the criteria framework applied in the site selection of hydrogen production facilities.

Category	Criteria	Data Type	Data Source	Exclusion/ Suitability Threshold
Technical Factors	- Land use type	Raster	[39]	Corine 122, 123, 124, 131, 132, 141, 142, 311, 312, 313, 324, 411, 511, 512, 111, 112, 223
	- Slope	Raster derived from DEM	[33]	Areas with slope >10°
	- Global Horizontal Irradiance (GHI)	Raster	[34]	GHI <1500 kWh/m^2/year
	- Average wind speed	Raster	[35]	Wind speed <5.5 m/s
Environmental Factors	- Distance to fault lines	Vector	[36]	<1000 m
	- Distance to coastline	Vector	[37]	>40 km
	- Distance to water resources	Vector	[37]	<100 m
Infrastructural Factors	- Distance to transmission lines	Vector	[37]	–
	- Distance to natural gas grid	Vector	[37]	–
	- Distance to roads	Vector	[37]	<25
	- Distance to existing wind farms	Vector	[38]	<1000 m
Logistic and Industrial Access	- Distance to organized industrial zones	Vector	[38]	–
Socio-economic Factors	- Distance to settlements	Vector	[37]	<300 m

2.4. Decision-making framework for hydrogen production facility siting

A GIS-supported spatial multi-criteria decision-making (SMCDM) approach was developed to evaluate potential sites for green hydrogen production. The sequential stages of this combined spatial and decision-making framework are summarized in Fig. 1.

The spatial modelling process was structured into the following sequential steps.

2.4.1. Data collection and preprocessing

Thirteen spatial criteria were defined and grouped into five thematic categories: technical, environmental, infrastructural, logistic/industrial access, and socio-economic. Relevant spatial datasets—including digital elevation models (DEM), solar radiation (GHI) maps, wind speed rasters, fault lines, road and pipeline networks, industrial zone locations, and land cover data—were obtained from national and global sources. All layers were projected into a common coordinate reference system (UTM Zone 35 N, WGS84).

2.4.2. Spatial criterion mapping and normalization

Each criterion was transformed into a raster-based suitability layer using appropriate geoprocessing tools. *Euclidean Distance* and *Near* analyses were applied to derive continuous distance-based indicators (e.g., distance to roads, pipelines, fault lines, settlements, and ports). Slope was calculated from the DEM. All resulting rasters were then normalized to a common scale from 0 (least suitable) to 1 (most suitable), based on their defined suitability relationships.

2.4.3. Generation of candidate planning units

The high-suitability zones identified through the integrated spatial analysis were systematically divided into uniform planning units, each measuring 10 ha. This subdivision yielded a total of 4,795 candidate locations. For each unit, relevant spatial information—corresponding to all evaluation criteria was extracted and associated by overlaying the unit boundaries with the respective thematic layers. The resulting dataset was then compiled into a structured table format for use in subsequent non-spatial multi-criteria decision-making (MCDM) analyses.

2.5. Objective weighting approach

This study employs three weighting methodologies to enhance the reliability of the evaluation process: the Entropy method, the FAHP, and a Hybrid approach combining the two. The Entropy method provides an objective basis by quantifying the variability of each criterion, whereas FAHP incorporates expert judgments expressed through linguistic scales. The Hybrid scheme integrates these objective and subjective perspectives, yielding a more balanced representation of criteria

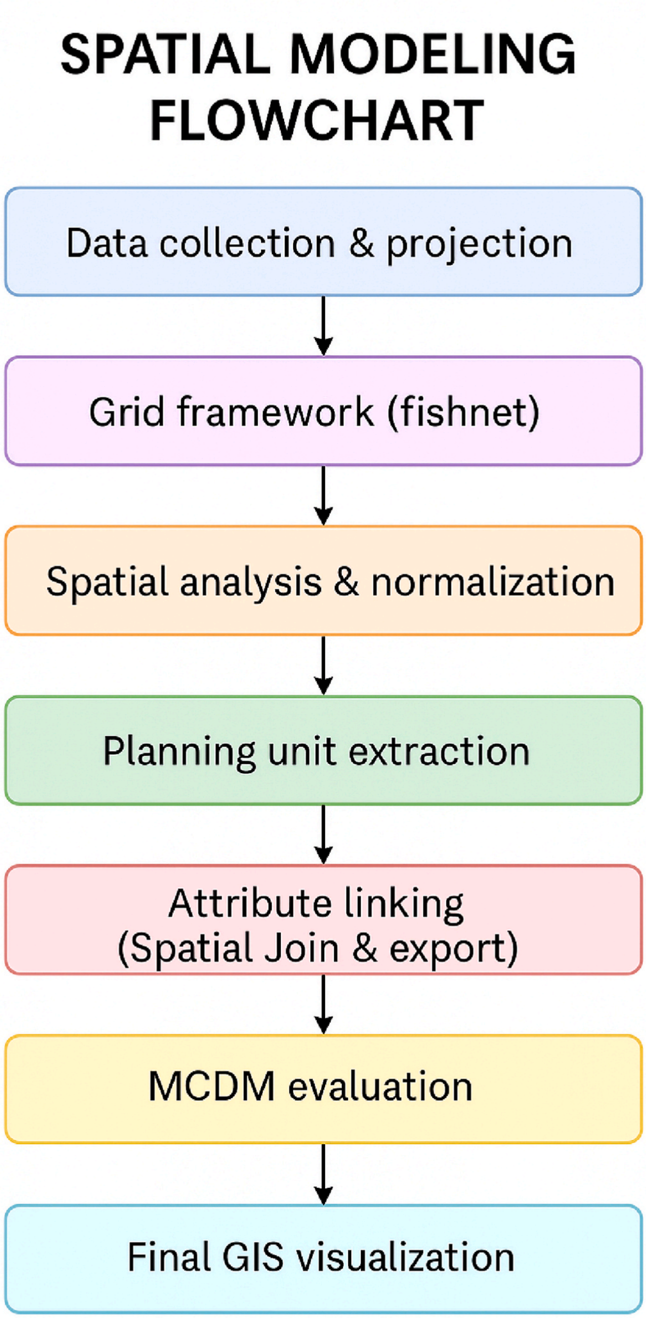

Fig. 1. Flowchart of the spatial modelling and multi-criteria decision-making (SMCDM) process for green hydrogen site selection. (For interpretation of the references to colour in this figure legend, the reader is referred to the Web version of this article.)

importance in hydrogen plant site selection.

2.5.1. Entropy-based objective weight determination methodology

The Entropy method was used to determine the objective weights of criteria by measuring the dispersion of their values across alternatives [40]. A higher variation indicates that a criterion carries more information and thus higher importance.

The procedure starts with constructing the decision matrix:

First, we constructed the decision matrix,

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

where x_{ij} is the value of the j-th criterion for the i-th alternative, and $i = 1, 2, \ldots \ldots, m$; $j = 1, 2, \ldots \ldots, n$. 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 then calculated as:

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

where, $k = -1/\ln(m)$

Finally, the Entropy weights are derived, assigning greater importance to criteria with lower Entropy:

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

In this study, 13 spatial criteria were extracted for 4,795 candidate locations using GIS. Raster indicators (slope, solar irradiance, wind speed) were processed by zonal statistics, while distance-based factors were derived via Euclidean proximity analysis. These normalized datasets formed the decision matrix used for objective weighting.

2.5.2. Fuzzy-AHP-based objective weight determination methodology

To incorporate expert judgment under uncertainty, the **FAHP** was applied. Seven domain experts (from academia, industry, public administration, and environmental planning) performed pairwise comparisons using linguistic terms converted into **triangular fuzzy numbers (TFNs)** (Table 2).

Seven domain experts—comprising an energy academic, investor, public administration specialist, geographer, environmental engineer, policymaker, and green hydrogen practitioner—participated in the evaluation. Their inputs were aggregated using the geometric mean method, which balances the diversity of expert opinions while reducing individual bias. If individual judgments for each criterion pair were expressed (l_k, m_k, u_k) for $k = 1, 2, \ldots, 7$ the aggregated TFN (l', m', u') was obtained by multiplying the respective lower, middle, and upper values across all experts. The resulting aggregated Fuzzy pairwise comparison matrix served as the foundation for the subsequent FAHP procedure, where Fuzzy synthetic extent values were calculated and defuzzified to derive the final weights. These weights were then applied in the spatial decision-making framework for hydrogen plant site selection. Expert judgments were expressed using linguistic terms defined in Table 2, which were subsequently converted into TFNs to construct the Fuzzy pairwise comparison matrix.

The aggregated triangular Fuzzy number (l, m, u) was calculated with Equation (5) [41]:

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

Table 2
Linguistic terms and corresponding TFNs used in pairwise comparisons.

Linguistic Term	TFN (l, m, u)
Equally Important	(1, 1, 1)
Moderately Important	(2, 3, 4)
Strongly More Important	(3, 5, 7)
Very Strongly to Extremely Important	(5, 7, 9)

The aggregated Fuzzy pairwise comparison matrix served as the input for the subsequent phase of the FAHP process, wherein Fuzzy synthetic extent values were calculated to derive the relative weights of the criteria.

This aggregation approach ensures that the collective knowledge of the expert panel is represented in a balanced manner, reducing the influence of individual bias or extreme values while preserving the fuzziness of subjective reasoning. As a result, a unified 13 × 13 aggregated Fuzzy comparison matrix was formed, where each element $\widetilde{a}_{ij} = (l_{ij}, m_{ij}, u_{ij})$ reflects the synthesized Fuzzy judgment of criterion i over criterion j.

Once the aggregated Fuzzy pairwise comparison matrix was constructed, the Fuzzy synthetic extent values for each criterion were calculated using Chang's extent analysis method [42]. The method works by comparing the Fuzzy score of each criterion with the total Fuzzy scores across all criteria, which makes it possible to see how much weight each one carries. The application of FAHP here involved three stages. The first step was to calculate the Fuzzy geometric mean of each criterion, expressed as:

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

In the second step, the Fuzzy weights were determined by normalizing each geometric mean against the total Fuzzy sum, as expressed in Equation (7):

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

Finally, the defuzzification process was carried out using the centroid method:

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

The resulting defuzzied weights were then normalized to sum to 1 and used as the final criteria weights in subsequent decision-making analyses.

In order to minimize possible bias and ensure a balanced interpretation of the experts' judgments, the Fuzzy pairwise comparison matrices obtained from the seven participants were combined using the geometric mean method. This approach was preferred because it respects the relative ratios within each matrix while preventing any single expert's opinion from dominating the overall result. Since the expert group included people from different backgrounds—such as energy systems, environmental studies, and policy—some variation in their assessments was expected and, in fact, welcomed for a broader perspective. To check the stability of the aggregated results, a simple sensitivity analysis was performed by comparing each expert's weight vector with the aggregated one. The results showed an average correlation of 0.15 and an average deviation of 0.064, indicating moderate diversity in views but an acceptable level of overall consistency. These findings confirm that the geometric mean aggregation provided a fair and representative reflection of the group's collective judgment.

2.5.3. Hybrid weighting method

To integrate the benefits of subjective expert judgment with objective data-based evaluation, a Hybrid weighting procedure was employed, combining the FAHP and Entropy weighting. FAHP incorporates expert knowledge under uncertainty by means of triangular Fuzzy numbers and pairwise comparisons, whereas Entropy weighting derives objective values by analyzing the degree of diversification in the dataset. The normalized weights from FAHP (F_i) and Entropy (E_i) were subsequently averaged to produce the Hybrid weights, as described in Equation (9):

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

Here, H_i represents the Hybrid weight of criterion i. This equally weighted combination provides a balanced reflection of expert assessments and intrinsic data characteristics.

This balanced representation of expert judgment and data dispersion was used for the main SMCDM analysis. Comparative results of all weighting methods are given in Table 3.

2.6. SMCDM methods

Three MCDM methods—TOPSIS, MOORA, and VIKOR were employed to rank the 4,795 candidate sites. To avoid redundancy, all methods used the same normalized decision matrix and criterion weights obtained from Entropy, FAHP, or Hybrid schemes.

2.6.1. TOPSIS method

TOPSIS ranks alternatives by their distance from ideal and anti-ideal solutions [43,44]. Normalization and weighting follow with Equations (10) and (11) respectively:

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

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

where w_j is the weight of criterion j, and v_{ij} is the weighted normalized value.

Distances and closeness coefficients are given by Equations respectively:

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

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

Alternatives are ranked in descending order of C_i.

2.6.2. MOORA method

MOORA follows a ratio-based approach [45]:

The raw data was first normalized using vector normalization:

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

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

Table 3
Final criterion weights obtained by FAHP, Entropy, and Hybrid approaches.

No	Criterion	Entropy	Fuzzy-AHP	Hybrid
1	Land Use Type	0.029962	0.1315	0.080731
2	Distance to Coastline	0.123442	0.0299	0.076671
3	Slope	0.090045	0.0823	0.086173
4	Distance to Fault Line	0.078917	0.1291	0.104009
5	Distance to Natural Gas Network	0.203028	0.0404	0.121714
6	Global Horizontal Irradiance (GHI)	0.000394	0.1213	0.060847
7	Distance to Port	0.086283	0.026	0.056142
8	Distance to Industrial Zones	0.108082	0.0327	0.070391
9	Distance to Water Resources	0.065284	0.1344	0.099842
10	Wind Speed	0.001674	0.1112	0.056437
11	Distance to Wind Turbines	0.060396	0.0348	0.047598
12	Distance to Settlements	0.058061	0.0846	0.071331
13	Distance to Roads	0.094433	0.0418	0.068117

normalized value.

The weighted normalized value is expressed as:

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

For each alternative, the overall MOORA performance score Y_i was calculated as:

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

where B and C represent the sets of beneficial and cost-type (non-beneficial) criteria, respectively.

The alternatives were ranked in descending order of their Y_i scores. Alternatives with higher Y_i are more suitable.

2.6.3. VIKOR method

VIKOR identifies a **compromise solution** between group utility and individual regret [46].

For each criterion, the best (f_j^*) and worst (f_j^-) values were identified.

For beneficial criteria, normalization was conducted using this Equation (17).

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

For non-beneficial criteria, the normalization Equation is:

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

Each normalized value is then weighted using the corresponding criterion weight w_j, typically derived from FAHP, Entropy, or a Hybrid scheme:

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

S_i: the group utility measure, sum of all weighted deviations for alternative i:

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

R_i: the individual regret measure, maximum weighted deviation for alternative i:

$$R_i = \max_j (v_{ij}) \tag{21}$$

Q_i: the VIKOR index, reflecting the compromise ranking:

$$Q_i = v . \frac{S_i - S^*}{S^- - S^*} \tag{21a}$$

$S^* = \min S_i$, $S^- = \max S_i$, $R^* = \min R_i$, $R^- = \max R_i$, V = 0.5 is the weight of the strategy of maximum group utility. The best option satisfies the **acceptable advantage** and **stability** conditions.

Total of 4,795 alternatives were ranked using three MCDM methods, and the results were integrated into the GIS environment. The final scores and ranks were joined with the corresponding spatial planning units, enabling the generation of thematic maps that display the spatial distribution of site suitability. These maps highlight the most favourable zones identified by each method, allowing for direct spatial comparison of the outputs. Areas consistently ranked in the top percentiles were emphasized as priority regions for potential green hydrogen facility development.

2.6.4. Comparative overview of MCDM methods

To provide a concise conceptual summary of the three decision-making methods applied in this study—TOPSIS, MOORA, and VIKOR—a comparative table is presented below (Table 4) [47–49].

Table 4
Comparative overview of the three MCDM methods applied in this study.

Method	Main Principle	Strengths	Limitations
TOPSIS	Evaluates alternatives based on their relative closeness to the ideal (best) and anti-ideal (worst) solutions.	Simple, intuitive, widely used; allows for simultaneous consideration of positive and negative benchmarks; computationally efficient.	Sensitive to the normalization method and to correlation among criteria; results may vary with scaling.
MOORA	Compares beneficial and non-beneficial criteria using a ratio system, normalizing data to derive overall performance scores.	Straightforward and transparent; less sensitive to scale differences; suitable for large datasets.	Does not explicitly consider the concept of ideal and anti-ideal solutions.
VIKOR	Determines a compromise ranking by balancing group utility (majority satisfaction) and individual regret (minimum dissatisfaction).	Handles conflicting criteria well; provides compromise solutions; useful for decision contexts requiring trade-offs.	Requires the selection of a parameter (v); may cause rank reversals under small changes in data.

3. Results and discussion

This section presents the spatial decision-making results for the optimal siting of a green hydrogen production facility powered by photovoltaic and wind energy in Balıkesir province, Turkey. Following the exclusion analysis based on thirteen spatial criteria implemented in a GIS environment, a total of 4795 suitable land parcels were identified. Each of these candidate sites corresponds to a standardized 10-ha polygon, satisfying all minimum threshold values required for technical, environmental, infrastructural, and socio-economic viability.

Fig. 2 illustrates the spatial distribution of these 4795 suitable parcels across Balıkesir. The red-highlighted polygons represent areas that remained after applying all exclusionary filters such as slope thresholds, fault line proximity, land cover constraints, and minimum renewable energy potential. The map clearly shows clusters of viable sites in districts such as Bandırma, Gönen, and Burhaniye, which exhibit favourable geographic and infrastructural attributes for renewable-based hydrogen production.

In this study, a multi-criteria decision-making (MCDM) framework was applied to systematically prioritize the 4,795 alternatives, utilizing three established methods—TOPSIS, MOORA, and VIKOR—under three weighting strategies: Entropy-based objective weights, FAHP-based expert weights, and a Hybrid combination of both. This procedure generated nine ranking scenarios, providing a comprehensive prioritization of all parcels. The following results present a comparative analysis of these scenarios, highlight consistently high-ranking locations, and examine spatial patterns of convergence and divergence across methods and weighting schemes, supported by GIS-based visualizations and correlation analyses.

3.1. Overall performance of MCDM rankings

MCDM configurations were constructed by combining three ranking methods with three weighting approaches to determine the most suitable locations for green hydrogen production in Balıkesir province. Each MCDM method was applied under three different configurations—Entropy-based, FAHP-based, and Hybrid Entropy–FAHP weighting—to evaluate the influence of weighting strategies on ranking outcomes. The different configurations captured a range of perspectives, from purely data-driven results to expert-based judgments and mixed approaches. When the nine ranking scenarios were compared, some sites were repeatedly placed at the top, suggesting they are strong candidates

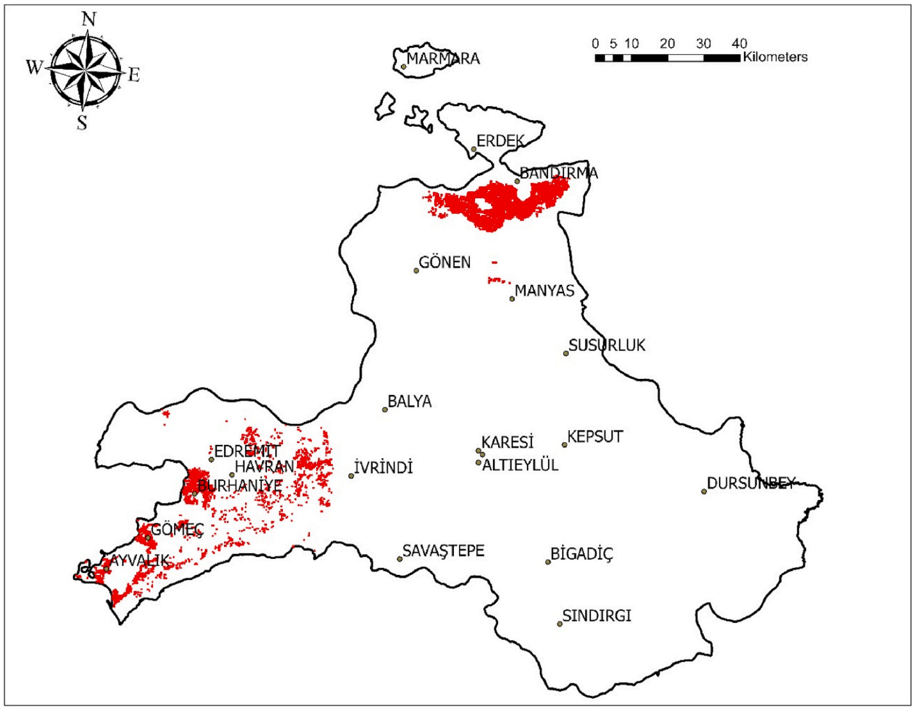

Fig. 2. Spatial distribution of the 4,795 suitable parcels across Balıkesir after exclusionary filters.

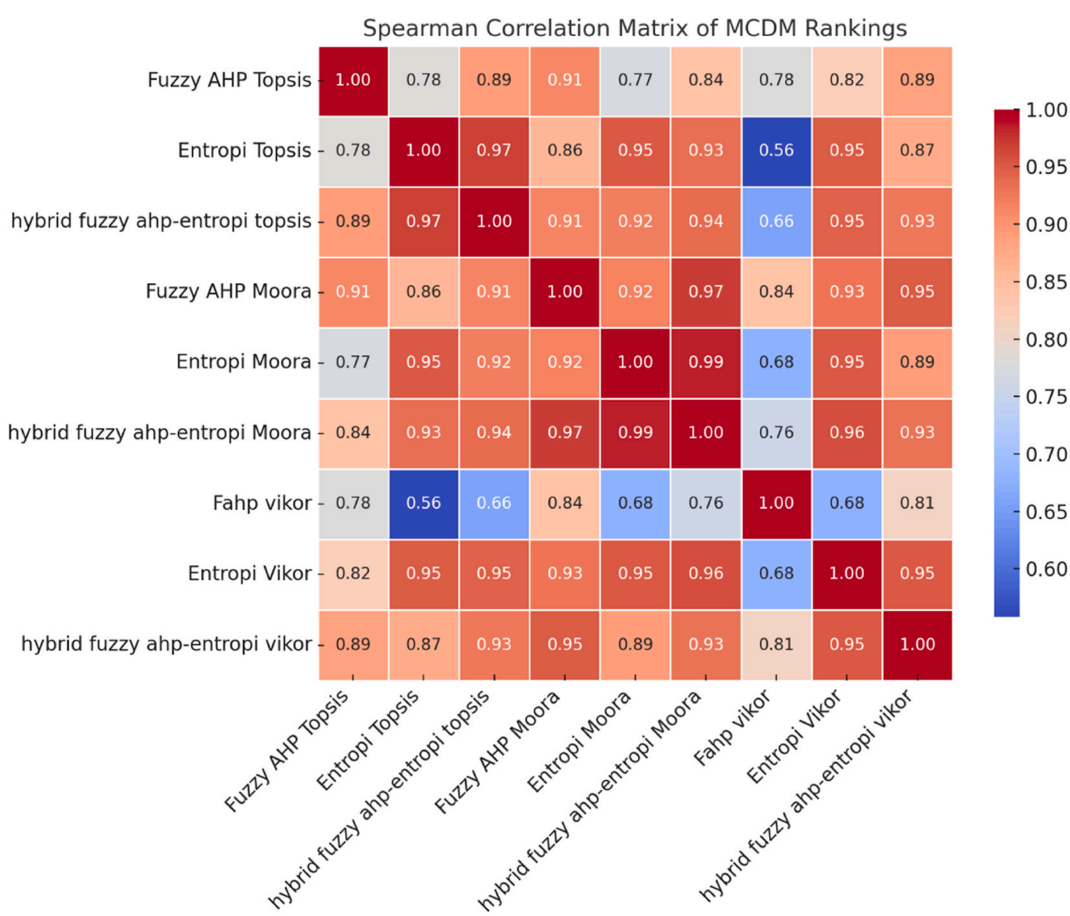

Fig. 3. Correlation matrix of MCDM rankings.

regardless of the method, while others shifted noticeably depending on the weighting strategy or decision logic used.

Entropy-based rankings tended to highlight criteria with high variation, producing clusters of top-ranked sites. In contrast, FAHP introduced more variety, drawing attention to locations that reflected expert priorities. The Hybrid approach produced middle-ground results, resembling Entropy rankings when expert opinions were divided and leaning toward FAHP when experts showed stronger agreement. These outcomes show that the choice of weighting method can significantly shape the ranking and that using multiple perspectives increases the reliability of the decisions.

To test the consistency between the nine ranking scenarios, a Spearman correlation was applied. The results, illustrated in Fig. 3, revealed both areas of alignment and points of difference between the methods.

Strong positive correlations were observed among rankings that shared similar weighting strategies and employed the same decision-making method. Notably, Entropy-weighted and Hybrid-weighted TOPSIS rankings showed a very high correlation ($\rho = 0.98$), while MOORA under Entropy and Hybrid weights also exhibited strong alignment ($\rho = 0.97$), indicating methodological consistency under similar weighting logic.

In contrast, the lowest correlation was found between FAHP–weighted VIKOR and Entropy-based TOPSIS ($\rho = 0.56$), underscoring the divergent prioritization logic introduced by combining expert-driven Fuzzy evaluations with a compromise-based decision model. Similarly, FAHP–weighted rankings of VIKOR and MOORA showed lower correlations with their Entropy counterparts, indicating that expert knowledge significantly influences the outcome—often prioritizing contextually important but objectively less prominent alternatives.

No single MCDM method is universally superior. However, VIKOR with FAHP and Hybrid weights showed higher discriminatory power and revealed subtle differences between the alternatives. On the other hand, Entropy-based TOPSIS and MOORA yielded highly correlated and consistent outputs, which may be preferable in decision contexts requiring procedural transparency and data-driven consistency.

While the nine MCDM configurations generated diverse ranking outputs, a subset of locations consistently emerged as highly suitable across all methods and weighting schemes. To identify these robust candidates, the average rank and standard deviation of each site's position across all nine scenarios were calculated. Sites with both low average ranks and minimal variation were considered the most suitable and stable alternatives.

Fig. 4 illustrates the distribution of standard deviations of ranks across all 4795 candidate polygons evaluated under the nine MCDM configurations. The histogram reveals a right-skewed distribution, indicating that the majority of alternatives exhibit relatively low standard deviation in their rankings—suggesting stable performance across methods. However, a notable tail toward higher values points to a subset of alternatives whose rankings fluctuate significantly depending on the method and weighting scheme used. These unstable candidates highlight the sensitivity of spatial MCDM to methodological variations and underscore the necessity of incorporating consensus-based approaches to filter out inconsistent locations.

From the initial pool of 4795 candidate polygons, the top 25 alternatives were selected based on this dual criterion. These locations not only scored favourably across all MCDM methods but also demonstrated resilience against variations in the decision-making approach. Fig. 5 presents a heatmap visualization of these 25 alternatives, highlighting their performance across all nine ranking configurations. Certain alternatives consistently ranked high under both expert-informed and data-driven weightings, showing that these sites have balanced characteristics across all criteria.

Fig. 6 illustrates the degree of overlap among the top 50 ranked alternatives derived from different combinations of MCDM methods and weighting strategies. The results reveal notable methodological convergence in certain configurations. For example, Entropy MOORA and Hybrid MOORA share 48 common alternatives, while FAHP TOPSIS and Hybrid TOPSIS exhibit a similarly high intersection count of 45, reflecting strong alignment under shared or complementary weighting schemes. On the other hand, the lowest overlap is observed between Entropy TOPSIS and FAHP VIKOR (only 12 common alternatives), highlighting the contrasting decision logic of data-driven and expert-based compromise methods. These patterns suggest that while some method-weight combinations yield robust and consistent rankings, others—particularly those incorporating Fuzzy logic or compromise-based mechanisms like VIKOR—contribute valuable variability, thereby enriching the decision-making process with alternative yet rational prioritizations.

For clarity, the principal relationships among the nine MCDM configurations are summarized in Table 5. This table combines the Spearman rank correlations (Fig. 3) and Top 50 intersection counts (Fig. 6), illustrating the consistency or divergence between weighting–ranking pairs. High-consistency pairs, such as Entropy–Hybrid TOPSIS ($\rho = 0.97$; 88 %), confirm that Hybrid weighting minimally affects the outcome, while the lower correlation and overlap observed between FAHP TOPSIS and Entropy VIKOR ($\rho = 0.56$; 26 %) highlight

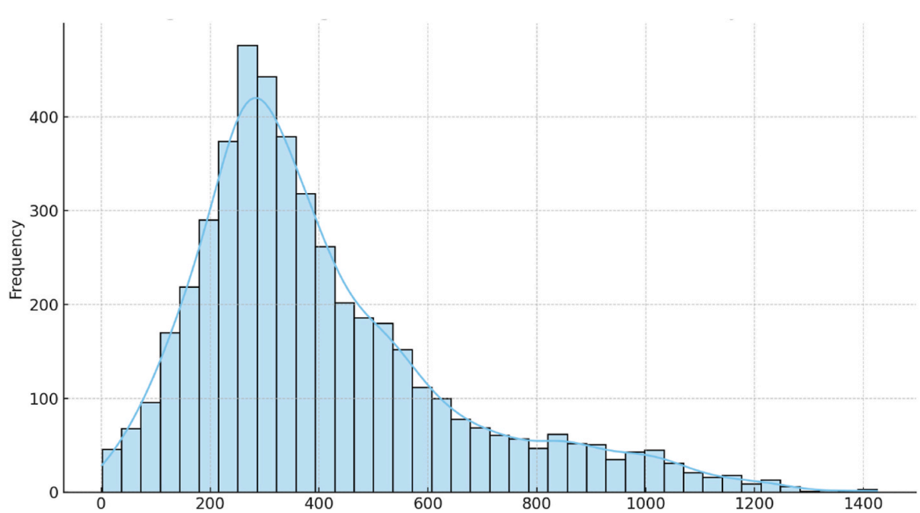

Fig. 4. Distribution of consensus rank standard deviations across all 4,795 alternatives.

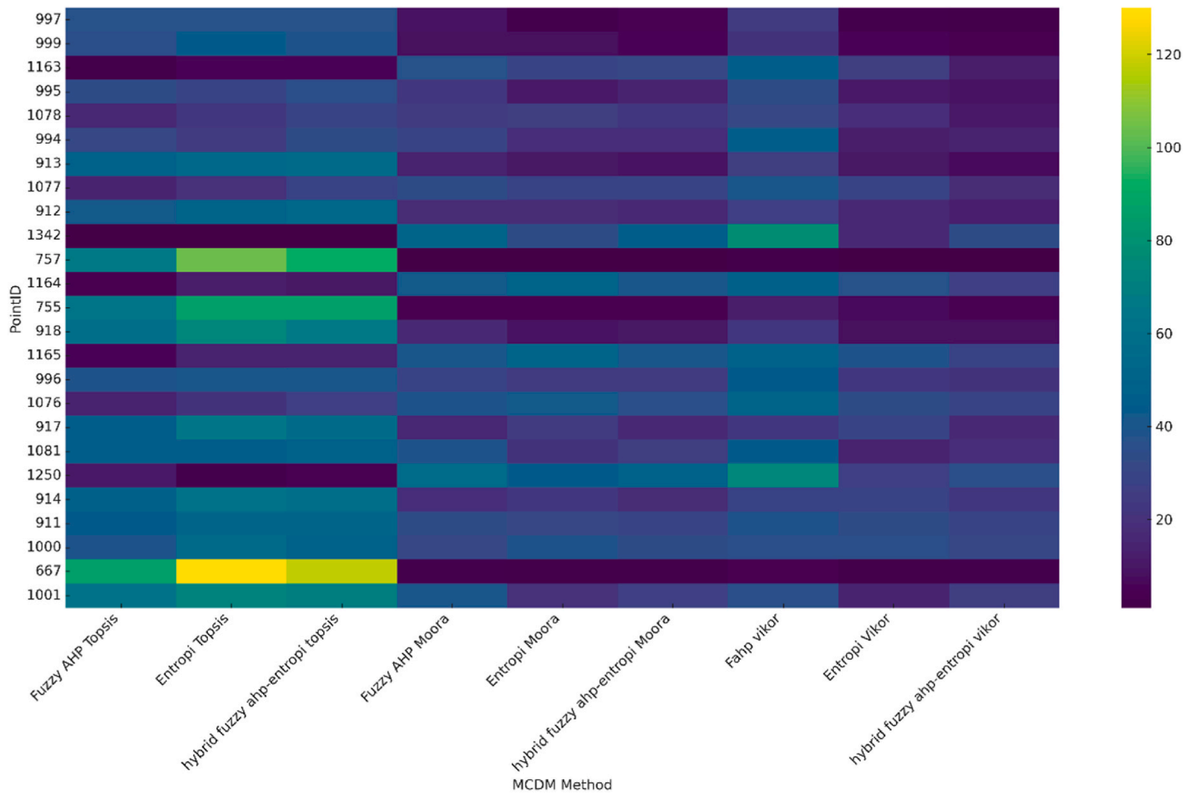

Fig. 5. Heatmap of the top 25 most suitable and stable candidate locations based on average ranks.

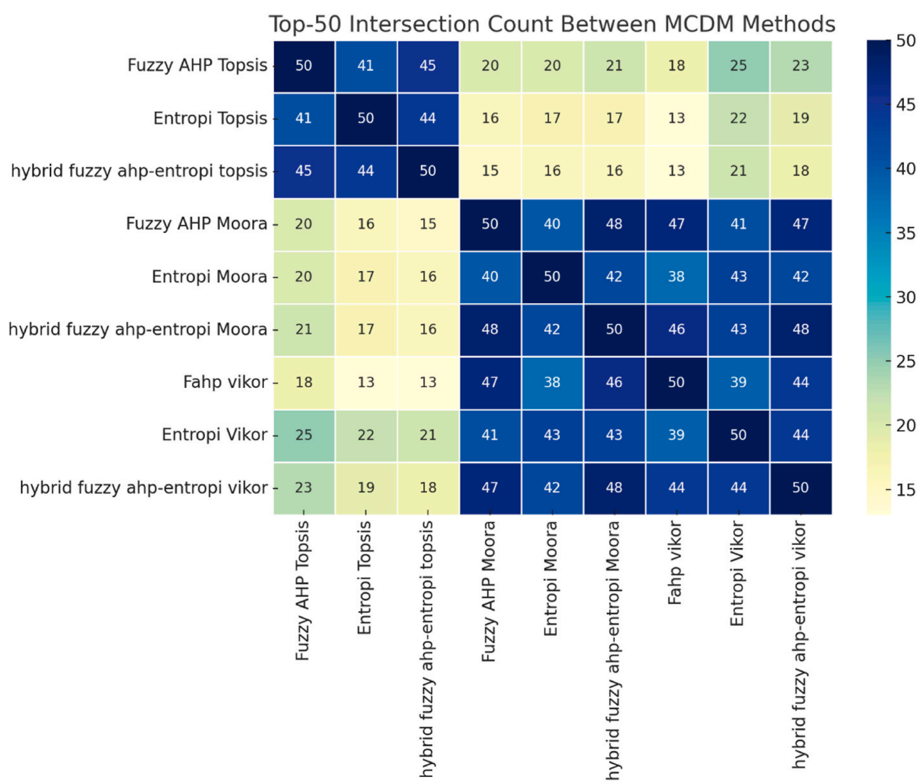

Fig. 6. Heatmap of top 50 intersection counts between different MCDM methods and weighting strategies.

the distinct compromise logic of VIKOR. Overall, the summarized results provide a compact yet comprehensive view of methodological stability across the applied MCDM approaches.

This comparative evidence reveals that objective (Entropy) and hybrid configurations produce nearly identical results, confirming the low bias and high robustness of the data-driven weighting. In contrast,

Table 5
Summary of consistency patterns across weighting and ranking approaches.

Similarity level	Method pair	Avg. ρ	Top 50 Overlap	One-line takeaway
High	Entropy – Hybrid (TOPSIS)	0.97	44/50 (88 %)	Hybridizing weights hardly alters TOPSIS; almost identical rankings.
High	FAHP – Entropy (MOORA)	0.92–0.99	40/50 (80 %)	MOORA yields highly consistent results across subjective and objective weights.
Moderate	FAHP – Entropy (TOPSIS)	0.78	41/50 (82 %)	Similar ranking logic with different weighting schemes.
Moderate	FAHP – Hybrid (MOORA)	0.97	38/50 (76 %)	Acceptable variation: Hybrid weighting slightly smooths expert bias.
Low–Moderate	FAHP – Entropy (VIKOR)	0.68	39/50 (78 %)	Partial consistency: compromise effects start to appear.
Low	FAHP – Entropy (TOPSIS vs VIKOR)	0.56	13/50 (26 %)	Strong divergence between distance-based and compromise-based logics.

FAHP-based schemes exhibit greater variability, reflecting expert-specific subjectivity and the influence of human judgment. Overall, the Hybrid approach demonstrates the most stable and balanced performance, effectively bridging the objectivity of Entropy and the contextual insight of FAHP.

3.2. Comparison of weighting approaches

Each MCDM method was implemented under three distinct weighting strategies: Entropy-based (objective), FAHP-based (subjective expert-driven), and Hybrid (a combination of Entropy and FAHP). The weighting strategies capture different balances between expert opinion and data-driven evidence, which helps test how stable and sensitive the rankings are.

Comparing results across these approaches shows how much the choice of weighting method can affect site selection, while also ensuring that both data variability and expert input are considered. Figs. 7–9 display the spatial distribution of the top-ranked sites produced by VIKOR, TOPSIS, and MOORA under three weighting options: Entropy, FAHP, and the Hybrid method. Each map provides insight into how weighting schemes influence the geographic prioritization of optimal locations for green hydrogen production.

Fig. 7 focuses on VIKOR results. The Entropy- and Hybrid-weighted configurations yield relatively similar spatial clusters, while the FAHP-weighted VIKOR highlights distinct regions, particularly emphasizing a northwestern cluster that is less prominent in the other two. This divergence underscores VIKOR's sensitivity to expert-derived weights and its capacity to reveal alternative spatial patterns.

Fig. 8 presents the results for the TOPSIS method. All three configurations—Entropy (a), FAHP (b), and Hybrid (c)—demonstrate a strong spatial consistency, with high-suitability areas consistently concentrated in the central part of the study region. Compared to VIKOR, the TOPSIS method exhibits less sensitivity to the chosen weighting strategy, particularly under Entropy and Hybrid conditions, suggesting that TOPSIS outcomes are more closely aligned with data-driven indicators.

Fig. 9 displays the spatial results of the MOORA method under the same weighting schemes. Similar to TOPSIS, MOORA rankings show minimal variation between weighting strategies. The Entropy-based and Hybrid-weighted MOORA results are nearly identical, indicating methodological redundancy. Although the FAHP configuration introduces slight variation, it does not significantly alter the spatial focus of high-ranking alternatives.

Entropy weights, derived from the intrinsic variability of criterion values, tended to emphasize criteria with high information dispersion. This led to more centralized and compact clusters of top-ranked sites. In contrast, FAHP weights incorporated expert judgment, resulting in more spatially diverse and dispersed suitability zones. The Hybrid approach yielded intermediate behavior, aligning more closely with Entropy-based outcomes when expert consensus was weak, and with FAHP results when expert agreement was strong.

Quantitative comparisons of top-ranked alternatives confirmed that Entropy and Hybrid configurations shared the highest number of common locations, while FAHP-based rankings—especially with VIKOR—-produced the most distinct prioritizations. The findings make clear that the weighting approach plays a decisive role in spatial MCDM applications. Entropy ensures consistency and reproducibility, while FAHP brings diversity by incorporating expert input. To avoid relying too heavily on any single method, a consensus ranking was created by averaging the ranks of all candidate sites across the nine combinations of methods and weighting schemes. These consensus scores act as a balanced indicator, blending objective data variability with expert judgment.

This consensus ranking enabled the identification of alternatives that consistently performed well across all configurations, reflecting a high degree of methodological agreement. Locations with low average ranks and minimal rank standard deviation were considered not only suitable but also resilient to methodological variation, making them highly reliable for strategic planning. As seen in Fig. 10a, these stable locations cluster in the central zone of the study area, around Bandırma. In contrast, Fig. 10b highlights unstable alternatives—those whose ranks fluctuate significantly across methods—most of which appear in peripheral southern regions, such as Edremit and Ayvalık. These sites may present higher uncertainty due to conflicting prioritization across methods.

This analysis also serves as a quantitative performance evaluation of the consensus ranking, as it directly relates ranking stability and deviation metrics to measurable site characteristics and underlying spatial factors. A quantitative assessment of ranking stability revealed that consistency across methods was closely linked to the physical and infrastructural characteristics of candidate sites. Stable locations, exhibiting low average ranking deviation (≈180), generally featured

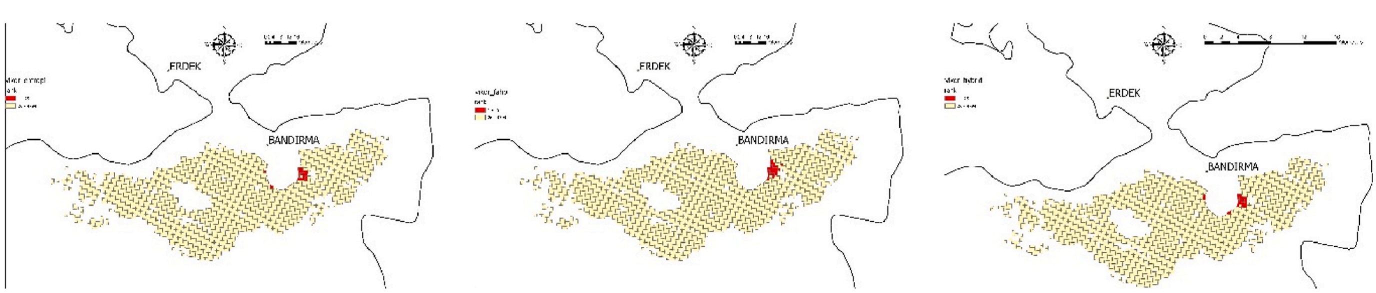

Fig. 7. Spatial distribution on GIS of top-ranked alternatives using the VIKOR method under three weighting strategies.

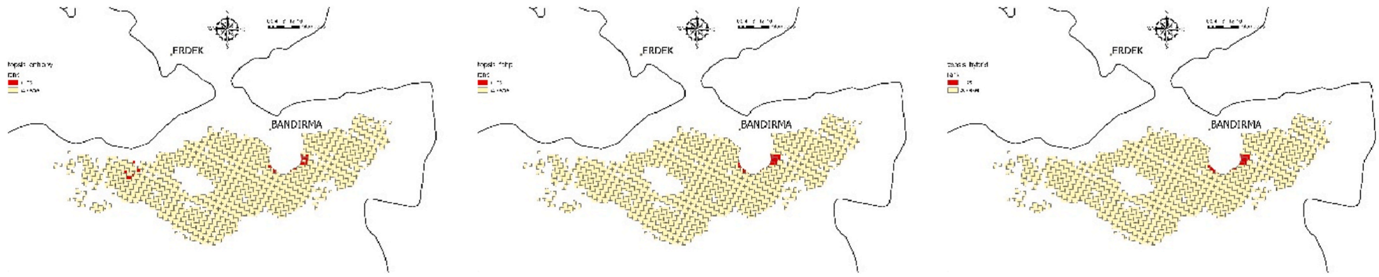

Fig. 8. Spatial distribution on GIS of top-ranked alternatives using the TOPSIS method under three weighting strategies.

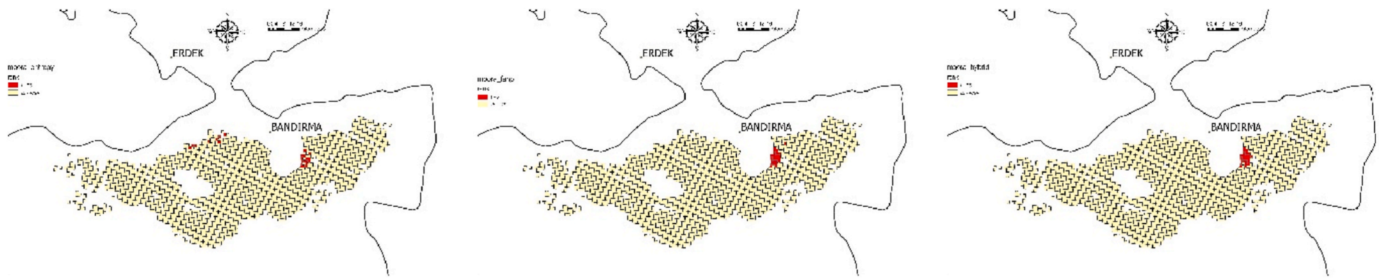

Fig. 9. Spatial distribution on GIS of top-ranked alternatives using the MOORA method under three weighting strategies.

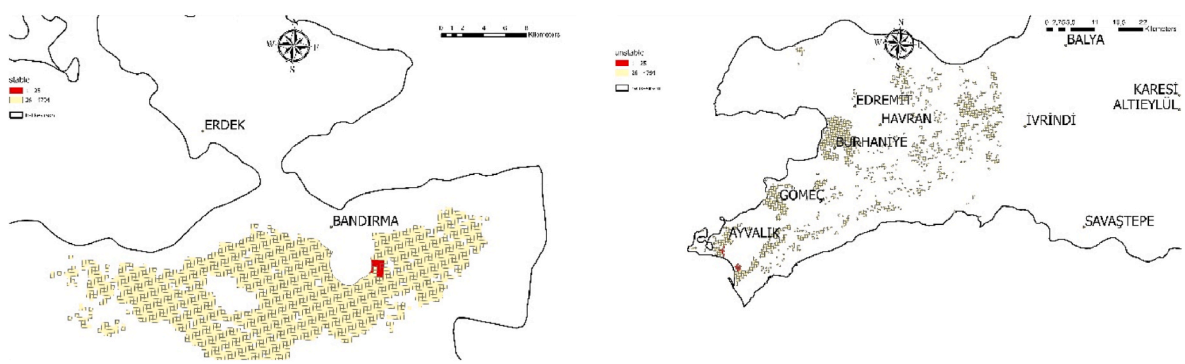

Fig. 10. **a)** The most stable alternatives with high consensus; **b)** The most unstable alternatives with high rank variability across methods.

gentle slopes below 5°, strong wind resources exceeding 6 m s^{-1}, and proximity (within 10 km) to transmission lines or organized industrial zones. These factors provided inherent advantages that remained valid under all weighting–ranking combinations. In contrast, unstable sites—with ranking deviations exceeding 700—were typically situated on steeper terrain, farther from energy and transport infrastructure, and characterized by weaker renewable potential. Even small changes in weighting therefore caused pronounced shifts in their relative priority. Overall, the results indicate that topographic smoothness and infrastructure accessibility act as stabilizing forces in spatial MCDM analyses, whereas remoteness and terrain complexity amplify ranking sensitivity across methods.

Fig. 11 presents the top-ranked locations identified through consensus ranking, overlaid onto a high-resolution satellite basemap of the Bandırma region. The black-outlined grid cells represent the most consistently preferred alternatives, determined by averaging the ranks from all nine MCDM configurations (three methods × three weighting strategies). These locations were selected not only for their high overall suitability but also for their robustness, demonstrated by low standard deviation across rankings.

Spatially, the preferred locations exhibit a strong concentration immediately south of the urban core of Bandırma, near the Bandırma Organized Industrial Zone (OSB), Bandırma Port, and major transportation infrastructure including the regional highway and railway connections. This placement indicates a favourable alignment with logistic, industrial, and infrastructural criteria—factors that frequently emerged as dominant across multiple decision-making strategies.

Additionally, the selected sites lie within a relatively flat and undeveloped area, reducing the risk of topographical or land use conflicts. Their distance from dense urban residential zones also minimizes potential environmental and social constraints, such as land acquisition difficulties or community opposition. From a planning perspective, the spatial clustering of optimal cells facilitates the creation of a contiguous development footprint, which is advantageous for economies of scale in infrastructure deployment.

Fig. 11 shows satellite imagery that confirms the consensus results. The most suitable sites are mainly located just south of Bandırma's industrial and port area, while other potential clusters appear further north along the Gönen corridor. This pattern indicates that Bandırma remains the primary focus, but alternative locations also exist within its broader surroundings. The visibility of ports, industrial facilities, and available open land makes the Bandırma cluster especially compelling, while the supplementary western and eastern alternatives indicate potential pathways for future expansion. These findings are also consistent with international hydrogen siting studies: Pinto et al. demonstrated that including export logistics criteria altered site rankings in North

Fig. 11. Top-ranked locations derived from consensus ranking overlaid on satellite basemap.

Africa, while studies in India and China emphasized the decisive role of grid and port access [50–52]. In this context, the results suggest that the Southern Marmara region holds both domestic and export-oriented potential for green hydrogen development. While this qualitative correspondence with CBAM-related objectives is noteworthy, it should be viewed as a supportive observation. Overall, the alignment between model outputs and existing industrial geography highlights the value of spatial validation and consensus-based analysis for strategic energy planning. The top sites stand out not only in quantitative rankings but also in terms of practical feasibility, giving confidence that these locations can play a key role in future initiatives such as green hydrogen production and clean energy hub development in Southern Marmara. Although the present case study focuses on Balıkesir Province, the methodological framework—combining GIS-based spatial analysis, hybrid weighting, and multi-model MCDM evaluation—is fully transferable. With context-specific data and locally relevant criteria, the same procedure can be applied to other regions or countries to support green hydrogen infrastructure planning under different policy and resource conditions.

4. Conclusion

This study developed and applied a consensus-based GIS–MCDM framework to identify optimal green-hydrogen production sites in Balıkesir Province, Türkiye. The integration of TOPSIS, MOORA, and VIKOR under Entropy, FAHP, and Hybrid weighting generated nine distinct scenarios, whose consensus ranking revealed a highly stable cluster south of Bandırma. These top-ranked zones coincide with Bandırma's organized industrial area, port, and transport corridor—confirming their quantitative superiority in suitability (average normalized score >0.85) and validating the siting of Türkiye's first Hydrogen Valley. Additional promising alternatives were detected along the Gönen corridor, suggesting further expansion potential toward the northwest.

Beyond methodological robustness, the results carry direct policy relevance. The spatial patterns identified here delineate priority zones that can guide Türkiye's National Hydrogen Roadmap, particularly in defining renewable-based industrial clusters, pipeline alignments, and coastal export terminals. The concentration of high-suitability areas around Bandırma underscores the region's readiness to serve as a hydrogen export gateway connecting Anatolia to European markets via the Southern Marmara logistics network. This geographic alignment provides practical evidence for developing CBAM-compliant hydrogen corridors, where certified low-carbon hydrogen could be produced and shipped through existing port infrastructure to EU demand centers.

The study also highlights how transparent, data-driven site-selection methods can support evidence-based planning under Türkiye's 2053 Net Zero Vision. By integrating technical (renewable potential and slope), infrastructural (grid, gas, and road proximity), and logistic (port and industrial access) criteria, the proposed framework offers a replicable analytical foundation for regional energy master plans. Applied nationwide, it can assist decision-makers in prioritizing investment zones, minimizing land-use conflicts, and enhancing the competitiveness of Türkiye's emerging hydrogen economy.

Overall, this research demonstrates that combining GIS-based spatial analysis with multi-model MCDM and consensus evaluation not only ensures methodological transparency but also bridges the gap between spatial analytics and strategic policymaking. The findings thus provide a quantitative, map-based input to the implementation of national hydrogen strategies and CBAM-aligned clean-energy export corridors in Türkiye and comparable regions.

CRediT authorship contribution statement

Metin Gül: Writing – review & editing, Visualization, Software, Methodology, Data curation, Conceptualization. **Ersin Akyüz:** Writing – review & editing, Validation, Supervision, Funding acquisition, Conceptualization.

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.

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